Inventory Replenishment Policies for a Grocery Supply Chain Using RFID to Improve the Performance Frontier

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This paper examines the use of RFID as an automatic identification data capture (AIDC) technology and as a tool for data analysis. The primary purpose of this paper is to provide an example of how RFID, for collecting timely and relevant data, could be applied to supply chain analytics. We use a simulation study of a two-echelon system of a retail store and a distribution center (DC) to model an inventory replenishment method that examines the value of using RFID for decision making. We report on five of seven collected performance measures for each of the simulated scenarios. One important finding of this research is that with the improved inventory record accuracy that RFID technologies provide, grocery stores can take advantage of more efficient reordering policies. The paper concludes with a discussion on RFID's implication for facilitating an inventory replenishment system generated by the DC instead of the retail stores.

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I. INTRODUCTION

Global supply chain management environments have always been information-intense for collecting and processing data for the end-purpose of disseminating information that ultimately determines its capabilities, productivities, delivery performance, and overall competitiveness (Reyes *et al.*, 2020). Over the past several decades, methods for capturing data have evolved from unstructured formats (letters, facsimile, and emails) to more structured systems that are paperless and highly efficient (electronic data interchange and extensible markup language). In recent years, much attention has been on automatic identification data capture (AIDC) technologies, which have been used in a variety of industries including manufacturing, transportation, distribution, retail, health care, and many other sectors (AIDCTI, 2011).

The most well-known and widely dispersed AIDC technology is the bar code (dating back to the 1970s), which at that time was driven by the need for accurate and timely data that was gathered from the manufacturing, inspection, transportation, and inventory cycles within a business operation (Mara, 1987). Over time, the bar-code expanded to the logistics and retail sectors, where it gained exposure to the general public. However, the AIDC technology radio frequency identification (RFID) dates to the 1940s and over time it was used as a propriety system for asset tracking in the 1970s and then in the early 1990s, RFID applications began to extend to open systems for supply chain management processes (Reyes, 2011).

The application of RFID technology to improve supply chain coordination and control promises a variety of performance benefits (Angeles, 2005; Prater *et al.*, 2005; Reyes & Jaska, 2006; Visich *et al.*, 2009; Attaran, 2012; Reyes *et al.*, 2012, Reyes *et al.*, 2016). The promises include both forms of operating and information technological innovations, where cost reductions and improved customer service are based on a more advanced automated process: replenishment systems, procurement, inbound logistics, storage, and outbound logistics. Additional benefits include improved operating efficiencies, accuracy, and security of information (Adenso-Diaz & Gascón, 1999; Kärkkäinen, 2003; Kelly & Erickson, 2005; Reyes *et al.*, 2007, Visich *et al.*, 2009; Reyes *et al.*, 2016).

Since RFID offers increased visibility of material flow throughout the global supply chain, retailers have sought to implement RFID systems to reduce costs (operating and inventory) while still retaining high service levels to avoid lost sales due to stockouts. Only recently has the cost of RFID technologies dropped enough where its implementation is cost-effective enough to keep both service levels high and global supply chain costs low. The challenge for firms implementing RFID in their supply chain is how to utilize RFID technology to enable a high velocity pull system tied to customer demand, where goods need to be replenished more frequently and with a smaller average order size.

According to Gu (2016), the integration of RFID information into supply chain practices and the extent of the benefits that can be expected from this change have not been specifically addressed in the literature. Moreover, while performance frontiers have been discussed in a manufacturing setting (Schmenner and Swink, 1998), to the best of our knowledge they have not been addressed in a global supply chain setting. This paper investigates the use of RFID technology to provide real-time inventory tracking and more efficient inventory management. This capability will allow supply chains to accomplish three key things as a direct result of item-level information visibility. First, the increased certainty of inventory levels improves replenishment coordination and will allow inventory management and order replenishment to be done at the distribution center and not at the individual store level. Second, the improved replenishment coordination will allow for reduced overall inventory levels while maintaining currently high service levels. Finally, it will allow for reduced shelf space requirements at individual stores, thus allowing a greater variety of products to be stocked. In this paper, we model and simulate the effects of these issues. The simulation is based on interviews with grocery supply chain professionals on best practices and available data from various grocery retailers. We assume that the focal firm is already at its operating frontier and seeks to move to a better asset frontier by the adoption of RFID. In our simulation, we investigate the trade-offs in performance improvements by the adoption of RFID.

The primary purpose of this paper is to provide an example of how RFID, as an AIDC technology for collecting timely and relevant data, could be applied to supply chain analytics. We use a simulation study to examine the value of using RFID in a two-echelon system. The remainder of this paper is organized as follows. We first review the extant literature that is specific to our study. Next, we describe our inventory models. We then present our experimental methodology followed by the results of our simulation example. Finally, we summarize the results and conclusions of performance trade-offs.

II. LITERATURE REVIEW

In 2003, both Wal-Mart and the U.S. Department of Defense (DOD) sparked massive interest in RFID technology when they announced plans to issue mandates to their suppliers to use RFID to improve customer service and help automate inventory replenishment. This announcement was referred to as the *big bang of RFID* by Reyes *et al.* (2016). Since the *big bang of RFID* in 2003, several large-scale empirical studies have been conducted to investigate the adoption, benefits, and challenges of RFID implementation. Because of the proliferation of the RFID literature since the *big bang of RFID*, we begin with a summary of RFID in the supply chain followed by a brief review of RFID and simulation modeling relevant to our simulation study.

2.1. RFID in the Supply Chain

Specific publications found in the literature have provided extensive literature reviews on RFID in the supply chain and have been frequently cited in recent years. They serve as our extant review of the RFID in the supply chain literature and are summarized in Table 1.

Li and Visich (2006) were perhaps the first to introduce a comprehensive literature review to demonstrate the challenges and opportunities of RFID implementation in supply chain management. They examined two dimensions: the impacts of RFID on each supply chain partner and the impact of RFID on the supply chain as a whole. By implementing RFID at multiple entities, beyond the application at one company, RFID provides a continuous flow of information throughout the entire supply chain. This then provides an increased synchronization of information flow and therefore enables better supply chain coordination, collaboration planning, forecasting, and replenishment decisions.

Using a bibliometric technique and a historical review method, Chao *et al.* (2007) analyzed RFID innovation, adoption by organizations, and market diffusion found in Science Citation Index journals from 1991 to 2005. Their analysis found supply chain management, the health industry, and privacy issues as the major trends in RFID, and concluded that RFID contributions will be more ubiquitously diffused and assimilated into our daily lives in the near future.

With the RFID academic research explosion, Ngai *et al.* (2008) identified several journals producing special issues on

RFID. Due to this strong academic interest in RFID, they organized a review of 85 academic journals published between 1995 and 2005. The framework for their review included a "content-oriented classification" of the RFID literature for the scope of their investigation. The papers were classified into four main categories: technological issues, application areas, policy and security issues, and other issues. The technological issues focused on the RFID system itself, such as tags, readers, and communication infrastructure. The application areas consisted of applications beyond supply chain management, manufacturing, and logistics, including library services, animal detection, and museums. Policy and security issues related to the studies involved existing human rights policies, constitutional protections, and data protection law. Plus, other issues covered general overviews or usages of RFID.

