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A MULTIPLE-PURPOSE SIMULATION-BASED INVENTORY OPTIMIZATION SYSTEM: APPLIED TO A LARGE DETERGENT COMPANY IN CHINA

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ABSTRACT

In this paper, we introduce a practical simulation system to analyze a real inventory system of a top 3 detergent manufacturer in China. The simulation system has been actively executed to support weekly inventory policy decision making since online. We detail how we simulate the client's finished product inventory at its manufacturing sites and warehouses. We concentrate on describing its structure, as well as its applications. We also demonstrate how to apply this simulation system to obtain an optimized policy to manage the stock keeping unit (SKU) level inventory through numeric experiments.

1 INTRODUCTION

Our client is a manufacturer that specializes in a great variety of detergent products, ranging from clothes to home care products, and from laundry detergents to hand sanitizer. In term of market share, it has been among the top 3 in China in recent years. The client maintains nearly 400 SKUs in its product line, which are manufactured in multiple in-house factories and distributed via several regional warehouses.

The client initialized the project with two main pain points. The first was that they had observed a high average inventory in the distribution network. The second was that their scheduler had noticed different inventory performances. Before the simulation model implementation, the inventory allocation between factory and regional warehouses were made by schedulers, who based their decisions heavily on their experience. Thus, the client demanded a tool that would help refine its inventory policy for different SKUs to reduce its inventory hold-up and at the same time maintain an acceptable out of stock risk.

To evaluate the merit of an inventory policy, a demand forecasting system of high accuracy has to be in place. We firstly developed a forecasting system that utilizes up to 4 year's historical sales data to predict the monthly SKU level demand 12 to 18 months into the future. We do admit that the forecasting accuracy will quickly deteriorate as it goes further into the future, but the demand forecast of 3 months ahead will still remain quite usable. The monthly demand forecast is decomposed to a daily forecast via empirical daily demand distributions derived from historical sales data. The forecasted demand can be further manually manipulated to be aligned with the pre-set weekly sales progress. The detailed explanation of demand forecasting is not provided here due to the focus of the current paper.

When analyzing the problem of our interest, if the relationships that compose the supply chain model are simple enough, it may be possible to obtain an analytical solution. However, most real-world systems are too complex to allow realistic models to be evaluated analytically. The complexity of the current inventory problem results deeply from multiple sources of uncertainty such as demand and lead time as well as the large operational scale. Moreover, the client would like the tool to be able to include details such as warehouse throughput and number of containers. Therefore, we decided to develop a large-scale simulation system with multiple uncertainties and operational details. The system could be used to evaluate the problem numerically and answer several important strategic and operational questions. A simulation system is employed so that we can use a computer to evaluate the problem numerically. Data are gathered in order to estimate the desired true characteristics of the inventory system.

We first provide a review of the related literature in section 2. Later, in section 3, the simulation system is described in details. In section 4, we summarize several application scenarios where the simulation system can be utilized to help achieve business objectives. In section 5, we conclude the paper.

2 LITERATURE REVIEW

Inventory management is critical in supply chain management. In the Fast Moving Consumer Goods (FMCG) sector, inventory cost generally accounts for up to 40% of the total logistical costs (Cachon and Terwiesch 2012). The goal of inventory management is to minimize the inventory holding cost and the related cost while maintaining acceptable customer service levels. There are two decisions at each stocking location in the supply chain network: when to order new items and what quantity to order. Due to the importance, inventory optimization has been widely investigated by using either the mathematical analytical model or the simulation-based optimization. Since the development of the economic order quantity (EOQ) formula, researchers have been actively concerned with the analysis and modeling of inventory systems under different operating parameters and modeling assumptions (Bottani et al. 2010; Cheng and Sethi 1999; Shen et al. 2003). However, the analytical models are highly abstracted ones with various restrictive assumptions that may not cover the required complexities for the real applications.

