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The Application of Big Data Analytics in Supply Planning

Makmur[1], Maria Theresa Viega[2], Gunawan Wang[3]
Information Systems Management Department, *BINUS Graduate Program – Master of Information Systems*
Bina Nusantara University, Jakarta, Indonesia, 11480.
[1]makmur.a@binus.ac.id, [2]maria.viega001@binus.ac.id, [3]gwang@binus.edu.

ABSTRACT

Big Data (BD) refers to the ability to proccess data with following characteristic: velocity, variety, and volume. Analytics include the ability to get different point of view from data by manipulating the data using statistics, mathematics, economics, simulations, optimizations, or other techniques that will enhance decision making of business organizations. BD is led by the widespread use of digital technologies in companies in various sectors, including Fast-moving consumer goods (FMCG) company. The amount of data produced and communicated in is piled up everyday. Data in database include items sold, store inventory, and warehouse inventory of retail partner for specific stock keeping units (SKUs) produced by the manufacturer. These records called Point-of-Sale (POS) data. In modern days dynamic consumer markets, supply chains need to be value driven and consumer oriented. Demand planning allows supply chain members to focus on the consumer and create optimal value.

Key words: Fresh Food, Retail, Distribution center, Supply chain analysis, Product availability, Point-of-sale, Big data, Predictive analysis, Bullwhip effect

1.INTRODUCTION

A. The need for understanding customer demand

This study addresses a key opportunity in today's supply chain of FMCG companies: how to effectively use large volume of demand data to improve overall supply performance. In particular this study focuses on the use of Point-of-Sale (POS) data to adjust production-planning schedule of one of FMCG company in Indonesia, which we will refer to PT. XYZ, tbk. We started this project by first interviewing the key stakeholders in PT. XYZ, tbk key divisions such as manufacturing, supply chain, inventory management, IT, demand planning, finance, sales and marketing. Once we understood their needs and expectations, we collected POS data on specific SKUs from three largest retailer customer. The intent was to find meaningful relationship between downstream demand and retailer orders. Using the two datasets we created a production plan and scheduling model that would emulate and improve on the current planning process of PT. XYZ, tbk; the objective, in fact, was to identify and quantify the added value of integrating POS data in the supply planning process.

B. Big data and the era of digital for supply chain to work with

Supply chains generate big data. Big Supply-chain analytics turn that data into real insight. The explosive impact of e-commerce on traditional brick and mortar retailers is just one notable example of the data-driven revolution that is sweeping many industries and business functions today. Few companies, however, have been able to apply to the same degree the "big analytics" techniques that could transform the way the define and manage their supply chains.

The full impact of big data in the supply chain is restrained by two major challenges. First, there is a lack of capabilities. Supply chain managers even those with a high degree of technical skill have little or no experience with the data analysis techniques used by data scientists. As a result, they often lack the vision to see what might be possible with big data analytics. Second, most companies lack a structured process to explore, evaluate and capture big data opportunities in their supply chains.

C. Big supply-chain analytics

Big supply chain analytics uses data and quantitative methods to improve decision making for all activities across the supply chain. In particular, it does two new things. First, it expands the dataset for analysis beyond the traditional internal data held on Enterprise Resource Planning (ERP) and supply chain management (SCM) systems. Second, it applies powerful statistical methods to both new and existing data sources. This creates new insights that help improve supply chain decision-making, all the way from the improvement of front-line operations, to strategic choices, such as the selection of the right supply chain operating models.

D. Sales, Inventpry and Operations Planning

Typically, planning is already the most data-driven process in the supply chain, using a wide range of inputs from Enterprise Resource Planning (ERP) and SCM planning tools. There is now significant potential to truly redefine the planning process, however, using new internal and external data sources to make real-time demand and supply

We can think about managing inventory in a supply chain similar to the way electricity is managed: Storing electricity is expensive and difficult; power companies bring in additional consumers or start and stop plants to ensure a balanced power grid. Retailers now have the opportunity to use a similar approach. Visibility of point-of-sale (POS) data, inventory data, and production volumes can be analyzed in real time to identify mismatches between supply and demand. These can then drive actions, like price changes, the timing of promotions or the addition of new lines, to realign things.

Retailer can also use new data sources to improve planning processes and their demand-sensing capabilities. For example, PT. XYZ has developed data intensive forecasting methods now deployed into retailing where 130,000 SKUs and 200 influencing variables generate 150,000,000 probability distributions every day. This has dramatically increased forecast accuracy; enabled a better view of the company's logistics capacity needs; and reduced obsolescence, inventory levels, and stockouts.

Having truly mastered big-data forecasting, the next level of sophistication is to start actively shaping demand. Leading online retailers, for example, use big data analytics, inventory data, and forecasting to change the products recommended to customers. This effectively steers demand towards items that are available to stock.

E. PT. XYZ, tbk Background: Current Planning Process

In order to distribute high quality fresh products to consumers, the planning process for the availability of production capacity, the planning process for the availability of material requirements, the production process and the distribution planning process must be integrated to ensure the product can be available on time, because if there is a planning error from one of these processes then it will delay the availability of fresh products in stores.

In retail stores, the determination of product demand cannot be determined directly because consumers do not make orders but buy what is available on retail store shelves, so the actual sales data from Point-of-Sale (POS) is used as a basis for determining needs. In this case, when out-of-stock occurs, the product demand data becomes less than the actual needs, so the quantitative accuracy of the demand forecasting model depends on the quality of the historical sales data. Uncertainty about product demand stems from two problems [16] overstocking and understocking. Uncertain product demand caused by overstocking result in insufficient shelf space in stores, price reductions and expired products. Uncertain product demand resulting from understocking lead to out-of-stock, low customer confidence and brand damage which in long run will lead to loss of brand loyalty and brand trust. In the worst case, the company loses market share and ultimately has to close. The process of forecasting demand by calculating the actual product demand by stores and SKUs level as one of the influential factors in the forecasting model will improve the accuracy of demand forecasting. Apart from this, if the retail store is in a tourist area, the effect of the uncertainty on product needs will have a profound effect. To overcome this in the process of forecasting demand, some companies use quantitative / statistical methods, while others use qualitative / judgmental methods.

The process of planning the availability of production capacity and planning for the availability of raw material needs requires information on sales volume targets per SKU/ month conducted in Sales and Operation Planning (S&OP) meetings based on Annual Sales Targets involving representatives from the Sales, Marketing, supply chain, PP, IC, and production departments. The results of this S&OP meeting are a guideline for Inventory Control (IC) to prepare material requirements and warehouse area availability by working with the Purchasing department to determine lead-time and negotiate raw material prices. All of these processes are carried out to ensure raw material readiness and production capacity for the following month.