Visich *et al.* (2009) provided an extensive literature review by classifying the existing empirical evidence of RFID on supply chain performance. They used the process-oriented framework proposed by Mooney *et al*. (1996) to classify the evidence by operational or managerial process and then for each process by the effect: automational, informational, and transformational. The empirical evidence from this study showed that the major effects from the implementation of RFID are automational effects on operational processes followed by informational effects on managerial processes. They noted that RFID implementation has not reached the transformational level on either operational or managerial processes. RFID has an automational effect on operational processes through inventory control and efficiency improvements. An informational effect for managerial processes is observed for improved decision quality, production control, and the effectiveness of retail sales and promotions coordination. They concluded their study by proposing a three-stage model to explain the effects of RFID on the supply chain.

Lim *et al.* (2013) reviewed the 1995-2010 literature for RFID use in the warehouse and summarized its applications, benefits, challenges, and future trends. Applications primarily focused on the basic warehouse operations around the flow of materials in the facility: receiving, put away, storage, order picking, and dispatching. Benefits are grouped into three categories: product/resource related (reduction in shrinkage, product tracking, space utilization, reduction in stockouts and lower inventories), operational (reduction in material handling, quality control, reduction in labor, and lower costs), and informational (increase data accuracy, improved information sharing, and better determining of arrival and dispatch times). The obstacles were grouped into internal obstacles (uncertain return on investment and the integration with legacy systems) and external obstacles (standards development and concerns about privacy and security). Finally, they explored future trends to include opens systems, data sharing, integration with other technologies, and the Internet of Things as part of supply chains based on RFID.

Reyes *et al.* (2016) is one of the more recent studies about RFID implementation in the supply chain. They conducted an extensive review of the determinants for RFID implementation in the supply chain leading to a comprehensive adoption and implementation framework. Their framework for RFID implementation in the supply chain is based on five constructs: (1) internal and external drivers, (2) dimensions of management leadership, (3) barriers, (4) level of RFID adoption, and (5) benefits. Their results offer new insights into RFID adoption factors and a broader understanding of RFID technology in the supply chain.

de Oliveira *et al.* (2019) complied a quantitative analysis of RFID publications from 2006 to 2016. Their analysis highlight that RFID technology has been widely implemented across many supply chain management applications that include agrifood systems, food logistics, hospitals, cold chain monitoring, and retail sectors. They summarize the many advantages of RFID for improving operational efficiency (such as cost reduction and improved inventory visibility) and improvements in service quality. While cost, security, and privacy remain as challenges to overcome, other challenges and barriers were identified. The hidden tag problem exists with a multipath or interference effect caused by water and metals. Other factors include lack of technical expertise, the complexity and uncertainty of the technology, and data management problems. The general finding is that RFID promotes the integration between operations and in a supply chain with other inter-organizational systems as they involve managing customer-supplier relationships. They further discuss how RFID can be integrated with EDI, collaborative planning, forecasting and replenishment (CPFR) systems, efficient consumer response (ECR), vendor-managed inventory (VMI), and other systems.

In addition to the summary of extensive literature reviews presented, empirical studies specific to the retail sector and the food industry supply chain by Jones *et al.* (2005), Bhattachary (2015), and Kumar *et al.* (2015) investigated the major benefits from the RFID adoption and the major challenges for the RFID adoption. The major (perceived) benefits from the RFID adoption predominantly focused on improving inventory management, such as reduction in inventory, out of stock, and shrinkage. Additional benefits for improving other operational efficiencies listed improved data accuracy, improved visibility of orders, monitoring worker productivity. Reduction of overall costs, like reducing labor costs and improving labor productivity) is a general theme among the literature. A consensus regarding the major challenges for the RFID adoption lists the cost of implementation, privacy, and security as the foremost challenges. Other general challenges include unclear return on investment, the complexity of the technology, and resistance to change.

2.2 RFID and Simulation Modeling

Lee and Özer (2007), in a special issue on RFID in the journal of *Production and Operations Management*, highlight several approaches to "unlocking the value of RFID" and labeled RFID not only a disruptive technology but also as a new information capturing technology for the supply chain management. They began with the current views on the value of RFID (labor cost savings, inventory reduction, and reduction in shrinkage and out-of-stock inventory), and then extended the value of RFID to (1) visibility within a company, (2) visibility across companies with downstream information shared upstream, and (3) visibility across companies with upstream information shared downstream. As a result, many quantitative research papers on the application of RFID and "unlocking the value" have been published. We present four papers that are relevant to our simulation study and are detailed in Table 2.

TABLE 1: SUMMARY OF EXTENSIVE LITERATURE REVIEWS

Authors	RFID in the Literature
Li and Visich (2006)	Challenges and opportunities for RFID implementation in supply chain management • Impacts of RFID on each supply chain partner • Impact of RFID on the supply chain as a whole
Chao *et al.* (2007)	Technology innovation of RFID Organization adoption of RFID Organizational diffusion • Supply chain management • Health • Privacy and others
Ngai *et al.* (2008)	Technological issues Application areas Policy and security issues Other
Visich *et al.* (2009)	RFID overview literature RFID empirical studies RFID analytical studies Dimensions of RFID operational business value Dimensions of RFID managerial business value
Lim *et al.* (2013)	Domains of RFID in different warehouse operations A matrix to examine the perceived benefits Potential obstacles in adopting RFID in the warehouse Future trends in the use of RFID in the warehouse
Reyes *et al.* (2016)	Constructs for RFID implementation • Implementation drivers • Management leadership • Barriers • RFID adoption stage • Benefits
de Oliveira *et al.* (2019)	Many advantages include greater operational efficiency and improvements in service quality Challenges to overcome • The hidden tag problem • Technical expertise • Complexity and uncertainty of the technology • Data management problems

Gaukler *et al.* (2007) developed an analytical model to explore the benefits of item-level RFID to manufacturers and retailers within a retail supply chain setting. The goal was to compare the expected profits under item-level RFID with the achievable expected profits without RFID. The model scenarios consisted of a centralized system (the base model) compared to a decentralized wholesale price contract. Both examined with and without item-level RFID tagging. Additionally, two sub-cases were explored within the decentralized systems: either the manufacturer or the retailer as the Stackelberg leader with the major market power for the allocation of the item-level

RFID tag cost between manufacturers and retailers for maximizing supply chain profits.

With the introduction of advanced information systems, such as RFID, Rekik and Sahin (2012) examined the economic impact of inventory record inaccuracies. The inventory management system is controlled by an infinite horizon, single-stage, single-product periodic review policy that is subject to shrinkage errors. These shrinkage errors are caused by the difference between the actual physical and information system inventory levels. They model two scenarios for comparison. The first scenario is the current practice where RFID technology is not used to track shrinkage and the inventory is therefore controlled by estimating the expected shrinkage rate. The second scenario then permits management of the joint ordering and inspection policy based on the information obtained on shrinkage errors when using the RFID technology. By comparison, the study shows how RFID deployment produces two benefits: total visibility of the shrinkage rate and the elimination of shrinkage errors.

Gu (2016) presented a new concept and definition of advanced supply information (ASI). His research studied the value of advanced supply information in which retailers use upstream information about the supplier's current availability and remaining lead time of orders to make inventory decisions. In contrast to using demand information for the replenishment decision (which has been extensively investigated in previous research), the ASI refers to the information on future supply in terms of quantity and timing. Two simulation models were developed to identify the value of ASI under various conditions. With RFID, the sharing of ASI efficiently and effectively between supplier and buyer is possible. Gu's model integrates the real-time ASI facilitated by the RFID system into the retailer's inventory replenishment decision-making process.