To address the drawbacks of the analytical models, simulation is often conducted. Simulation is a powerful computer-based tool that enables an easier decision making process via its ability to incorporate all the inherent internal and external uncertainties in complex real systems (Glover et al. 1999). However, simulation is not an optimization tool by itself. Simulation cannot find the best parameter configurations. Further decisions have to be made after obtaining the simulation results. Usually, a proper optimization algorithm is integrated into the simulation to optimize the parameters (Fu 2002). Numerous optimization approaches have been utilized in simulation-based inventory optimization, e.g., response surface methodology (Joines et al. 2000), ranking and selection (Kim and Nelson 2006), metaheuristics (Amodeo et al. 2009) including genetic algorithms (Köchel and Nieländer 2005), Particle Swarm Optimization (Varga et al. 2013), scatter search (Keskin et al. 2010), and a hybrid approach using Sample Average Approximation (SAA) technique combined with a cutting plane method and Ranking and Selection (R&S) procedure (Tsai and Zheng 2013). Köchel and Nieländer (2005) proposed a simulation optimization approach where a simulator is combined with an optimization algorithm (Genetic Algorithm) to optimize the multi-echelon inventory systems. Keskin et al. (2010) proposed a simulation-optimization approach for integrated sourcing and inventory decisions. In their paper, a discrete-event simulation model is built to evaluate the objective function that works in concert with a scatter search-based metaheuristic optimization approach to search the solution space. Schwartz et al. (2006) presented a simulation-based optimization framework using simultaneous perturbation stochastic approximation (SPSA) for inventory management in supply chains under conditions involving supply and demand uncertainty. Sezen and KitapÇi (2007) developed a sample spreadsheet simulation model for a single distribution channel facing various demand fluctuations (high, medium and low demand variance). Due to the easy implementation, this approach has potential value to the operational managers. Farasyn et al. (2008) also proposed spreadsheet models in helping Procter & Gamble (P&G) set inventory targets and they reported that the models contributed to inventory reductions of over $350 million and significant intangible benefits.

Though inventory management field has been extensively studied, the gaps between inventory management theory and practice still exist. Kumar et al. (2013) identified them through a critical examination of the emerging trends in the academic research and the practice in the FMCG industry. The simulation-based inventory management implemented at a detergent manufacturer in the paper will help bridge the gaps and advance the simulation-based inventory management in the FMCG industry.

3 SIMULATION SYSTEM

The simulation system is a standalone B/S (browser/server) tool with a user-friendly graphical interface, which runs on any operating system with an internet browser. In order to provide data to the system, one has to prepare a number of flat files in the Comma-Separated Values (CSV) format.

The simulation system is able to simulate the inventory model of a single SKU of interest or multiple SKUs at the same time. In theory, the system supports the simulation of all SKUs provided that sufficient computer memory is in place. The time duration of the simulation is user-specified. Our system allows the simulation to start from any specified date and end at the end of a selected month. Of course, the ending month has to be at least the month that the starting date belongs to.

For each SKU, the client specifies a supply chain setup, which describes how factories fulfill warehouses. In our client's case, each warehouse has one dedicated fulfillment factory. Moreover, for each SKU-Warehouse-Factory setup, the client specifies an inventory policy, which consists of three parameters, the number of days of *safety stock*, the *allocation frequency* and the *order frequency*.

The following relational diagram in Figure 1 depicts the supply chain system of our interest. It is essentially a two–echelon system with upstream manufacturing factories/factory warehouses, regional warehouses and downstream customer demands. User is allowed to define the supply chain system of his/her interest down to the SKU level, i.e., each SKU has a two-echelon supply chain network and no single supply chain network applies to all SKUs due to production line configuration in different factories.

We will introduce the system in Figure 1 in a bottom-up manner. The uncertain customer demand used in the simulation is generated based on a forecasting tool developed by us in the same project. The forecasting tool provides the function of generating the mean and standard deviation of the monthly demand of each SKU at each warehouse. The mean and standard deviation of the forecasted demand can either be imported to the simulation system directly or after being further adjusted by the user to reflect the change in the expectation of the future demand. The forecasting tool also generates the expected weekly progress of the demand fulfillment in each month, which can either be directly used in the simulation system or user-adjusted to reflect the change in expectations of future weekly progress.

For each SKU, with randomly generated demand, governed by a distribution learned from the forecasting tool, consuming the inventory, each regional warehouse needs to maintain an inventory control policy consisting of three key parameters, the *number of days of safety stock*, the *allocation frequency* and the *order frequency*. All the three parameters are described in days. The allocation frequency describes the number of days between two shipments from a factory to a warehouse, and the order frequency is the number of days between two consecutive orders from a warehouse to a factory.