However, due to the relatively short shelf life of the fresh product, the Sales department carries out a daily or weekly forecasting process per store and SKUs by referring to the monthly sales volume target that has been discussed in the S&OP meeting which is included with the promotion plan from the marketing department for the next 1-3 months. The process of forecasting daily and weekly order's forecast is inputted by the sales team into the system two days before the scheduled delivery. The results of forecasting daily and weekly demand are guidelines for the IC (Inventory Control), PP (Production Planning), Production and supply chain for fresh product delivery needs for the next two to nine days.

F. Problem Statement and Scope of Project

The basis of the process of forecasting daily and weekly requests is from POS data from modern retail stores spread throughout Indonesia, around 28,000 stores. This POS data is provided by few accounts in Indonesia and can be downloaded from their private portal which is carried out every three days to seven days in the form of CSV files (comma-separated values) and stored in the computers of each regional sales personnel. The data is processed using the Microsoft Excel application.

However, due to the skill, method and formulation of demand forecasting carried out by each regional sales personnel based on their observations, logic and judgment, the accuracy of daily / weekly demand forecasting is relatively low, resulting in high sales returns due to overstocking or loss of sales (Loss of Sales) due to product unavailability in stores (out-of-stock / understocking).

PT . XYZ, tbk has at its disposal a vast amount of retailer POS data as it collects demand signals from retailers on a daily basis. The key question was how to extract value from those demand signals by directly affecting the manufacturing production schedule and cycles. The scope was intentionally narrowed to a particular SKU to test the usability and added value of POS data. The initial list of more than 40 SKUs was narrowed down to a key list of four SKUs to be most representative of the production platform selected for this research. Despite the nature of POS, the main focus of the PT. XYZ, tbk was not to produce a new forecasting technique or to change the current demand planning process. On the other hand, the emphasis was to produce a methodology and a framework to justify and prove the validity of the use of POS data for adjusting the upstream manufacturing planning process. To illustrate the value of POS data, we focused on the impact of our model on two key relevant manufacturing costs: change over costs and inventory holding costs. We therefore focused on how POS data integration in the supply planning process could produce direct benefits for those costs while maintaining the item fill rate target.

G. Hypothesis: Expecting and Managing the Bullwhip Effect

Our expectation is that by analyzing POS data, then PT XYZ, tbk can better understand the reasons behind the behavior of the retailer orders and eventually have a better visibility on the very downstream segment of the supply chain. Our main hypothesis is that as the customer orders are driven by inventory policy of the retailer, PT. XYZ, tbk should face a bullwhip effect when it comes to generating a forecast and production planning schedule against the customer orders. Consequently, we are expecting to see a POS data historical pattern exhibiting a degree of volatility lower than the historical demand pattern of retailer orders to manufacturer. We therefore tested this hypothesis to see if we could encounter a bullwhip effect, quantify it and take advantage of it by better planning for the production schedule. Figure 1 illustrates bullwhip effect.

According to [9], 'the bullwhip effect is the amplification of demand variability from a downstream site to an upstream site'. Very often, companies attempt to forecast demand by gathering a suitable amount of raw materials and resources needed in order to satisfy customer demand in a professional and timely way. However, while going up the supply chain from consumer demand to raw material suppliers, variations can often be amplified, causing issues with time, cost and inventory in supply chain management. The bullwhip effect leads to tremendous supply chain inefficiencies that include undue inventory investment, misguided capacity plans, poor transport plans and missed production schedules [9]. Reference [11] suggest that the excess inventory within the supply chain results in capital costs, handling and storage cost and cost of risk. In recognition of these costs and drawbacks associated with poor demand forecasts, it is therefore necessary to seek ways to improve the effectiveness of the demand planning task. 'The value of collaborative demand and supply planning between partners can be understood through improved operational, financial benefits, process and relationship benefits' [7].

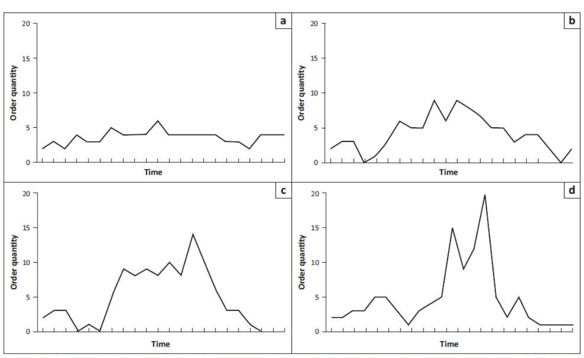
The causes of the bullwhip effect such as Order batching, Price fluctuations, Demand information, Lack of communication, Free return policies.

The negative impact of the bullwhip effect can prove costly to any company. So as to maintain a manageable and useful inventory, businesses usually work very hard. However, the variables that cause the bullwhip effect can lead companies to have either an excess or lack of inventory which can both be unfavorable for different reasons. Overstated orders based on misguided forecasts lead to incorrect inventory levels. Meanwhile a surplus of inventory could prove costly to the company and if consumer demand does not increase, it could result in wasted resources. Moreover, insufficient inventory can lead to poor customer relations due to unfulfilled orders and unavailable products. Such mistakes can seriously affect the goodwill and profitability of a company.

There is some way in order to minimize the bullwhip effect, such as: Improved communication, better forecasts, eliminate delays, Reduce size of orders & good customer service.

The existence of the bullwhip effect in fact could lead to two different usages of POS data:

- Better prediction of customer order, thus planning for the bullwhip
- Better prediction of future POS therefore reducing the bullwhip



Source: Lee, H.L., Padmanabhan, V. & Whang, S., 2004, 'Information distortion in a supply chain: The bullwhip effect', *Management Science*, 50(12 supplement), 1875–1888. https://doi.org/10.1287/mnsc.1040.0266

Figure 1: Bullwhip effect – Increased variability of orders up the supply chain. (a) Consumer sales, (b) retailer's order to manufacturer, (c) wholesaler's orders to manufacturer and (d) manufacturer's order to supplier.

H. Project Goal and Approach in Building the Model

The main goal of the project was therefore to share a model that could be used to provide a framework and a methodology in leveraging POS data and capturing their value on the production planning process. We first built a conversion rate by observing and measuring the POS data relationship with the customer orders. This rate would convert a set of observed POS data into a projected set of customer orders by injecting the noise of the bullwhip effect into the downstream sales signals. This conversion allowed us to integrate the POS data in a production planning model that was built to recreate the current scheduling environment. We designed an optimization problem, which in the literature is referred as a multi-period production planning linier program. Through the model, we solved for the optimal production scheduling of the SKUs by minimizing holding and change over costs while keeping a target item fill rate. We then compared the results of the optimization with two other versions of the model where we simulated two different environments: a modelling of the as is process and a modeling of an optimal integrated supply chain. The final results showed the potential gains of integrating POS data in the production planning process and helped define a framework on how to spot opportunities in leveraging POS data depending on the characteristic of the individual SKU.