Gu *et al.* (2017) modeled a three-echelon supply chain of a retailer, distributor, and manufacturer. In the non-RFID base model, the distributor and the retailer have a vendor-managed inventory agreement and replenishment quantities are based on an economic order quantity. In the RFID enabled model, information is shared along the supply chain and the manufacturer has access to real-time demand information at the retailer to better plan production lot sizes. Their results showed the financial benefits of lot-splitting by the manufacturer as well as the mitigation of the bullwhip effect along the supply chain.

III. INVENTORY MODELS

The two-echelon (distributor-retailer) system has been the primary focus of the multi-echelon inventory research stream during recent decades. More specifically, the single distributor-multiple retailer problem has received the breadth of the research (for examples, see Chen and Zheng, 1994a, 1994b and 1997; Graves, 1996; Cachon and Fisher, 2000; Chen et al., 2002; Marklund, 2002; Mitra and Chatterjee, 2004). Among the models that have been researched are the continuous periodic review models with (R, nQ) policies.

The main body of literature dealing with (R, nQ) policies can be characterized by the form of mathematical models and the corresponding assumptions: planning horizon, demand, and the number of items (Qu et al., 1999). The planning horizon may vary from a single period to multiple periods to infinite periods. Demand is either deterministic or stochastic and modeled as a single item or multiple items. Examples can be found in Axsäter (1993), Chen and Zheng (1994a and 1994b), Graves (1996), Bassok et al. (1999), Cachon and Fisher (2000), Chen et al. (2002), Chan and Song (2003), and Mitra and Chatterjee (2004).

TABLE 2: RFID SIMULATION MODELING

Authors	Assumptions and Scenarios
Gaukler *et al.* (2007)	One manufacturer and one retailer A single product supply chain Backroom stocking decisions are made within a one-period newsvendor framework based on demand distribution knowledge Focus on product availability on the retail shelf Compares expected profits under item-level RFID with expected profits without RFID The base model is a centralized system compared to a decentralized system; both comparing with and without item-level RFID There is no cooperative between manufacturer and retailer in the decentralized model scenarios
Rekik and Sahin (2012)	Inventory management controlled by an infinite horizon, single-stage, single-product periodic-review policy Focus on the behavior of a store inventory system exposed to inventory record inaccuracy Shrinkage errors caused by a difference between the physical and information system inventory level Two situations are compared: the impact of shrinkage errors and the value of considering the inventory inaccuracy issues when optimizing the inventory and inspection policy RFID as a visibility provider RFID as an anti-shrinkage tool
Gu (2016)	Distributor and retailers use a periodic review base-stock policy ASI sharing enables the focus retailer to predict the occurrences of a disturbance (e.g. a possible stock out at the distributor at a future time) Single-product supply chain Three lead-time distribution patterns and three distributors expected service level Explore how much ASI sharing can bring benefits to the retailer
Gu *et al.* (2017)	Three-echelon supply chain: manufacturer, distributor, retailer The non-RFID base model has a vendor managed inventory agreement between the distributor and the retailer The RFID-enabled model allows information sharing along the supply chain The demand follows a normal distribution with 3 different standard deviations The number of production lots during each distributor ordering cycle is tested at four levels The production cycle time is varied across eight levels and though back-ordering is allowed there are no partial shipments

Cost evaluation techniques are investigated for the one-warehouse and multiple retailer systems. Axsäter (1993) presented a way to obtain the exact and approximated method for evaluating long-run costs for the general installation stock policies by using only local stock information, where batch-ordering policies are followed at both the retailer and distribution center. In a parallel study, Forsberg (1997) provided an exact solution. Chen and Zheng (1997) extended their prior work (Chen and Zheng, 1994a and 1994b) and examined a class of replenishment policies that use centralized stock information, where each installation uses a continuous review policy. They argue that centralized stock information can be utilized through echelon stock policies (i.e., the distribution center's inventory plus all the downstream inventories). These examples are all based on independent review periods and identical retailers with Poisson demand.

Graves (1996) presented a model for multi-echelon inventory systems, with two key assumptions: a fixed replenishment schedule at all sites, and a dynamic allocation rule for committing stock at an upper echelon. Given the assumption of regularly scheduled shipments (which are common practice to achieve effective utilization of transportation resources), the order-up-to policy with base stocks is used. The allocation rule allows for committed inventory to be re-allocated to another site based on more critical needs. Another studied policy includes a single-period inventory model with a substitution (Bassok et al., 1999); however, the environment for the substitution was a downward engineering substitution within a bill of material structure.

A related inventory policy is the (r, nQ, T) policy, which models periodic ordering. Shang and Zhou (2009; 2010) analyzed and developed solution approaches for the (r, nQ, T) policy, where each stage reviews its inventory every T periods and orders according to the (r, nQ) policy to minimize the average total cost per period. Lagodimos, et al. (2012a and 2012b) investigated a single-echelon installation under the (r, nQ, T) policy, also to minimize the average total cost per period. They proposed an exact algorithm to optimally compute the policy variables. Both sets of authors assumed that backorders are allowed when an item is temporarily out of stock.

In our paper, review periods are not uniform but are predetermined based on annual sales. We assume identical and independent multiple retailers and Poisson demand for multiple products, which is consistent with prior work. Our work differs from prior work by not allowing backorders at the distribution center (DC). If the DC does not have inventory to replenish the retailer's order, then the retailer would have to re-order during the next order-cycle, which is consistent with our interviews with the grocery supply chain professionals. We also examine the trade-offs between service levels and the long-run costs when the potential for product substitution exists.

Since retailers order in batches, the distribution center faces an aggregated version of demand that is more volatile than the true customer demand. By using information technologies, such as RFID for automatic identification and data capture, the availability of centralized information for stock replenishment allows for reduced lead times and the potential for reducing the volatile demand patterns at the distribution center.

Our research simulation begins by modeling the effect of two different inventory replenishment models on the performance of a grocery supply chain system. One represents the current method of operation used by many grocery retailers, and the other represents an alternative method facilitated using RFID technology for data capture and as a tool for data analytics.

Our simulation design details and parameter ranges are based on our literature review, interviews with grocery supply chain professionals at retail stores and distribution centers regarding best practice, and to address our theoretical research interest. We considered our output analysis based on the model's parameter ranges. We verified and validated our simulation design based on best practice as an accurate representation of the real-world system that we explored.

3.1. Model 1

The first inventory model (Model 1) reflects a common policy used at local retail stores of two large national grocery chains in the U.S. With this policy, at the order review time an order is placed for a product if the current inventory level is at least one case short of its full shelf space allocation (S). A common practice is that a store must order in increments of full case quantities (case packs, or CP). The reorder point for product *i* is

$$ROP_i = S_i - CP_i. \quad (1)$$

The order quantity for product *i* (Q_i) is equal to the available shelf space minus the current inventory level at review time (I_{it}), rounded down to a whole case pack quantity.

$$Q_i = CP_i * (\mathit{Rounddown}[(S_i - I_{it})/CP_i]) \quad (2)$$

The order quantity is rounded downward to avoid overfilling the available shelf space.

The rationale for this policy is to keep the shelves full to provide a high level of customer service (i.e., to better prevent temporary stockouts). This policy disregards the operating costs associated with carrying higher inventories and placing orders and is included in this study since it is a common policy in the grocery industry.