Let's deviate a little to understand why days of supply (DoS) instead of units are used to control the inventory. Based on the prior demand pattern analysis, we found that the daily demand in a month is not anywhere near being uniform. The daily demand is consistently higher in some of the weekdays while lower in others. Towards the end of month, the daily demand possesses an increasing trend. The imbalanced pattern means that we could not use a consistent inventory control policy in terms of units. But in terms of days of supply, the inventory policy could be consistent for a long duration of time.

Whenever the inventory hits the point of safety stock plus order frequency, the system will place an order to the virtual factory warehouse to bring the days of inventory up to the sum of safety stock, order frequency and allocation frequency. The audience could view it as a (s, S) policy except that it uses days of supply to address the nature of imbalanced daily demand pattern in a month.

We mentioned the virtual factory warehouse because physically our client has multiple warehouses in each manufacturing site. But since the inventory is centrally controlled and the warehouses located in the same city possess similar cost structures, we group these warehouses as one virtual warehouse. For example, the warehouse leasing fee per square meters is comparable, and the shipping costs from a factory's different warehouses to a regional warehouse are the same. The lead time uncertainty from a virtual factory warehouse to a regional warehouse is characterized by an empirical distribution.

A virtual factory warehouse accepts product inflows from the corresponding factory. The inflow is determined by the production plan consisting of production dates and quantities, which are prepared by the user of the simulation system.

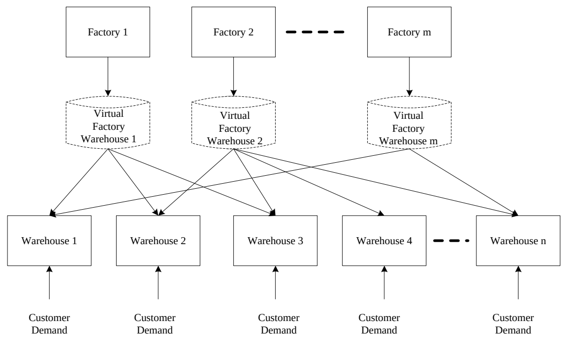

Figure 1: Supply chain setup.

After outlining the supply chain networks and key components, we would like to elaborate on the backend logic. The system we develop is a discrete event simulation system that runs by day. I start with explaining the simulation initialization, then describe what the events are and how they are processed, and finally introduce the system interface.

3.1 Simulation Initialization

In this step, the user has to prepare data files required by the simulation system. These files are required to be in the CSV format and fall into three different categories: master data, initial state data, and scenario-specific data. The master data are mostly unchanged or only periodically updated during the usage of this simulation tool, e.g. the SKU data. The initial state data define the initial state of the simulation system, e.g. the on-hand and pipeline inventory. The scenario-specific data describe the setup of a scenario.

All these parameters in the data files are considered tunable and can be manually configured per users' needs. We include Table 1 that best describes all the tunable parameters in this simulation system.

Table 1: Simulation tunable parameters.

Data Category	Tunable Parameter
Master Data	SKU Supply chain nodes and setup
Initial State Data	On-hand inventory Pipeline inventory Backlog inventory Transportation lead time distribution and cost
Scenario-Specific Data	Production plan Warehouse capacity, throughput and leasing price Inventory policy Forecasted demand Mean and standard deviation of monthly demand Weekly sales progress

3.2 Simulation Events

The simulation runs by day and processes the following events in sequence as shown in Figure 2.

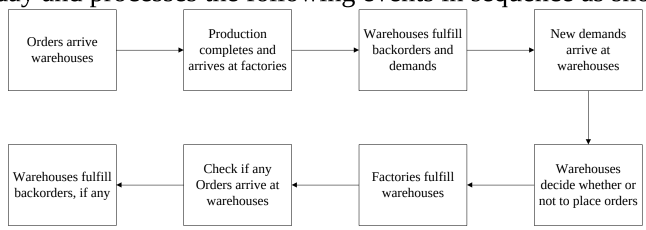

Figure 2: Simulation events processing sequence.

Each event is further explained below.