2.LITERATURE REVIEW

I. Introduction

Point-of-sale data can substantially improve the degree of a supply chain's visibility. Latest reincarnation of this hype is being associated with "BIG DATA". [9] contends that the more visible the demand, the better the chance of accurate demand forecasts. POS data are comprised of the information that is collected at the point where a product is bought by the end-consumer and allows the measurement of demand in the last part of the supply chain, more specifically, the amount of product that the consumer buys [18]. POS data are available to supply chain members either directly from the retailers themselves or in syndicated data from syndicated data vendors like AC Nielsen and Information Resource Inc. who are third parties in these information transactions [18]. In order for POS data to be used to create real value, one must prove the benefits outweigh the costs and convince internal business units and external trade partners to support the gathering and use of it. Demand planners use different data sets to determine forecasts: these could be previous shipments from the manufacturer's warehouse or distribution center to the retailer; orders placed by customers (retailers); or POS data. Of all these forms of data, POS data are the closest representative of the true consumer consumption of a product as these suffer minimal distortion caused by consumer-level promotions and discounts [15]. POS data have the following attributes that deem them the most valuable form of data in demand planning:

- Improve forecast accuracy [12].
- Enhance the implementation of collaborative strategies [5].
- These are the best reflection of demand [21].
- These are free from inventory decisions [12].

J. BDBA for Inventory Planning

Managing process and operationals activities to fulfill demand and deal with variance of demand and process is the main element in supply chain management. Reaching a match between demand and process capacity is often blocked by process variation and demand variability. Accurate demand forecasting, capability to translate forecast into capacity requirements, and suppy chain operations capable of meeting anticipated demands are required in order to achieve effective capacity planning. So it can be concluded that demand planning is critical to supply chain operation planning[3].

Business organizations are piling a huge number of datasets within database continuously includes historic demand and forecasting data and POS data for each SKU. Supply and demand fluctuations is still giving impact on ideal inventory level.

As a part of BDBA, Supply Chain Analytic (SCA) supports organizations in handling the most complex retail, wholesale, and multi-channel challenges in inventory management by designing modern inventory optimization needed[10]. SCA can also help organization by predicting accurately inventory needs and responsive to changing customer demands, utilizing statistical forecasting techinques[10], as well as to reducing inventory cost[20]. SCA assist organization to get a whole view at inventory levels accross suplly chain and also helps in decisions related to safety stock optimizations.

K. Past: Lack of POS data and Poor Collection Efforts

The ability for manufacturers to start collecting POS data is a recent innovation in the supply chain planning process. As [3] correctly points out the lack of POS data in the past forced companies to produce a forecast and demand planning based merely on shipment data out of the factory on a monthly basis. This type of information available at the most upstream echelon of the supply chain is far from the truth in predicting the actual product consumption of the end customers. According to [14] forecast accuracy has historically remained flat as many suppliers have not been focusing in what he refers as a “consumer-centric approach”. Despite gaining visibility of POS data from the retailers, many companies did not have the capacity at their system level to absorb such volume of raw data and therefore they were not able in the past to leverage them. In addition, they were not comfortable using them as they were getting just a fraction of the total volume of sales. According to the author it could be a weakness to use POS data just as a set of extra data points without fully integrating them into the planning process.

Reference [5] also highlights the difficulty in the past of collecting POS data, which was primarily due to the lack of today’s technology in effectively collecting such data, as well as the high number of retailers that populated the market few decades ago.

L. Present: Methods of POS Collection and Different Contents

Although the notion of whether to use POS data to improve supply chain operations is generally supported, the actual implementation of integrating POS data into the supply chain is still in its infancy. Companies are still defining the benefits of POS while at the same time appropriating the cost, time, and effort of collecting, analyzing and using the data. Reference [15] explains that POS implementation requires a companywide IT system integration and also the buy-in from each department to participate and use the data.

The advance of technology and the consolidation of retailers in few big players has significantly reduced the cost of collecting POS data today, according to [5]. Not only is POS data now shared more easily and effectively between the retailer and the manufacturer, but the proliferation of third parties, such as Nielsen, have contributed to a vast collection of data which is then sold across the different stakeholders of the supply chains. POS data are usually collected at the SKU level where each product has a unique universal product code (UPC). A typical query from a POS database would be able to generate information such as price, inventory level in store, inventory level at distribution center and the number of units sold. In some cases, it is possible to identify with flags those items on promotion.

Reference [21] provides a general overview of the different type of POS data currently available. In some cases, POS data come from proprietary software available at the retailer level. This type of data that is usually used by the retailer to generate the forecast. POS data can also be generated through the transmission of EDI documents. [21] points out the difficulties in managing such data as the lack of normalization can further complicate how manufactures can collect and interpret the data for their purposes. There can also be issues in the transmission of the data itself and the lack of standardization across the different retailers. Finally, In some case, POS data are transmitter via excel spreadsheet. In this latter case the accuracy and the usability of the data is more compromised that the ones generated through EDI transmission.

M. Future: Usage and Benefits for a Perfect Visibility in the Supply Chain

Reference [1] examine quantitative differences in forecast accuracy between using POS and order history. The study conducted on grocery stores, revealed results that were both expected and counter to conventional thought. It concluded that POS data can generate forecasts that were more accurate more frequently, although order history was producing a more accurate forecast, the magnitude of the benefits was much higher. This result signifies that human input (order history) still generates a tremendous value but the amount of skilled human resources cannot be compared to the ever-available POS data. The resulting action is to use human input to generate forecasts that have a major impact on the business.

N. Conclusion

There is no doubt that POS data represent a powerful tool in the hands of supply chain planners. The collection of such data has been considerably improved over the last decades and its volume has become a significant portion of the overall available information for a manufacturer to make intelligent decisions about its supply chain planning. It is now time to leverage this increased visibility in the supply chain which provides more insights into the end-consumer’s frequency and willingness to buy a given product. We explore the different POS data available in PT. XYZ, tbk and provides a unique methodology on how integrating the data in the current production planning process with the final objective of reducing costs while keeping a target service level. The model we proposed takes inspiration from the lessons learned in the literature to design a new integrated customer driven supply demand process.

3.METHODOLOGY

This section explores how we interpreted and used the data to design and apply both quantitative and qualitative analysis. The core objective was to find meaningful relationships between POS data and customer ordering behavior to optimally adjust production planning and scheduling.