3.2. Model 2

The second inventory model (Model 2) tries to minimize the operating costs by reducing the average inventory as a performance measurement of holding inventory costs and reducing the frequency of placing orders (ordering costs) while trying to achieve the desired service level (additional safety stock and holding costs). As is common in the grocery industry, replenishment orders are allowed only at a few designated times during the week due to transportation economies, so inventory levels are reviewed only at the time of order placement (this policy applies to both models). Although RFID technology could be used with either inventory model, Model 2 is practical only with a high level of inventory record accuracy. With the use of RFID technology, inventory levels are accurately known and are available in real-time throughout the supply chain. Therefore, RFID technology is an enabling technology for the use of Model 2.

With Model 2, an order is placed if at the inventory review time the current inventory level is *below* a threshold value (reorder point). The reorder point is set just high enough to cover the total expected demand from the current time until the next inventory review time (n_t), expected demand during the replenishment lead time (LT), and a safety stock level to provide the desired level of customer service (SS_{it}). For example, suppose the order placement times are the end of Monday and the end of Wednesday, and the replenishment lead time is one day. If the current inventory level at the end of Monday is exactly at the reorder point (so the order is not placed), then there should be enough inventory on hand to cover at least three days: the time until the next order placement time at the end of Wednesday plus the one day replenishment lead time. So, the reorder point for product *i* at review time t (ROP_{it}) with daily average demand rate d_i is expressed as

$$ROP_{it} = (n_t + LT)d_i + SS_{it}. \quad (3)$$

The safety stock level is set so that if the current inventory level is exactly at the reorder point and an order is not placed, then there is a 98% probability of having enough units on hand to meet demand until the following order and delivery time. (The arbitrary 98% level used here could be changed to any level desired by store management.) The safety stock level for product *i* at time *t* (SS_{it}) is then expressed as

$$SS_{it} = Z\sqrt{(n_t + LT)\sigma_{di}^2}\ . \quad (4)$$

The sum (n_t + LT) is the number of days until the next order review time plus the replenishment lead time. The replenishment lead time is the time from order placement until order delivery. The term σ_{di}^2 is the variance of daily demand for product *i*.

The order quantity (when the current inventory level is below the reorder point) is computed as the reorder point level (ROP_{it}) minus the current inventory level (I_{it}), rounded up to a whole case pack quantity (CP_i). The order quantity for product *i* at review time *t* (Q_{it}) is expressed as

$$Q_{it} = CP_i * (\mathit{Roundup}[(ROP_{it} - I_{it})/CP_i]). \quad (5)$$

According to the retail store managers, the current and more common practice is to "round down" to a whole case pack to avoid overfilling the available space, as described in Model 1 (formula 2). However, some retail stores would "round up" and then manage the temporary overstock. Hence, an interesting research question outcome from the interviews is to explore how the stores would measure performance based on the temporary overstock. It was also noted as a common practice that when the shelves are fully stocked during the over-night stocking period, the partial case packs are either temporarily stored above the shelves or temporarily stored in the backroom. During the day, the partial packs are later stocked as space is available. The stores have staff assigned to "maintain" the shelves to continually monitor and keep the products "facing" forward.

IV. EXPERIMENTAL METHODOLOGY

As discussed previously, retailers are interested in both minimizing their operating costs as well as maximizing their customer service levels, which are generally viewed as conflicting goals. The total cost of a supply chain system and the level of customer service provided depend on a variety of design factors and decision policies. This research focuses on many of these factors and policies to identify potential improvements in supply chain performance. The specific research questions addressed by the simulation experiment are:

#1: How does the inventory model affect supply chain performance?
#2: How does the case pack size affect supply chain performance?
#3: How does the frequency of delivery affect supply chain performance?
#4: How does the distribution center substitution policy affect supply chain performance?
#5: How does the distribution center's access to current retail store inventory data affect supply chain performance?

#6: Are these results affected by the levels of product demands at the stores?
#7: Are these results affected by the existence of artificial outlier demands at the stores?

The following subsections discuss details of the research methodology, including the environment and assumptions, main treatment factors, environmental factors, simulation design details, and performance measures.

4.1. Environment and Assumptions

Deliveries from the distribution center to the retail stores are made a fixed number of times per week, on specified days determined by the company. One day before the delivery (the replenishment lead time), an inventory review occurs at the retail store. Only at the inventory review time is a decision made about whether to place an order for each product and how many case packs to order. As soon as the inventory reviews are conducted, an order is placed, and the products are delivered the next day (usually a 24-hour fixed replenishment lead time). Inventory reviews and order placements are assumed to take place at the end of a day, and deliveries are assumed to be made at the end of the following day and not available for use in the store until the beginning of the day after delivery. For example, if an order is placed by the store on Monday night, the products are delivered to the store on Tuesday night, they are placed on the shelves late Tuesday night, and are available for sale to customers at the beginning of Wednesday morning.

Decisions about how to allocate shelf space among the products are typically made once or twice a year by staff analysts at the corporate office and are usually beyond the control of retail store managers. Given this typical policy, shelf space allocations for the different products are considered fixed for this simulation.

The product environment analyzed consists of a hypothetical product category with 5 similar products, or stock keeping units (SKUs), such as 5 competing brands of canned diced tomatoes. Each product is assumed to have a fixed amount of shelf space available to it in the retail store. The amount of storage space allocated to each product in the distribution center (DC) is set equal to the DC's order quantity (in pallets) from the manufacturer plus one additional pallet. One pallet is assumed to be equal to 864 units, or cans, of the product (equivalent to 2 cases wide by 3 cases deep by 6 cases high, for cases of 24 cans), regardless of the case pack quantity. It is also assumed that the distribution center can only order full pallet increments of a product from the manufacturer.

If a product is out of stock at the retail store, some degree of product substitution by the consumer is assumed. Based on marketing research information from previous research studies in the literature, a conservative estimate of 60% is used for the percentage of consumer demand that will be substituted with another product if the first product desired is out of stock in the store. The other 40% of unmet demand is considered lost sales. The alternate product that the consumer substitutes in an out-of-stock situation are evenly assigned among the other products that are in stock in the category.

No back-room inventory stock is allowed at the retail stores—since in reality it is assumed that all deliveries are stocked directly to the shelves. Also, backorders are not allowed—if the retail store does not receive the product ordered at the scheduled delivery time, then the store must place another order for the product at the next designated order placement time (a common policy in the grocery industry).

The supply chain environment that we analyze consists of one distribution center that supplies 10 retail stores, as shown in Figure 1. Each retail store is assumed to be the same size and have the same average product demand rates and shelf space allocations. A given combination of experimental factors is applied to all stores during each experimental scenario.