- Ordered finished products arrive at the warehouse.
- Production is completed and arrives at the visual inventory pools.
- Warehouses fulfill the backlogged demands, if any. If the inventory is sufficient, all the backlogged demands are fulfilled. Otherwise, the backlogged demands are partially fulfilled and the unfulfilled remain backlogged.
- New demands arrive at warehouses. If the inventory is sufficient, all the new demands are fulfilled. Otherwise, the new demands are partially fulfilled and the unfulfilled are backlogged.
- Check against the inventory policy if new orders should be issued to the virtual factory warehouse. If so, do it and do nothing otherwise.
- Virtual factory warehouses fulfill their own backlogged orders, if any, first. If the inventory is insufficient, the backlogged orders are partially fulfilled and the unfulfilled remain backlogged. The newly arrived orders, if any, will become backlogged. If the inventory is sufficient to fulfill the backlogged orders, the backlogs are fulfilled first. The newly arrived orders, if any, are fulfilled later. If the inventory is sufficient, all the new orders are fulfilled. Otherwise, the new orders are partially fulfilled and unfulfilled are backlogged.
- Check if there are any newly arrived finished products shipped from the factory warehouses.
- Warehouses fulfill their backlogged demands, if any. If the inventory is sufficient, all the backlogged demands are fulfilled. Otherwise, the backlogged demands are partially fulfilled and the unfulfilled remain backlogged.

3.3 Simulation Interface

The simulation system consists of three main interfaces, which correspond to the management and configuration of the three categories of data files. A three-level data input design is motivated by the change frequencies of the three data sets. The supply chain master data that contains chain nodes are where the client set up factories and regional warehouses which may last for years. The simulation initial states management contains the initialization data of a simulation such as the backorders, on-hand inventory and pipeline inventory at the beginning of the simulation. The Simulation scenario-specific data management is where users could play with the parameters such as the production plan, inventory control policy etc. as frequently as wanted. Remember that when a user sets up a scenario to simulate, he/she needs to refer to a particular initialization states configured in the second interface.

3.3.1 Supply Chain Master Data Management Interface

The user configures the supply chain nodes data, supply chain network setup data, and etc. via this interface. Note that the management of SKU data is under the demand forecasting system and are administrated by a superuser. The system provides the function of initializing a new version of the supply chain, which is characterized by the supply chain nodes and setup CSV files imported by the user. The use of CSV file gives users flexibility to define any supply chain network they are interested in. Users can set up a supply chain network that reflects the current practice or one that includes planned new factories and warehouses in the future. After a version of supply chain is created, it is shown in a list view along with all the other versions of supply chain that have been created. Users are given the function of modifying the data files that are associated with each supply chain version.

3.3.2 Simulation Initial States Management

The user manages the data that describe the initial status of the simulation via this interface. The user first selects the supply chain version that the starting date data will be associated with, sets the starting date and the ending month of the simulation and then import the data files. The interface will pop out a window for users to import CSV files such as initial on-hand inventory, initial pipeline inventory, initial backlog inventory, and transportation time distribution and cost. All created copies of initial status data are listed in a list view of the interface, where users are allowed to modify the imported data files.

3.3.3 Simulation Scenario-Specific Data Management

The user manages simulation scenario-specific data, initializes simulation runs and outputs simulation results via this interface. The interface pops out a window where a user creates scenarios and imports scenario-specific data files. After a scenario is defined and associated data are imported, it is shown in a list view along with all the previously created scenarios. The user manages these scenarios through this interface, where he/she can modify a scenario or run a scenario if all the required data are in place. After running a scenario, the results can be exported as Excel files or visually represented. The visual representation of the simulation results will be further discussed in more detail in the next section.

4 EXPERIMENT

In this section, we introduce five application scenarios of this inventory simulation system, co-defined with the client. Of course, as the business progresses, more business needs will emerge and the scalability and expandability of the simulation system is able to adapt to fulfill the new needs.

4.1 Application Scenario 1: Inventory Policy Optimization

The system provides a visual representation of the inventory performance of each SKU. Each SKU is represented as a node in a two-dimensional chart with the X-axis being the out of stock rate and the Y-axis the number of days of inventory. The chart is able to show the SKUs' monthly inventory performances at warehouse or nationwide level, and user is provided with a drop-down box to select the warehouse and simulation month that he/she is interested in. After running a simulation, the system averages the out of stock rate and number of days of inventory in each repetition for each SKU, at each warehouse and in each simulation month and generates inventory control scoreboard.