O. Data Collection

Two types of data were collected: Retailer data and manufacturing data. Retailer data is provided by the retailer on a daily basis to PT. XYZ, tbk under csv format. This type of data provides all relevant sale in sales out, return and inventory information for each store and SKU. Manufacturing data is generated by PT. XYZ, tbk and maintained on a daily or weekly basis depending on the type of data. This dataset provides all information regarding inventory positioning, customer order and production scheduling for each SKU.

P. Retailer Data: Point-of-Sale (POS)

The Retailer data we decided to focus on came from a large customer of PT. XYZ, tbk. We focused on four key SKUs, which we refer to SKU1, SKU2, SKU3 and SKU4 and which are produced in one specific manufacturing. The other reason we choose those SKUs as the most representative sample of all products produced in the same category. In fact, those items represent the largest share of retailer orders and for this reason were selected as the most suitable for our analysis. We filtered the data to have enough days to cover a significant period of sales. This resulted in collecting daily POS data points from July 1st, 2018 through December 31st, 2019. The POS data included:

- *Store ID*: A unique identifier for the retail store where POS originated.
- *Price look-up codes (PLU)*: A unique identifier for the SKU according to the retailer product coding
- *Date*: Date of POS transactions
- *Stock*: The daily inventory position of each SKU1n each store & their warehouse
- *Sell In*: The number of units received for a given SKU1n a given day
- *Sell Out*: The number of units sold for a given SKU1n a given day
- *Return*: The number of units returned to Distribution Center for a given SKU1n a given day.

Q. Manufacturer Data: Production Planning, Inventory and Customer Orders

We were able to collect a dataset that covered the same period as the retailer data, from July 1st, 2018 through December 31st, 2019. Manufacturing data included:

- Production Quantity: The quantity produced per SKU per week per plant and measured in cases
- Inventory Quantity: The total inventory on hand in Distribution Centers (DCs) per SKU and per month

Customer Orders: The orders placed by the retailer on a weekly basis disaggregated by SKU

R. Analytic Techniques in SCA

Analytic technique is the core for the success of supply chain strategy implementation and day to day operations in each business organization. In this case, we use quantitative approaches, which is make a future prediction from collected past data. Moving Average method to predict the demand using obtained POS data for each SKU available. Moving average method is easy to use and still relevant to be used in forecasting inventory using existing sales data in a dynamic retail environment [22] to extract insightful patterns and statistics. The available historical data will be used to forecast the future ideal number of goods stock.

With the characteristic that Big data has (variety, volume, velocity), modeling and simultation in SCA offers more deep analysis and processing and also new methods fow problem simulations with large amount of data [7].

S. Exploratory Data Analysis

We merged the two datasets in order to visualize all key parameter

- Customer Orders (manufacturer data)
- Production Planning (manufacturer data)
- POS Sales (retailer data)
- Store Inventory (retailer data)
- Warehouse Inventory (retailer data)

We visualized the variables to identify any potential correlations between POS sales and Customer Orders, and between POS sale and inventory position of the retailer. The assumption behind our observations was that the retailer had a significantly stable periodic inventory policy that could be used to better predict the future Customer Orders when looking at the combination of the POS sales and their inventory level. We tested several approaches to develop an explanatory model that could better project the Customer Orders by determining the reorder point of the retailer and the ratio between the POS sales and its target inventory level. For those SKUs where we could find a stable relationship between POS sales and Customer Order, we analyzed their corresponding distribution functions to better understand and predict their behavior. We then executed a normality test for both Customer Orders and POS sales datasets. Our hypothesis was that a normal distribution with a similar trend level could be applicable for both types of demand data; the only difference between the two distributions would therefore be the degree of volatility as we were expecting to see a bullwhip effect. With this hypothesis confirmed, we could then find a way to convert the POS sale into projected Customer Orders and finally solve for the adjusted production planning and scheduling. The projection of Customer Order was a necessary step in the optimization problem as it allowed us to project the expected beginning and end of inventory for every week, thus determining the expected stock at the end of the production freeze period.

T. Defining the Decision Variables

We set decision variables for quantities to be produced in four consecutive weeks and starting 3
weeks ahead of the present week. The linear programming solved simultaneously for all products
involved and assigned a given quantity for each SKU1n each of the four consecutive weeks. Below
are the decision variables:

- X_{ij}: number of units of product i produced in week j
- Y_{ij}: binary variable which is equal to 1 if product i is produced in week j and equal to 0 if product i is not produced in week j

U. Defining the Objective Function

The objective is to minimize all relevant costs as per below notation:

$$Minimize \quad \sum_{i=1}^{n}\sum_{j=1}^{m} S_{ij} * Y_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{m} H_{ij} * B_{ij}$$

where S_{ij} is the changeover costs for a product i in week j and H_{ij} is the holding cost for a product i in week j; B_{ij} represents the average inventory (average between beginning and end of inventory) for product i in week j. The notation for B_{ji} is described in below formula:

$$B_{ij} = B_{ij-1} + X_{ij} - D_{ij}$$

D_{ij} is the expected demand of the retailer for product i in week j as derived by our projection from observing the POS sale of weeks J-1, J-2, J-3 and J-4

V. Defining the Constraints

The capacity constraint is given by below definition:

$$Subject\ to\ \sum_{i=1}^{n} X_{ij} \leq C_j \qquad for\ j = 1,2, \ldots m\ and\ i = 1,2, \ldots n;$$

Where C_{ij} is the maximum capacity of production quantity for all products in week j. The target inventory constraint is given by below definition:

$$Subject\ to\ B_{ij} \geq T_{ij} \qquad for\ j = 1,2, \ldots m\ and\ i = 1,2, \ldots n;$$

Where the target days of supply (T) of inventory is based in the following calculation:

$$T = \frac{F_{L+R} + RMSE * k * \sqrt{L+R}}{F_R} * 7$$

Where:

- F_{L+R} is the forecasted demand over period L (lead-time) and period R (review period).
- RMSE is the squared root of the average of the forecast errors. In our model we used a value proportional to the standard deviation of the Customer Orders for each SKU
- k is the safety factor derived from a given service level. This is in turn derived from an Item Fill Rate of 98.5 %, which was kept constant across the model.