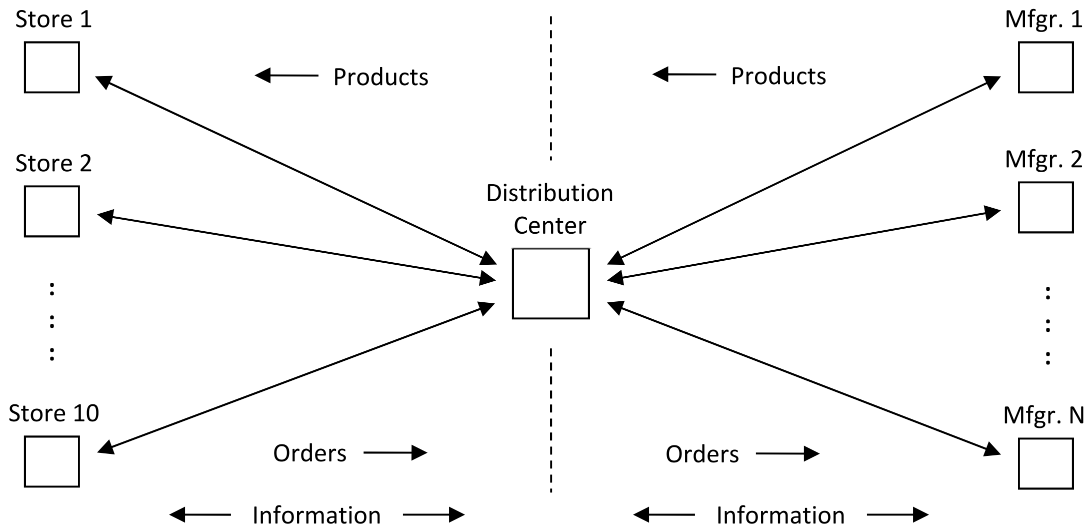

FIGURE 1. SIMULATED GROCERY SUPPLY CHAIN

While the replenishment policy at the retail stores is varied as the first main treatment factor in the experiment, the replenishment policy at the distribution center is assumed to be based on the economic order quantity (EOQ) model. Using reasonable parameters similar to those used by a local distribution center of a national grocery chain, an EOQ quantity is determined for each product which is then rounded up to a full pallet-sized quantity. Given the relatively small size of the supply chain system used for this study (i.e., 10 stores), the EOQ quantities at the DC are less than one pallet for each product, so the resulting DC order quantity used for each product in the simulation is one full pallet.

The replenishment time from the manufacturer is assumed to be a constant 3 working days. Replenishment orders to the manufacturer are placed at the end of a day. For example, an order placed by the DC at the end of Monday will arrive from the manufacturer at the end of Thursday and will then be available for use at the beginning of Friday. The reorder point at the DC is based on expected demands from stores during the manufacturer's lead-time period. Figure 2 shows a summary of the order replenishment decision process used in the simulation.

A simulation experiment was developed to evaluate the impact of policy changes on the total cost in the supply chain and on the supply chain's ability to react to demand uncertainty. The simulation experiment includes five main treatment factors and two environmental factors. Five of these seven factors are focused on the retail store level, and two are focused on the distributor level.

4.2. Main Treatment Factors

The *first* main treatment factor is the inventory replenishment policy used in the retail store. This 2-level factor consists of the two inventory models discussed in Section 4.

The *second* main treatment factor is the case pack size. Case pack sizes of products delivered to retail stores are evaluated at three levels: 24, 12, and 6 units (or cans) per case. Some retail stores (such as Sam's) have been requesting smaller case sizes to increase the breadth of the category and/or to decrease the average inventory on the shelf on a given day (AIDCTI, 2011).

The *third* main treatment factor is the frequency of delivery to retail stores. The common approach in the grocery industry is to deliver to the store on certain specified days during the week. Two levels of this factor are evaluated: 3 and 6 delivery times per week. Orders are placed at the end of the day. With 3 delivery times per week, half of the stores place orders on Sunday, Tuesday, and Thursday nights, and the other half place orders on Monday, Wednesday, and Friday nights. Orders are received by the store at the end of the next day after the order is placed. With 6 delivery times per week, all stores place orders every day except Saturday. It is assumed that no deliveries from the distribution center are received on Sundays (a common practice).

The *fourth* main treatment factor is the stockout substitution policy at the distribution center (DC) with two levels. The first level assumes that if a product is out of stock at the DC when a store places an order for it, then nothing is sent to the store and the store must reorder that product the next time it places an order. The second level assumes that if a product is out of stock at the DC, then the DC will send a substitute product in the category to the store instead of the out-of-stock product that was ordered. The substitute product could be another product within that category at the store that is closest to its reorder point at that time unless that product was also ordered by the store. For example, suppose the DC is out of product 2. If a store places an order for product 2 and product 4, and if product 3 is closer to its reorder point at the store than is product 1 or 5, then the DC will substitute a case of product 3 as a substitute for product 2. The store must place another order for product 2 at its next order placement time. The rationale behind this DC substitution policy is that since most customers are willing to substitute for an out of stock product at the store, the company would like to make sure that there are plenty of other products on the store shelves to substitute, so the DC would prefer to ship another item that is starting to get low at the store than to ship nothing.

The *fifth* main treatment factor is the type of data about current store inventory levels that is available to the DC when it evaluates its inventory levels for possible reorder from the manufacturer. Two levels of this factor are evaluated. The first level assumes that no data on the stores' current inventory levels are available to the DC, except for the orders that are received from stores (representing the traditional environment). The second level assumes that the DC has real-time data on the stores' current inventory levels, which is available with RFID tags. Real-time data about store inventory levels allows the DC to better anticipate upcoming orders from stores during the next couple of days. This advanced information then allows the DC to temporarily increase its reorder point if higher than average orders are expected from stores during the manufacturer lead-time period.