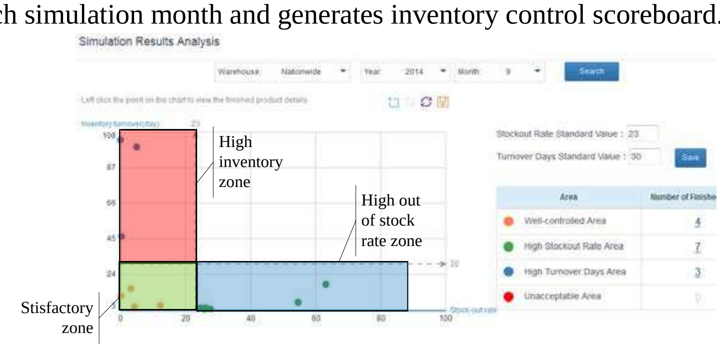

Figure 3: Inventory control scoreboard.

SKUs are spread in the first quadrant of the coordinate system and categorized into three zones as shown in Figure 3.

- High inventory zone: SKUs that fall in this zone are over stocked during the simulation and there are rooms for users to reconfigure the inventory policies to reduce the inventory levels while still maintaining low out of stock rates.
- High out of stock rate zone: SKUs that fall in this zone are facing shortages during the simulation. Users are expected to reconsider the inventory policies to reduce the out of stock rates of these SKUs.
- Satisfactory zone: SKUs that fall in this zone are considered to have healthy inventory performances. Users generally are not expected to worry about these SKUs.

The objective of application scenario 1 is to identify SKUs with unhealthy inventory performances and to modify the inventory polices to move these SKUs from either the high inventory zone or high out of stock rate zone to the satisfactory zone.

The following experiment illustrates how the simulation tool is used to adjust the inventory policy to move SKUs with low inventory performances to the satisfactory zone. We focus on one of the warehouses (warehouse 1) in this experiment and the same experiments can be applied to all the other warehouses as well. The simulation runs from September 23rd to November 30th.

Using the current inventory policy, the simulation returns a result that shows that there are two SKUs that have high inventory turnover days in the month of October. This implies that there is room to reduce the safety stock to reduce the inventory levels of these SKUs so as to reduce the inventory holding cost.

Figure 4: Inventory control scoreboard at warehouse 1.

The following are the detailed statistics of these two SKUs that have high inventory levels.

Table 2: Detailed statistics of SKUs with high inventory turnover days

SKU ID	SKU Description	Inventory Turnover Days	Stock Out Rate (%)	Percentage of the Entire Inventory at the warehouse (%)	Days of Safety Stock	Allocation Frequency	Order Frequency
10002380	AD006	41.68	0.00	9.52	31	9	1
10002383	AD009	59.17	2.00	2.59	23	9	7

Note that the numbers in the column ‘Percentage of the entire Inventory at the warehouse’ represent how important each SKU is in terms of inventory size at that warehouse. SKUs with large numbers in this column are those that require more attention. SKU 10002380 in this experiment requires most attention as it has a relatively high inventory turnover days and represents 9.52% of the entire inventory at the warehouse. The current inventory policy for this SKU sets the days of safety stock at 31 days. Users could reduce the days of safety stock of these troubled SKUs to move them into the satisfactory zone. Users could apply the trial and error to find the satisfactory days of safety stock for these SKUs.

After several simulation runs with different days of safety stock, users could come up with the refined inventory policies for these SKUs (shown in Figure 5). The statistics illustrated in Table 3 show that the inventory turnover days of these previous troubled SKUs are reduced and at the same time the stock out rates slightly increase but still are within the acceptable range.

Figure 5: Inventory control scoreboard at the same warehouse after inventory policy refinement.

Table 3: Detailed statistics of the previous troubled SKUs after inventory policy refinement.

SKU ID	SKU Description	Inventory Turnover Days	Stock Out Rate (%)	Percentage of the Entire Inventory at the warehouse(%)	Days of Safety Stock	Allocation Frequency	Order Frequency
10002380	AD006	29.43	5.00	6.60	15	9	1
10002383	AD009	35.85	5.00	1.64	12	9	7

For SKUs that fall in the high stock out rate zone, users can increase the days of safety stock for these SKUs in their inventory policy setups. Let's use an SKU 10002360 as an example. The current statistics of this SKU under the current inventory policy are shown in Table 4.