The big M method helps define the constraint for the changeover costs such that only when the solution is proposing to produce product i in week j we then charged those costs to product i in week j. Below the corresponding notation:

$$X_{ij} \leq M * Y_{ij} \qquad for\ j = 1,2, \ldots m\ and\ i = 1,2, \ldots n;$$

Finally, we completed the linear programming by adding the non-negativity and binary constraint of the decision variables such that:

$$X_{ij} \geq 0$$
$$Y_{ij} \in \{0,1\}$$

W. Production Planning Model: Converting, Projecting and Optimizing

We designed a multi-period production planning linear program to optimize production scheduling for a given set of weeks by minimizing the total relevant costs subject to capacity and inventory target constraints. The total relevant costs to minimize were the following:

- *Holding costs*: the inventory costs per unit per week calculated against the average inventory of the week (average between beginning and end of inventory)
- *Changeover costs*: the costs of converting the production line from running one product to another for a given week. In our model we are simplifying the sequence of the multiproduct production scheduling, thus assuming a changeover cost anytime we decided to produce a specific SKU (similar to setup costs).

The production constraints were the following:

- *Capacity constraints*: less than the maximum capacity of the single production line
- *Demand constraints*: the end of the inventory for each week must be greater than the target days of supply (inventory target)

To simplify the model, we assumed that all SKUs were being produced in the same plant so that in order to simplify the model we assumed that all SKUs were being produced in the same plant so that the linear programming had to assign each SKU production quantity to each week for a unique factory location. To set up the model dynamically and to replicate what happened during the same period covered by the datasets; we first prepared a total of 82 periods (82 weeks) from July 1st 2018 through December 31th, 2019. For each week we set up the following objects:

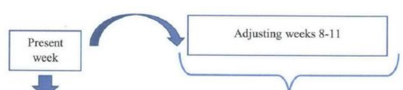
- *Beginning of inventory*: inventory at the end of previous week
- *Production planning*: the quantity produced for a given week
- *Customer Orders*: the orders received from the retailer
- *End of inventory*: beginning of the inventory plus the production quantity minus the Customer Order

Below is a table illustrating the logic of the production planning framework:.

	Weeks	1	2	...	26
SKU1	*Beginning of Inventory*	A	D	...	XX
	Production Planning	B	E	...	YY
	Customer Orders	C	F	...	ZZ
	End of Inventory	A+B-C=D	D+E-F=G	...	XX+YY-ZZ

Figure 2: Production Planning Framework

We then included a new row for the new production planning that would constitute the decision variables for the linear programming. The new production planning would represent how much to produce for a total of four consecutive weeks as solved by the optimization problem. We established a freeze period of production planning for three consecutive weeks. This implied that if we were in week 5, we could only adjust from week 8 onwards, as the production scheduling for weeks 5, 6 and 7 could not be modified. We then projected the new adjusted planning over a four-week horizon to allow the optimization model to run the linear programming for a minimum significant number of periods. This would imply that if we were in week 5, we could only adjust production planning for weeks 8,9,10 and 11. Figure 3 below shows an illustration of the model:



	Weeks	5	6	7	8	9	10	11
SKU1	*Beginning of Inventory*	347,953	298,705	268,033	241,681	207,121	336,340	329,977
	Production Planning	0	0	0	0	167,235	21,718	0
	New Planning	*Freeze*	*Freeze*	*Freeze*	0	0	46,607	0
	Customer Orders	49,248	30,672	26,352	34,560	38,016	28,080	30,240
	End of Inventory	298,705	268,033	241,681	207,121	336,340	329,977	299,737

Figure 3: Production Planning Rolling Schedule

The next step was to calculate a new set of expected Customer Orders from week 5 to week 11 (if we keep using the example period above). The new set of expected Customer Orders would trigger a new set of projected beginning and end of inventory which would in turn trigger a new set of production quantities for weeks 8-11 (as solved by the model). To reproduce such a set of expected Customer Orders, we converted the POS sales data into future retailer orders. In our example, where the current week is week 5, we therefore looked at the actual POS sales data for weeks 1 to 4 to develop a conversion formula that would translate the demand signals from the store into valuable information (expected Customer Orders) and anticipate the future behavior of the retailer. The conversion rate would result from the normal distribution test we described above. Once we calculated the new expected Customer Orders for weeks 5 to 11, we were able to generate the new expected inventory at the end of week 7; thus, we would be ready to run our new production scheduling for weeks 8-11.

X. Test 1: Orders-to-Orders Scenario

In the Orders-to-Orders scenario, we used the same logic and rules described above for the design of the linear programming model. In order to emulate the current planning scenario of our sponsor company, we simply did not apply the POS conversion rate to generate projected Customer Orders. We only applied the moving average of the previous four weeks for any given current period we were going to analyze. We chose not to use the actual forecast values of our sponsor company as we deliberately simplified the forecasting approach to use the same simple method across all models. This would better isolate the effect of the POS integration in the model when compared with our baseline. The projected Customer Order was therefore derived from equation below:

$$C_t = Average\ (C_{t-4};\ C_{t-3}; C_{t-2;} C_{t-1};)$$

where C_t would be the projected Customer Order for the period t when the optimization was run. This projected value would be then applied for seven consecutive weeks to allow production planning of four weeks beyond the freeze period of three weeks. All other parameters of the model were kept the same including the target DOS inventory level.

Y. Test 2: POS-to-POS Scenario

Two changes in the logic of our original model were required to design the POS-to-POS scenario. The first was to modify the conversion rate used to project the future orders. As in this scenario, we removed the retailer orders; the only projection we made were the purchases made by the final consumers in the retail stores. Therefore, the formula for the projected orders is as follows:

$$POS_t = Average(POS_{t-4}; POS_{t-3}; POS_{t-2}; POS_{t-1};)$$

where POS_t are the projected POS sales for the current period t that would be used to project final consumer demand over the following seven weeks. We therefore kept the observation of the POS sales for the previous four weeks, but we did not use any conversion rate to inject the noise of the Customer Orders. This is why we just used the moving average of the four observations. The second change we had to implement from the original model was to modify the target DOS. The DOS target inventory is a function, among other things, of the RMSE. The RMSE in turn is a function of the standard deviation of the historical data used to generate the statistical forecast. Because we remove the Customer Orders of the retailer in this test, we should expect an historical demand of POS sales that is less volatile than the historical demand of Customer Orders. This would require a revision of the DOS before running our optimization model. We first quantified the relationship between the RMSE and the bullwhip effect and then re-calculated the target DOS for each SKU based on the new expected RMSE while keeping the item fill rate at 98.5%.

4.DATA ANALYSIS AND RESULTS: ILLUSTRATION AND DISCUSSION

In this section we present and discuss the analysis and results of our methodology, described in the previous chapter. We start by stating and proving our initial hypothesis of expecting a bullwhip effect between Customer Orders and POS sales. Then we plot the manufacturer and retailer datasets together for each of the four SKUs to illustrate any potential patterns and relationships between the two datasets that could confirm the bullwhip. This initial analysis will be therefore presented at SKU level. Once we identify the SKUs with significant relationships between POS sale and Customer Orders, we then present the results of the multi-period production planning model using this relationship to adjust the master production scheduling. The results will show the differences in costs when comparing the model with the two test environments.