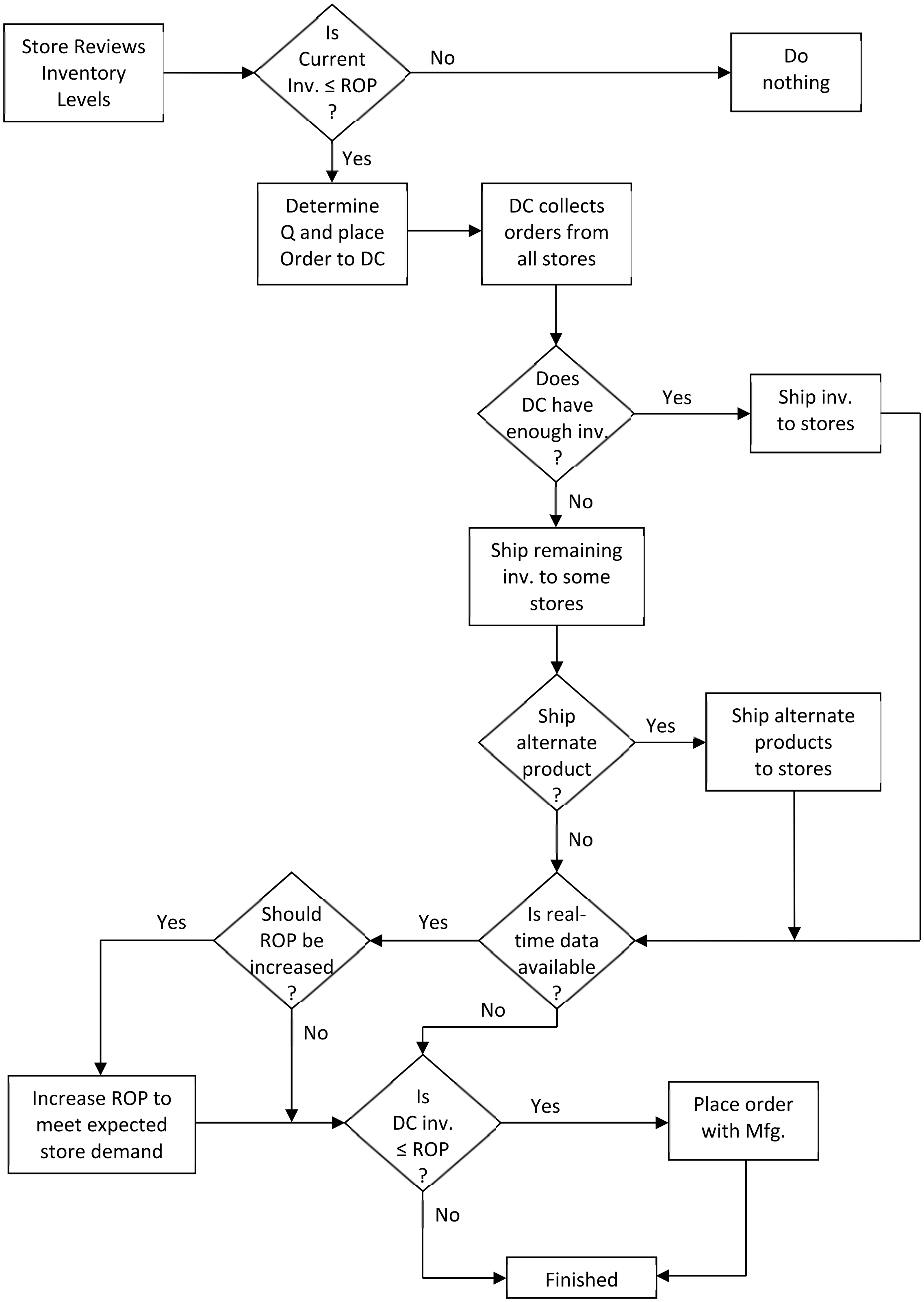

FIGURE 2. ORDER REPLENISHMENT DECISION PROCESS FOR SIMULATION EXPERIMENT

4.3. Environmental Factors

The first environmental factor is the demand level at the retail store, with two levels (high and low demand). In the first (high) level, the daily average demand rates are 15, 10, 8, 6, and 4 units per day for products 1, 2, 3, 4, and 5, respectively. In the second (low) level, the daily average demand rates are 6, 4, 4, 3, and 2 units per day. In our simulation, these two demand levels are an input to query our research questions. We used a random number generator for the daily demand for each product and it is assumed to follow a Poisson distribution, which is consistent with the prior work presented in section 2.2 and section 3.

The amount of shelf space allocated to each product is assumed to be fixed throughout the experiment. The shelf space allocated to the five products is assumed to be enough to hold 120, 96, 72, 60, and 48 units for products 1, 2, 3, 4, and 5, respectively. This is equivalent to 5 cases, 4 cases, 3 cases, 2.5 cases, and 2 cases for a case pack quantity of 24 units. Typically, in stores, cans are stacked 2 or 3 high, several cans (or facings) wide, and several cans deep on the shelf. These shelf space allocations are assumed fixed for all experimental conditions, regardless of case pack size.

The second environmental factor is the existence of artificial outlier demands, with two levels. This factor is included in the experiment to assess how the inventory models and policies handle uncertainty by reacting to an unexpected surge in daily demand. The first level does not include any additional artificial outlier demands. The second level includes occasional artificial demands equal to 2-4 times (uniformly distributed) the average daily demand rate for a product, added to the regular random demand for that day. The frequency of the artificial outlier demand for a product is modeled as each product having a 5% probability each day of experiencing the additional artificial outlier demand. We are not aware of any RFID-inventory studies that simulate outlier demand, hence the inclusion of outlier demand in our study fills a gap in the research.

4.4. Simulation Design Details

The simulated supply chain represents a scaled-down version of the type of grocery supply chains currently operated by national grocery store chains in the U.S. Our simulation design details, and parameter ranges are based on our literature review, interviews with grocery supply chain professional at retail stores, and distribution centers, and to address our research interest. The portion of the supply chain that is analyzed includes one company-owned distribution center and ten company-owned grocery retail stores. All grocery stores are assumed to be identical except for the timing of random demand.

A full factorial experimental design is used with the main treatment factors and environmental factors described in the prior section which resulted in 2x3x2x2x2x2x2=192 experimental scenarios and is summarized in Table 3. Each simulated scenario is replicated 50 times, yielding a total of 9,600 observations for analysis.

Discrete event simulation is performed, and each simulation run covers 1,195 days. The first 100 days sufficiently cover the transition time (or transient state; see Law and Kelton, 1991) before the simulation models achieve a steady-state level (based on average inventory per day). All shelves in the retail stores and all storage space at the distribution center are full on the first day of the simulation runs. After the first

100 days, the collected performance statistics are deleted and started fresh. The remaining 1,095 days of the simulation runs represent three years of 365 operating days each. Random numbers for the simulation were generated using the 0-1 uniform random number generator and were transformed into the appropriate distribution types. Common random number seeds were not used since the simulation durations were sufficiently long (3 years), 50 replications were used, and the first 100 days of results were truncated.

TABLE 3. FULL FACTORIAL EXPERIMENTAL DESIGN

<table>
<tr><th colspan="6">Model 1
(periodic review policy)</th></tr>
<tr><td colspan="2">Case pack size = 24 units</td><td colspan="2">Case pack size = 12 units</td><td colspan="2">Case pack size = 6 units</td></tr>
<tr><td colspan="3">Frequency of delivery = 3 delivery times per week</td><td colspan="3">Frequency of delivery = 6 delivery times per week</td></tr>
<tr><td colspan="3">Stockout substitution policy at the DC allowed = no</td><td colspan="3">Stockout substitution policy at the DC allowed = yes</td></tr>
<tr><td colspan="3">Real-time data of retail store inventory levels available at DC = no</td><td colspan="3">Real-time data of retail store inventory levels available at DC = yes</td></tr>
<tr><td colspan="3">Daily average demand level (Poisson distribution) = Low</td><td colspan="3">Daily average demand level (Poisson distribution) = High</td></tr>
<tr><td colspan="3">Existence of artificial outlier = no</td><td colspan="3">Existence of artificial outlier = yes</td></tr>
</table>

<table>
<tr><th colspan="6">Model 2
(periodic review policy facilitated by RFID)</th></tr>
<tr><td colspan="2">Case pack size = 24 units</td><td colspan="2">Case pack size = 12 units</td><td colspan="2">Case pack size = 6 units</td></tr>
<tr><td colspan="3">Frequency of delivery = 3 delivery times per week</td><td colspan="3">Frequency of delivery = 6 delivery times per week</td></tr>
<tr><td colspan="3">Stockout substitution policy at the DC allowed = no</td><td colspan="3">Stockout substitution policy at the DC allowed = yes</td></tr>
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<tr><td colspan="3">Daily average demand level (Poisson distribution) = Low</td><td colspan="3">Daily average demand level (Poisson distribution) = High</td></tr>
<tr><td colspan="3">Existence of artificial outlier = no</td><td colspan="3">Existence of artificial outlier = yes</td></tr>
</table>

4.5. Performance Measures

Several types of performance measures are collected for each of the simulated scenarios. The first two performance measures (average inventory and number of orders) reflect operating costs in the supply chain. The third type reflects customer service levels.