Table 4: Detailed statistics of SKU 10002360.

SKU ID	SKU Description	Inventory Turnover Days	Stock Out Rate (%)	Percentage of the Entire Inventory at the warehouse (%)	Days of Safety Stock	Allocation Frequency	Order Frequency
10002360	T0008	17.91	35.00	14.82	13	9	1

After increasing the days of safety stock to 35 days, users can move this SKU to the satisfactory zone. The new statistics of the SKU is shown blow in Table 5.

Table 5: Detailed statistics of SKU 10002360 after inventory policy refinement.

SKU ID	SKU Description	Inventory Turnover Days	Stock Out Rate (%)	Percentage of the Entire Inventory at the warehouse (%)	Days of Safety Stock	Allocation Frequency	Order Frequency
10002360	T0008	24.08	19.00	20.62	35	9	1

We can see that the stock out rate is reduced by from 35% to 19%, but the inventory turnover days only increase from 17.91 to 24.08 days.

4.2 Application Scenario 2: Robustness Test of Selected Policy

The demand volatility is the main source of randomness in the simulation. In real practice, even provided with rich historical sales data, one cannot fully predict what the demand will be like in the future. Thus, there is a strong need for robust inventory polices that guarantee healthy inventory performances even when demand is highly variable. Users can manipulate the standard deviation of monthly demand in the CSV input file to create scenarios with high or low demand volatility.

We continue with the experiment conducted in the first application scenario. If the user doubles the standard deviation of the demand for all the SKUs at the warehouse, we have the following comparison.

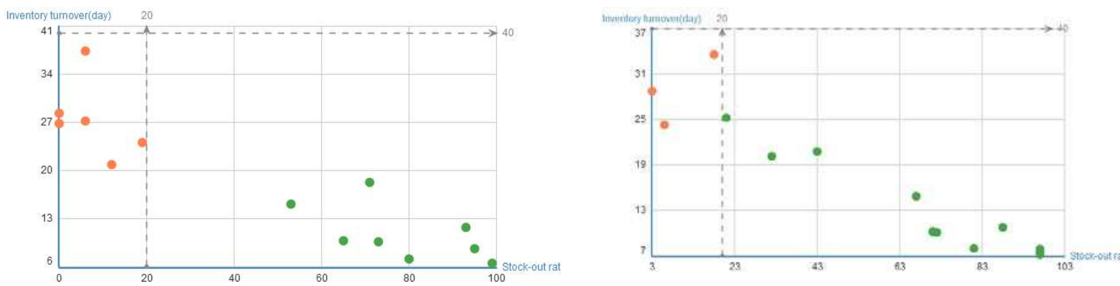

Figure 6: Inventory control scoreboard at warehouse 1 before and after doubling the standard deviation.

The chart on the left hand side of Figure 6 is the current inventory performance representation and the one on the right hand side is the inventory performance representation after doubling the standard deviation of the monthly demand. We can see that some of the SKUs that originally fell into the satisfactory zone are now in the high stock out rate zone. It is consistent with the common understanding that high demand uncertainty will induce high stock out rates. Users then can decide whether or not to increase the level of safety stock to account for the potentially higher demand uncertainty in the future.

4.3 Application Scenario 3：Production Plan Fine-Tuning

Another source of unhealthy inventory performance is from the supply side, which is directly determined by the production. If the production is not well planned, e.g., not aligned with demand, inventory hold-up and shortage will most likely happen. In such cases, SKUs with problematic production plans may still fall in the low inventory performance zones even after the endeavor to optimize the inventory policies. Users are provided with the functionality to configure the production plans in the simulation system. The following experiment illustrates how users could configure the production plan to mitigate the low inventory performance problems. We continue with the simulation scenario in the first application scenario. Let's focus on SKU 10002378. The current statistics of this SKU is shown below.

Table 6: Detailed statistics of SKU 10002378.

SKU ID	SKU Description	Inventory Turnover Days	Stock Out Rate (%)	Percentage of the Entire Inventory at the warehouse (%)	Days of Safety Stock	Allocation Frequency	Order Frequency
10002378	AD004	15.11	53.00	2.86	17	9	7

This SKU currently is experiencing a high stock out rate during the simulation. Users firstly attempt to increase the days of safety stock to reduce the stock out rate. However, after several experiments, the stock out rate remains above 35% even when the days of safety stock increases to 50 days. This draws the user's attention to look into the production plan to see if the total production is much lower than the total demand. In this experiment, the production of SKU 10002378 in October is shown below.