Z. Simulating the Bullwhip Effect in a Periodic Review Inventory Policy

Our main hypothesis is that by plotting Customer Orders and POS sales data on the same chart we would be able to easily spot the bullwhip effect even before we could measure it and prove its existence statistical tests. In the long term, the trend of POS sales and Customer Orders should be aligned. This long-run equilibrium between the two datasets labeled as "the inventory balance effect" [12]. The main difference between the two datasets, however, is the standard deviation, with the Customer Orders having a larger level of volatility than the POS sales. [13] quantify the bullwhip effect as the variance of the Customer Orders ("sell in") divided by the variance of the POS sales ("sell out"). The conclusion driven by the authors is that one of the drivers of the bullwhip effect is the demand forecast itself. In fact, the number of periods observed to produce the forecast is inversely correlated with the increase in the bullwhip: the higher the number of periods, the closer the standard deviation of POS sales with the standard deviation of Customer Orders. Another important factor is the lead-time, the increase of which affects the calculation of the safety stock, thus amplifying the bullwhip. Before observing the real data from the retailer, we re-created a similar environment whereby a retailer would use a periodic review inventory policy to replenish its inventory. We assumed that the retailer was reviewing its inventory level every week and was facing a lead-time of one week. We assumed a service level of 98% and that the retailer was using a moving average forecasting technique with an RMSE being a tenth of the observed values. Using those assumptions, we calculated the order-up-to point using below equation:

$$X = F_{L+R} + RMSE * k * \sqrt{L+R}$$

where:

- FL+R is the forecasted demand over period L (lead-time) and period R (review period). In our scenario therefore we are forecasting demand over a total of two weeks (L=l, R=1);
- RMSE is the forecast error

- k is the protecting factor corresponding to the normal Z value with probability of 98% (our service level target)
- L +R corresponds to the square root of the sum of lead-time and review period. In our case it is equal to the square root of 2.

We ran a Monte Carlo simulation of 10,000 iterations for a total of 52 weeks. The simulation was randomizing the demand for the products at retailer level assuming a normal distribution with a level of volatility similar to the POS data we observed. We wanted to calculate the expected value of two parameters: the ratio of variance of Customer Orders over the variance of POS sales and the ratio of the average of Customer Orders over the average of POS sales. We observed the following bullwhip effect:

- *Variance of Customer Orders/Variance of POS sales* = 588.73 units on average
- *Standard deviation of Customer Order/Standard Deviation of POS sales* = 752.33 units on average
- *Mean of Customer Orders/mean of POS sales* = 5,775.47 units on average

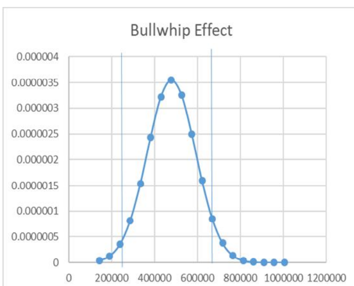


Figure 4: Normal Distribution Function of Bullwhip Effect

Figure 4 above shows that the 90% of the time the bullwhip was between 220,000 and 640,000 when measured in terms of variance of sell in over variance of sell out. The figure is plotting the normal distribution function of the bullwhip effect as resulted from the simulation runs. Figure 5 below plots the 82 weeks period where we can observe the differences in amplifications of the Customer Orders versus the POS sales.

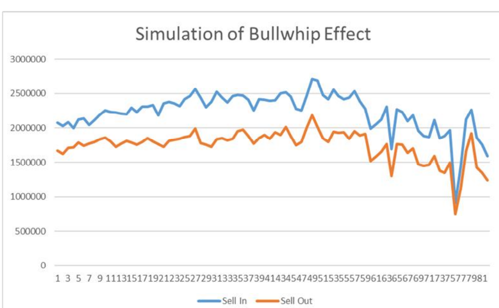


Figure 5: Customer Orders vs POS Sales in a Simulated Bullwhip Effect

The bullwhip effect measured above would be even larger if we increased the following parameters:

- Lead-time
- Service level
- Forecast error (inversely related to the number of observed periods used in the moving average)

The results confirm the existence of a bullwhip effect, based on our assumption on the existence of a periodic review policy, as well as the alignment of mean values between the two datasets. Now we are ready to explore the real data to see if we can observe the above behavior and use it to better predict the Customer Orders and eventually adjust the production planning.

AA. Analyzing SKU1

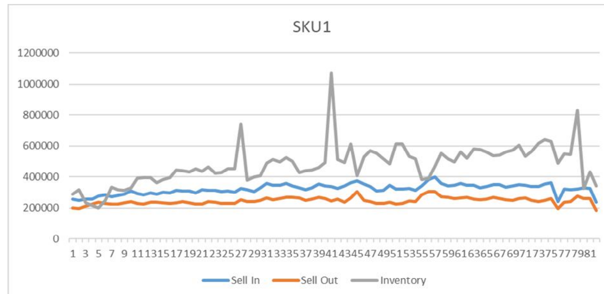


Figure 6:SKU1 Retailer and Manufacturer Data

To rule out the possibility that the difference in variances is random, we again performed the F-test. Table 1 below show the results of the test.

Variance	
Mean	479499.4024
Standard Error	12493.60958
Median	481219.5
Standard Deviation	113134.4465
Sample Variance	12799402991
Kurtosis	3.406749
Skewness	-1.164878359
Range	692428
Minimum	17
Maximum	692445
Sum	39318951
Count	82
Confidence Level(95.0%)	24858.36411

	Order	*POS Sales*
Mean	324079.2099	247369.5926
Variance	980132022	478835933.3
Observations	81	81
df	80	80
F	2.046905744	
P(F<=f) one-tail	0.000787647	
F Critical one-tail	1.447728084	

Figure 7:F-Test Statistic for Differences in Variances SKU1

At a first glance we can see that during the 82 weeks period the Customer Orders are not aligned with the POS sales as they are not following the same expected value in the long run. In other words, the mean values for the two datasets differ from each other. In fact, the average value for Customer Orders stands at 323,269 units while the mean of POS sales is 246,794 units. We also note that the customer inventory average is 478,360 units. If we calculate the ratio of customer inventory over the POS sales, we can observe that the retailer is keeping a stock 1.94 times larger than the weekly POS sales units with a coefficient of variation of 46.10%. This high level of volatility suggests that the retailer is not keeping a stable order-up-to point in its periodic review policy. However, we are not in a position to accept our hypothesis of the expected relationship between POS sales and Customer Orders, primarily because both datasets are not sharing the same expected level of mean demand. Therefore, we cannot use SKU1 data to better predict the Customer Orders and build on the new production planning model. There could be many reasons why we do not observe the expected pattern; any of those potential explanations could only be detected by engaging in a direct dialogue with the customer to understand its inventory policy. The fact that the retailer has been ordering on average a third of what was actually sold in the stores indicates that the retailer may have had a significantly high inventory level at the beginning of the observed period. This high level of stock may have been reviewed downward by the retailer to effectively mirror the actual sales in stores. This is why eventually the retailer ordered less then what was actually sold in the stores to reset its inventory level to a more accurate and lower target. It is difficult however to be sure of what actually happened by just looking at the data and laying out the key statistics. This sort of behavior illustrated by SKU1 as an alert to engage with the retailer in a more collaborative approach when it comes to understand the reasons behind the Customer Orders pattern.