The first performance measure, average inventory level, is collected at the retail store level (avgstinv) and the distribution center level (avgDCinv). We followed the scientific method for computing the average inventory per period. Our full factorial experimental design resulted in 192 experimental scenarios and each scenario was replicated 50 times, yielding a total of 9,600 observations for analysis. Hence, we are reporting the average of the average ending inventory for each of the 50 replications for each scenario. This metric is computed by averaging the ending daily inventory levels across all products. At the retail store level, the average inventory is totaled across all ten stores.

The second performance measure is the number of orders placed per store. The total number of orders placed by each store during the three years is collected and averaged over the ten stores (numorders).

The third type of performance measure reflects the service level or stockout performance. Statistics are collected on the number of product-days that products are out of stock in each retail store, which is then averaged across the ten stores. The total number of product-days stocked out at the DC is also collected (DCsodays). Statistics are collected on the total number of lost sales at the stores, taking into account product substitution by consumers. Finally, the actual service level is computed for retail stores (ServLev). To summarize, the collected performance measures include:

- Average inventory level at retail stores (avgstinv)
- Average inventory level at the distribution center (avgDCinv)
- The average number of orders placed by retail stores (numorders)
- The average number of product-days stocked out at retail stores
- Total number of product-days stocked out at distribution center (DCsodays)
- The average number of lost sales per store
- Actual service level % at retail stores: 1 - ((total number of lost sales)/(total demand)) (ServLev)

V. RESULTS

The results presented below address only five of the seven collected performance measures or response variables. The two measures not shown are the average number of lost sales at stores and the average number of stockout days at stores. Both of these measures are highly correlated with another performance measure, actual service level at stores (ServLev), so only this latter measure is shown. Due to the large volume of results, only the more significant results are presented below.

Descriptive statistics are collected for each response variable. An analysis of variance (ANOVA) is performed for each factor and each response variable. The ANOVA finds that there is a significant difference in the means of the seven response variables for each of the seven factors at □=0.05, with all p-values less than 0.0002. The following discussions compare means and standard deviations for different factors and interactions.

5.1. Comparison of the Two Models

The main treatment factor that has the largest impact on supply chain performance is the inventory replenishment model used in retail stores. A comparison of the two models in Table 4 suggests that substantial savings in operating costs can be obtained using Model 2, at the expense of a slight loss in service level at the stores. The average inventory at the retail stores (avgstinv) decreased by 2,015 units, or 71.6%, while the average inventory at the DC (avgDCinv) increased by less than 1%. Also, the standard deviation of average inventory was less for Model 2: 34.9% lower at the store level and 16.8% lower at the DC level. The average number of orders placed by stores (numorders) decreased by 1.3% with Model 2. The actual service level at the stores (ServLev) decreased from 99.94% to 98.62%, which is still a desirably high level of customer service for the grocery industry. At the DC, Model 2 reflected a 9.4% decrease in the average number of product-days out of stock (DCsodays).

It should be noted that the results for Model 1 are influenced by the amount of shelf space allocated to each product, which was arbitrarily set for this experiment. Although the level of performance with Model 1 will vary with different shelf space allocations, the relationships, and tradeoffs of performance measures with different management policies for Model 1 and Model 2 are still insightful.

TABLE 4. INVENTORY MODEL FACTOR

Response Variable	Model = 1		Model = 2	
	Mean	Std. Dev.	Mean	Std. Dev.
avgstinv	2,815	390.2	800	254.1
avgDCinv	2,136	74.9	2,156	62.3
numorders	2,181	914.3	2,152	884.5
DCsodays	170	96.9	154	76.2
ServLev	99.94	0.133	98.62	1.488

Reason: Model 1 shows a higher service compared to the Model 2 level due to the higher ROP amount. This ROP amount is much more than needed to keep the store in stock to cover the total expected demand from the current time until the next inventory review time (n_t) and the expected demand during the replenishment lead time (LT). Conversely, the ROP for Model 2 is set to equal the expected demand from the current time until the next inventory review time (n_t) and the expected demand during the replenishment lead time (LT) plus a safety stock at a 98% service level. The ROP for Model 1 is set higher than the ROP for Model 2, which is supported by the much higher average store inventory and higher number of store orders in Model 1. It is interesting to note that the service level for Model 1 is 98.62%, which is higher than the set service level of 98%.

Managerial Insights: A lower ROP in Model 2 allows for a significant reduction in the store inventory, at a slight decrease in service levels.

5.2. Comparison of the Case Pack Size Factor

The use of smaller case pack sizes and more frequent deliveries are tactics that support a Lean strategy for inventory replenishment. Tables 5 and 6 give the results of the case pack size for Models 1 and 2, respectively.

For Model 1, Table 5 shows that decreasing the case pack size results in a somewhat higher average inventory at the retail store, as is expected since the reorder point increases. The average inventory at the DC decreases only slightly as case pack size is reduced from 24 to 6 units, while the number of store orders more than doubles. The number of DC stockout days improves somewhat, while the actual customer service level at the stores improves only slightly from 99.91% to 99.96%.

TABLE 5. MODEL 1 AND CASE PACK SIZE FACTOR

Response Variable	Model = 1 Case Pack Size = 24		Model = 1 Case Pack Size = 12		Model = 1 Case Pack Size = 6	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
avgstinv	2,565	341.4	2,866	342.4	3,016	342.7
avgDCinv	2,142	79.8	2,137	73.2	2,129	70.8
numorders	1,397	479.1	2,221	653.5	2,927	823.2
DCsodays	202	98.5	161	92.8	148	90.9
ServLev	99.91	0.192	99.95	0.095	99.96	0.073

Reason: The smaller the case pack, the higher the ROP hence more inventory is carried in the stores which increases the service level. Average DC inventory is relatively flat, but because the case packs are smaller and hence more can fit on a pallet in the DC, the DC stockout days decrease with the decrease in pack size. However, the number of orders significantly increases.

Managerial Insights: Smaller case packs result in a very small increase in service levels (0.05) at the expense of higher inventory holding costs and order costs at the stores. The higher number of orders also results in higher order processing costs at the DC. Order processing costs include administrative work to record and track the order, and the costs to pick the order.

For Model 2, Table 6 shows that decreasing the case pack size results in a substantially lower average inventory at the retail store. As with Model 1, the average inventory at the DC decreases only slightly with case pack size, while the number of orders more than doubles. Also, the number of DC stockout days improves somewhat, but the actual customer service level at the stores decreases slightly from 99.01% to 98.23%.

TABLE 6. MODEL 2 AND CASE PACK SIZE FACTOR

Response Variable	Model = 2 Case Pack Size = 24		Model = 2 Case Pack Size = 12		Model = 2 Case Pack Size = 6	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
avgstinv	1,044	177.2	751	176.4	605	176.5
avgDCinv	2,162	73.3	2,157	58.5	2,150	52.6
numorders	1,397	483.2	2,202	649.3	2,856	789.7
DCsodays	188	84.6	144	67.2	130	62.7
ServLev	99.01	1.088	98.62	1.432	98.23	1.756

Reason: The smaller the case pack, the lower the ROP hence less inventory is carried in the stores which decreases the service level. Average DC inventory is relatively flat, but because the case packs are smaller and hence more can fit on a pallet in the DC, the DC stockout days decrease with the decrease in pack size. However, the number of orders significantly increases.

Managerial Insights: Smaller case packs result in a decrease in service levels (0.78) at the benefit of lower inventory holding costs at the expense of higher order costs at the stores. The higher number of orders also results in higher order processing costs at the DC. Order processing costs include administrative work to record and track the order, and the costs to pick the order. The lowest service level is 98.23%, above our 98% service level requirement.

