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A Bayesian Simulation Approach for Supply Chain Synchronization

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ABSTRACT

While simulation has been used extensively to model supply chain processes, the use of a Bayesian approach has been limited. However, Bayesian modeling brings key advantages, especially in cases of uncertainty. In this paper, we develop a data informatics model that could be used to realize a digital synchronized supply chain. To realize this model, we develop a hybrid model that combines Bayesian modeling with discrete-event simulation and apply it to the supply chain process at a Proctor & Gamble (P&G) manufacturing plant. Moreover, we use approximately one year of transactional data, including information on customer orders, production, raw materials, inventory, and shipments. A driving force for creating this model is to better understand Total Shareholder Return expressed in terms of cash, profit, and service.

1 INTRODUCTION

While simulation has been widely used to model supply chain processes (Jahangirian et al. 2010), the use of a Bayesian approach has been limited. However, Bayesian modeling brings key advantages, especially in cases of uncertainty (McNaught and Chan 2011). Moreover, the use of transactional data in informing these models has not been extensively explored. This could in part be due to the difficulties around stakeholder engagement when simulations require extensive data gathering and processing (McNaught and Chan 2011). In this paper, we describe the development of a data informatics model that could be used to realize a digital synchronized supply chain. To realize this model, we develop a hybrid model that combines a Bayesian approach with discrete-event simulation and apply it to the supply chain process of a Proctor & Gamble (P&G) manufacturing plant. We inform the model using approximately one year of transactional data. A driving force for creating this model is to better understand Total Shareholder Return (TSR), which is expressed in terms of cash, profit, and service.

2 METHODOLOGY

2.1 Informing the models through data

The development of a data model is critical in understanding data flows and informing the development of the simulation models. Using one year of transactional data, including information on customer orders, production, raw materials, inventory, shipments, and deliveries, the data model consists of a set of clean, accurate, and reliable tables, where the relationships between tables are understood and tables have been stored in a centralized location for easy access for model building. Development of the data model was a non-linear, highly iterative process between subject-matter experts, data experts, and modelers. It consisted of the following high-level steps: (1) data source discovery and acquisition, which included identifying and obtaining internal data to use in modeling; (2) data profiling to understand and describe the data; (3) data cleaning and restructuring for purposes of analysis; (4) data linkages to understand the relationships between tables; and (4) data exploration, including visualization, generation of descriptive statistics, and analysis of patterns and inconsistencies in the data.

2.2 End-to-End Model

Using a combination of Bayesian modeling and discrete-event simulation, a data informatics model to simulate the supply chain process of a P&G plant was developed. In order to capture the complete process from customer orders to deliveries, the model is broken out into the four simulators shown in Figure 1.

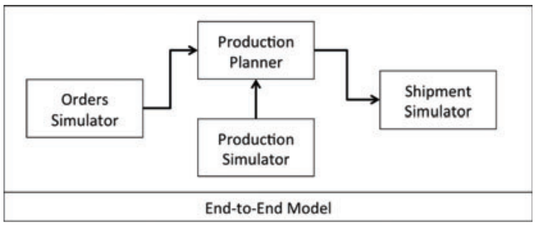

Figure 1: High-level process diagram of the simulators.

The Orders Simulator is a Bayesian model of order quantity matched to empirical patterns from customers. Orders are sampled from historical data, and the total monthly order quantity is matched by product group and customer using Bayesian updates. The Production Simulator is a Bayesian Hierarchical model that estimates the rate for each production run as a function of covariates such as stock keeping unit (SKU) and line using historical production data. The Production Simulator interacts with the Orders Simulator through the Production Planner, which is a discrete-event simulation that incorporates rules for scheduled production and adapts to the demand of incoming orders. The decision on which SKU to produce is based on many factors, including current inventory, minimum safety stock, and historical estimates of profitability. Finally, the Shipment Simulator is a discrete-event simulation that models the loading, shipment, and delivery of finished products to customers. There are two main inputs: orders, which is the output from the orders simulator, and inventory, which is an output from the production planner. At a high-level, the shipment simulator loops through each order, checks that there is available inventory, checks for available trucks and loading docks, loads order onto a truck, and calculates the estimated delivery date and time of the order. Based on the simulated production plan and shipments, we calculate profits by order and cash and service by SKU.

3 RESULTS AND DISCUSSION

The data informatics model is a framework for a data-driven understanding of supply chain dynamics. The simulated end-to-end process is used to identify drivers of cash investment, profit, and level of service by tuning model parameters related to orders, production, and inventory. For example, the impact of safety stock level on cash, profit, and service is demonstrated through the simulations in Figure 2, from which an optimum target safety stock by SKU can be chosen. This methodology allows for the flexibility to control and optimize the supply chain process.

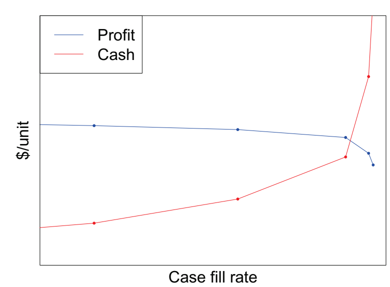

Figure 2: Simulated interaction between cash invested, profit, and service level (case fill rate).

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