BB. Analyzing SKU2

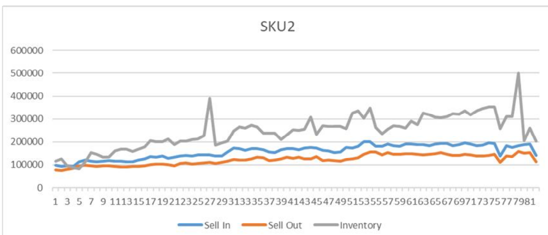


Figure 8:SKU2 Retailer and Manufacturer Data

The inventory level for the retailer is distributed with an average of 244,722 units. When we calculate the ratio of the retailer vis-a-vis the POS sales, we can observe that the inventory level stands at 1.99 weeks of equivalent POS sales with a coefficient of variation of 43.34%. We can therefore conclude that as with SKU1 the inventory policy of the retailer for SKU2 presents a relatively stable order-up-to point.

Contrary to what we observed with SKU1, however, SKU2 does present the behavior we expected to see when plotting Customer Orders with POS sales. In fact, we can observe how both Customer Orders and POS sales align with each other in the long run, with the Customer Orders fluctuating more than the POS sales do. If we isolate the two datasets in the chart, the expected behavior of the same trend and bullwhip effect are even more visible.

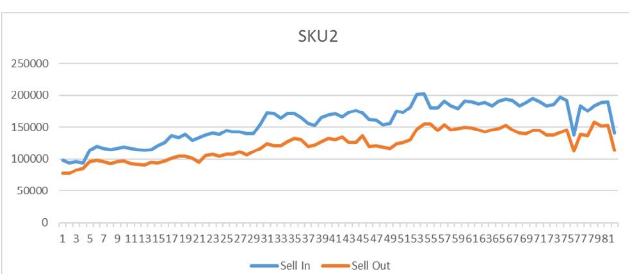


Figure 9: Bullwhip Effect on SKU2

The results confirm our observations. In fact, the average of Customer Orders stands at 158,227 units while the average of POS sales stands at 122,376 units. The two values are extremely close to each other, pointing towards the same direction of the results of our simulation where the two means align each other throughout the year. In addition, the data confirm the bullwhip effect. The ratio between the variance of the Customer Order with the variance of the POS sales stands at 0.09, while the ratio of the standard deviations stands at 3.46. To rule out the possibility that the ratio is randomly greater than 1, we run a F-test statistic to compare the variances of the two data samples. The null hypothesis is that the variance of Customer Orders is equal to the variance of the POS sale (the ratio is equal to 1) while the alternative hypothesis is that the variation of Customer Orders is greater than the variation of POS sales (one-tail test).

The P value is 0.002, suggesting that there is only a 0.2% chance that the variance of Customer Orders is larger than the variance of POS sales by chance. Therefore, we reject the null hypothesis. We can therefore consider SKU2 as a valid candidate for the design and implementation of the production planning model.

	Order	*POS Sales*
Mean	158227.4268	122376.2927
Variance	887727736.3	470264060.2
Observations	82	82
df	81	81
F	1.887721839	
P(F<=f) one-tail	0.00234941	
F Critical one-tail	1.444376055	

Figure 10:F Test Statistic for Differences in Variances SKU2

CC. Analyzing SKU3

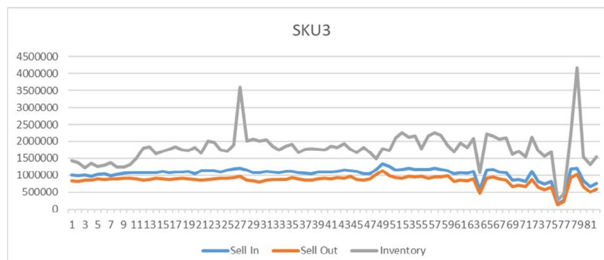


Figure 11:SKU3 Retailer and Manufacturer Data

To rule out the possibility that the difference in variances is random, we again performed the F-test as we did for SKU2. Figure 12 below show the results of the test.

	Order	*POS Sales*
Mean	1047691.659	850124.9756
Variance	34572245843	23239218674
Observations	82	82
df	81	81
F	1.487668167	
P(F<=f) one-tail	0.037854211	
F Critical one-tail	1.444376055	

Figure 12:F-Test Statistic for Differences in Variances SKU3

At a first glance, the POS sales and Customer Orders align with each other only at the very end of the 64 weeks period while for a large portion of the dataset they seem to have a different level of trend. In fact, the mean value for POS sales is 850,124 units while the mean of Customer Orders stands at 1,047,691 units. The average customer inventory is 1,786,628 units, which correspond to 2.10 weeks of POS sales. The coefficient of variation for the target inventory is 26.96%, suggesting a less stable inventory policy than the ones observed with the previous SKUs. Those results are affected among other things by the two visible peaks in week 27 and 79 respectively. The peak of POS sales in this case is suggesting the presence of an outlier likely produced by a promotional event. We could split the POS sales dataset in two segments: one from week 1 to week 27 and the other covering week 28 to week 82. If we proceed with this split, we can observe that the average of POS sales of the first segment (the outlier) stands at 889,049 units which corresponds to 1.06 times the average of the second segment of the dataset. This indicates the presence of a promotional effect on the product. Even with the split of data, however, the POS sales and Customer Orders still present significant differences between each other when comparing the respective mean values. For those reasons we are not considering SKU3 as a valid candidate for our production planning model. As explained above for SKU1, SKU3 visualization should be a flag to further investigate the inventory policy of the retailer. In this case we also observe a significant peak that would suggest a promotional event. However, it is not easy to detect a defined relationship between POS sales and retailer orders as the retailer built up inventory prior the start of the promotion and eventually reacted after two weeks of the POS peak with a corresponding peak of orders. This is an isolated element of relationship between POS and Customer Orders and there is therefore not enough evidence to detect a pattern between the two sets. Like for SKU1, a lack of a clear relationship between POS and Customer Orders should be investigated in order to understand the reasons behind such inventory policy.