Table 7: Production plan of SKU 10002378.

Factory ID	SKU ID	Production Date	Production Quantity
Factory 1	10002378	2014-10-08	2410
Factory 1	10002378	2014-10-13	4830
Factory 1	10002378	2014-10-20	2415
Factory 1	10002378	2014-10-27	4830

There are six warehouses that distribute SKU 10002378 as indicated in Table 8.

Table 8: Demand of SKU 10002378 at warehouses.

Warehouse ID	SKU ID	Year	Month	Average Demand
Warehouse 1	10002378	2014	10	3556
Warehouse 2	10002378	2014	10	403
Warehouse 3	10002378	2014	10	510
Warehouse 4	10002378	2014	10	5335
Warehouse 5	10002378	2014	10	1705
Warehouse 6	10002378	2014	10	8666

The overall demand is 20175 units on average. However, the total production quantity is 14485 according to the production plan. Even if accounting for the on-hand and pipeline inventory at the beginning of the simulation, the inventory is insufficient to satisfy the demand. The demand at warehouse 1 is 3556 units on average, which is less than the overall production quantity, but the total inventory at the factories is shared by the six warehouses. By setting a higher safety stock level at warehouse 1, a higher percentage of the total inventory will be assigned to warehouse 1. Yet, it is still insufficient to reduce the stock out rate to be less than 20%. At the same time, other warehouses will be sacrificed and end up with higher stock out rates in this process. Thus, the user has to look deeper into the production plan.

4.4 Application Scenario 4: Warehouse Leasing Decision

The simulation system also outputs the daily inventory and throughput at each warehouse. Users can compare these numbers with their current leased capacities of these warehouses to identify under-utilized warehouses, and then decide whether or not to lease fewer capacities. The detailed description of applying the simulation system in this scenario is omitted here.

4.5 Application Scenario 5: Supply Chain Network Design

The design of the current simulation system also responses to the client's request of analyzing the impact of supply chain network structure on the inventory performance. Recall that in the master data management interface, users are given the functionality to configure the supply chain nodes and setups for the simulation. Users are given the flexibility to either stay with the current supply chain nodes or go beyond depending on the simulation purposes. There are two scenarios of users' main interests.

4.5.1 Improve the Inventory Performance at Current Supply Chain Nodes

In this application scenario, the user is concerned that the fulfillment relationship among factories and warehouses are not properly designed for some SKUs. The user starts with a simulation with the initial supply chain setup and analyzes the monthly KPIs at each factory and warehouse for each SKU. For some

SKU, the user may identify warehouses with high out of stock rate, while some factories are having high average days of inventory. This pattern alerts that the current supply chain setup is not well designed. The inventory performance at the warehouses with high out of stock rates is highly likely to be improved by setting the factories with high number of days of inventory to fulfill these warehouses. After identifying the directions of improvement, the user then reconfigure the supply chain setup data file to enable the new fulfillment relationships and rerun a simulation. This improvement process may need several simulation runs before a satisfactory supply chain design is reached.

4.5.2 Analyze the Impact of Planned Factories or Warehouses in the Future

Our client proposed to us that new factories and warehouses are in their future plans and demanded the simulation tool to have the scalability to accommodate that. This application scenario requires more effort on the user side because it relies on the user to configure the supply chain nodes and setups that are not out there yet. However, the simulation that runs on this supply chain setup will help the user assess the impact on the inventory performances at all the supply chain nodes so the user will have a better idea on how to manage the supply chain network when new factories or warehouses are put to use in the future.

5 CONCLUSION

In this paper, we introduced a practical inventory simulation system to tackle a highly complex and expertise-relied inventory control system in a detergent manufacturing company. The simulation system is highly practical as it is used in conjunction of a high-precision forecasting system. The simulation includes multiple sources of uncertainties and incorporates various operational details to make it a multi-purpose tool from supply chain network design to inventory control as well as warehouse leasing decision making. A pioneer study of one major category of products indicated that the client could reduce the inventory by 20% while maintaining the 99% service level. We summarize our practices in the hope that the successful industry applications of simulation could advance the in-market research in this field.

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