DD. Analyzing SKU4

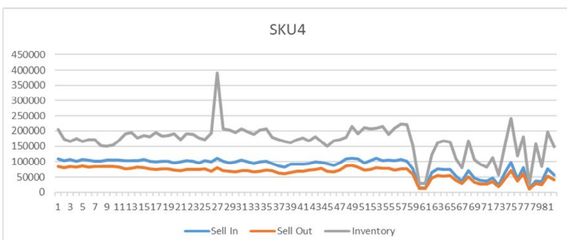


Figure 13:SKU4 Retailer and Manufacturer Data

The customer inventory average stands at 169,146 units, which correspond to 2.61 weeks of POS sales with a standard deviation of 29.62%. This shows that the inventory policy is less stable. The chart seems to suggest, as we observed for SKU2, that we have the expected relationship between POS sales and Customer Orders. The average value of POS sales is 64,588 units while the mean of Customer Orders is 86,591 units. The two values are close enough to support our hypothesis that the two datasets share the same trend. When it comes to the ratio between the two variances, we do observe the expected bullwhip effect. In fact, the variance of Customer Orders over the variance of POS sales stands at 3.73, while the ratio between the standard deviations stands at 1.93. The bullwhip effect for SKU4 is therefore more evident than the one observed for SKU2. The effect is even more visible when we isolate the two datasets as per figure 14 below.

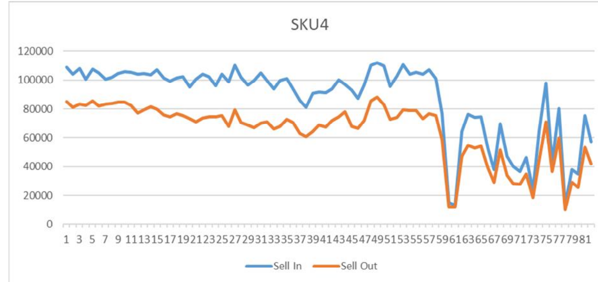


Figure 14: Bullwhip Effect on SKU4

To rule out the possibility that the difference in variances is random, we again performed the F-test as we did for SKU2. Figure 15 below show the results of the test.

	Order	*POS Sales*
Mean	86591.69512	64588.70732
Variance	681084914.7	392015685
Observations	82	82
df	81	81
F	1.737391999	
P(F<=f) one-tail	0.006896047	
F Critical one-tail	1.444376055	

Figure 15:F-Test Statistic for Differences in Variances SKU4

We reject the null hypothesis as the P value is close to 0 and therefore confirms that the variance of Customer Orders is significantly larger than the variance of the POS sales. The results shown above confirm that SKU4 follows the behavior we have simulated with a periodic review policy. It is therefore the second valid candidate together with SKU2 to introduce and develop the production planning model.

5.CONCLUSION: THE VALUE OF POS DATA

This article used SCA as one of the applications in BDBA. The technique used in this paper is Moving average method as a part of quantitative approach in predicting future inventory level based on historical POS Data collected. BDBA introduce advanced predictive insights into the strategy of execution process and will be complementing strategic management in a company.

We showed evidence that collecting POS data from the retailer and integrating them into the planning process of a FMCG company can generate business value. By studying the relationship between POS sales and Customer Orders at each SKU level, a manufacturing company can leverage such a relationship and better plan for the bullwhip effect to come. This in turn would improve the accuracy of the overall supply planning process as the company could use POS sales to adjust the production planning schedule by better projecting Customer Orders. As a result, savings in relevant supply chain costs, such as holding and change over costs, may materialize.

At the same time, this study shows a higher degree of value in using POS data when it comes to using historical POS to better predict future POS sales and adjust the production planning accordingly. In fact, in a business environment where the manufacturer could collaborate with the retailer, the bullwhip effect could be significantly reduced from the equation. The manufacturer could observe the POS data and leverage them to influence the ordering process of the retailer in order to reduce the bullwhip effect generated by the additional inventory planning layer. In the case of using POS to better project future demand, a reduction of the safety stock, thus a reduction of the overall target inventory level. This in turn would minimize production planning schedule constraints and meet the same item fill rate with minimum costs.

To capitalize on those benefits, manufacturers would need to both invest in collecting POS data from all their retailers and build better communication with them. Analyzing each SKUs, a necessary step to leverage the power of POS data, but it is not enough. A manufacturer should use the POS data to investigate and question the ordering behavior of the retailers and eventually involve them in a joint collaborative supply chain planning process.

As this study has shown, reconciling the Customer Orders with the POS sales could help the manufacturer visualize and quantify the bullwhip effect. After this initial step, it will be clearer for the company which SKUs to use in integrating POS data into the planning process with or without the retailer. The higher the bullwhip effect, the higher the value of integrating POS data in the supply planning process. The more misaligned the Customer Orders with POS sales, the higher the need for the manufacturer to understand the inventory policy of the retailer and eventually influence it. The manufacturer can therefore use the insights of our model to prompt a segmentation of its products based on the degree of bullwhip effect and the level of misalignment between POS sales and Customer Orders. This segmentation would help the company identify the products where POS data could bring the highest value and therefore push for a deeper investigation and understanding of the customer demand behavior.

However, there are some limitations to our model. The limited number of observed SKUs, as well as the limited number of observed days of POS data, require a further research on all other key products and retailers. Our model also takes as a main assumption that the manufacturing process only allows an adjustment of the production schedule after three weeks. It would therefore be relevant to analyze the effect of using POS data in our model when removing the three-week freeze period. In other words, it would be worthwhile investigating the power of POS data when a manufacturing company can adjust the production planning immediately the week after instead of waiting for two additional weeks. This further research could then evaluate if the costs incurred in designing a more flexible manufacturing and production schedule process would be offset by the savings produced by the POS data integration in the planning process.

Finally, the power of POS data can be leveraged to improve the planning and monitoring of promotional events, thereby involving other key stakeholders such as marketing, sales, and supply chain. This, along with the benefits for the production planning process, could trigger enormous benefits throughout the entire company's value chain.

POS data has still yet to show all of its potential value, but the methodology and approach described in this study as well as further suggested researches would help companies in unleashing the benefits hidden behind them. Companies who are able to integrate POS data into their demand and supply planning process could design more flexible and demand driven supply chains. Collecting, interpreting and integrating POS data is a must for any companies in the FMCG industry: it is the secret ingredient for a supply chain that meets the real demand and adapts quickly to customer behaviors changes.

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