5.3. Comparison of the Impact of Delivery Frequency Factor

Table 7 shows the impact of delivery frequency for each inventory model. Not surprisingly with Model 1, increasing the delivery frequency from 3 to 6 times per week results in a somewhat higher average inventory at the retail store (7%) since the reorder point is higher and evaluated more frequently. However, with Model 2, average store inventory decreases by 27% with more frequent deliveries. With both inventory models, the average DC inventory decreases slightly with more frequent deliveries, DC stockout days increases slightly, and the number of store orders increases by about 40%. The actual customer service level at the stores improves slightly with Model 1 from

99.91% to 99.97% and decreases slightly with Model 2 from 98.73% to 98.51%, with more frequent deliveries.

TABLE 7. MODEL AND DELIVERY FREQUENCY FACTORS

Response Variable	Model = 1 Frequency = 3		Model = 1 Frequency = 6		Model = 2 Frequency = 3		Model = 2 Frequency = 6	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
avgstinv	2,721	408.7	2,910	345.8	923	242.2	677	200.6
avgDCinv	2,149	73.1	2,122	74.4	2,163	62.4	2,150	61.6
numorders	1,817	473.3	2,546	1,087.2	1,797	463.2	2,507	1,047.8
DCsodays	164	93.2	176	100.1	153	77.8	155	74.6
ServLev	99.91	0.176	99.97	0.048	98.73	1.396	98.51	1.567

Reason: For both models, an increase in delivery frequency leads to an increase in the number of orders the stores place. For Model 1, this results in a higher average store inventory because the ROP in Model 1 is reached more frequently, as evidenced by the increase in orders. For Model 2, an increase in delivery frequency results in a lower ROP as the LT component of the formula is reduced.

Managerial Insights: There are significant major benefits to Model 2 when the order frequency increases. Average store inventory significantly decreases in Model 2, for both delivery frequencies. Average DC inventory, the number of orders, and the DC stockout days are similar for the same delivery frequency for both models. Service level is over 1% higher for Model 1 at both frequencies, but this is at the trade-off of the higher in-store inventory. Service level threshold of 98% still met for Model 2. The increase in delivery frequency is similar to a JIT manufacturing environment where smaller order quantities are delivered on a more frequent basis.

5.4. Comparison of the Availability of Real-Time Store Inventory Data at the DC Factor

The next factor of interest is the stockout substitution policy used at the DC. The results show that the use of a stockout substitution policy at the DC has a negligible impact on each of the response variables, so these results are not presented. Such a policy is not a very effective mechanism for improving customer service levels at the stores. Further research is needed to refine effective substitution policies within this type of environment.

Results for the last main treatment factor, the availability of real-time store inventory data at the DC, are shown in Table 8, for each inventory model. For both inventory models, the availability of real-time data at the DC shows a very small increase in average store inventory level and a slightly larger increase in the average inventory level at the DC. The number of store orders decreases only a little for both models as well, and there is also a very slight improvement in actual customer service levels at the stores. The biggest impact is on the number of DC stockout days, where the availability of real-time data reduces DC stockout days by 23% with Model 1 and 29% with Model 2.

TABLE 8. MODEL AND REAL-TIME DATA AT DC FACTORS

Response Variable	Model = 1 Real-Time = no		Model = 1 Real-Time = yes		Model = 2 Real-Time = no		Model = 2 Real-Time = yes	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
avgstinv	2,813	391.9	2,817	388.4	797	252.5	802	255.7
avgDCinv	2,116	73.6	2,156	70.7	2135	57.6	2,177	59.7
numorders	2,183	913.7	2,180	915.1	2,154	883.5	2,150	885.6
DCsodays	192	102.7	148	85.4	180	77.1	127	65.4
ServLev	99.93	0.140	99.94	0.127	98.57	1.516	98.67	1.458

Reason: The monitoring of real-time data allows the DC to make a more accurate assessment in the substitution policy if the item ordered by the store is out of stock at the DC. The high and almost identical service levels in Model 1 – with or without real-time data availability – is due to the high inventory carried by the stores, indicating the substitution policy is not needed under Model 1. However, in Model 2, inventory levels are much lower, and the availability of real-time data helps to improve the service level through the substitution policy.

Managerial Insights: Though the item ordered is out of stock at the DC and could possibly become out of stock at the store, it is unlikely the substitution product will become out of stock at the store, which helps to improve the store service level. Real-time data availability is not a necessary condition if the stores carry large amounts of inventory. However, if the stores are running lean on inventory, real-time data can help reduce store stockouts.

5.5. Comparison of the Demand Level and Artificial Outlier Demand Factors

The last two results discussed are for the impacts of the two environmental factors, demand level, and artificial outlier demand. Table 9 shows the impact of high and low levels of demand, for each inventory model. With Model 1, the average store inventory level decreases from 3,135 to 2,495 units, and with Model 2 it increases from 690 to 909 units. The standard deviation of average store inventory increases with higher levels of demand for both models. With both models, average DC inventory decreases slightly for higher demands, the number of store orders and DC stockout days increases substantially, and actual store service levels decrease slightly.

TABLE 9. DEMAND AND MODEL FACTORS

Response Variable	Demand = low Model = 1		Demand = low Model = 2		Demand = high Model = 1		Demand = high Model = 2	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
avgstinv	3,135.20	200.02	690.16	204.91	2,495.45	244.49	909.54	251.22
avgDCinv	2,153.04	45.70	2,169.81	48.59	2,118.32	92.37	2,143.08	71.07
numorders	1,736.86	723.97	1,708.59	693.23	2,626.34	867.40	2,595.07	831.53
DCsodays	116.52	50.44	111.15	47.61	223.91	102.42	196.62	75.52
ServLev	100	0.00	99.08	0.953	99.88	0.171	98.16	1.761

Reason: At low demand, Model 2 average store inventory is 4.5 times lower than Model 1. This low demand creates a low ROP for Model 2 (lower average demand during lead time and lower variance of demand – safety stock) whereas the ROP for Model 1 is not influenced by demand. When demand is high, Model 2 average store inventory is 2.7 times lower than Model 1, but Model 1 has a much higher service level than Model 2. In Model 2 it is more likely that the demand during the lead time is greater than the ROP value. This is due to the safety stock being set at 98%. However, at high demand Model 2 exceeds the required service level at 98.16%.

Managerial Insights: At high demand Model 2 is robust and slightly exceeds the set service level. The implication here is that a reduction of inventory at the store can still meet the desired service level if Model 2 is used as the inventory policy.

Table 10 shows the impact of artificial outlier demand for each model. With additional artificial outlier demands, average store inventory decreases by 4% with Model 1 and decreases by 11% with Model 2. However, the standard deviation of average store inventory levels increases with Model 1 but decreases with Model 2. Average DC inventory decreases somewhat with artificial outlier demands, and the number of store orders increases somewhat for both models. With both inventory models, the number of DC stockout days approximately doubles with additional artificial outlier demands. Finally, the actual store service level decreases from 100% to 99.88% with Model 1 and decreases from 99.89% to 97.35% with Model 2, with additional artificial outlier demands. This was the only scenario where the customer service level for Model 2 dropped below the 98% level used to set the safety stock.

TABLE 10. ARTIFICIAL OUTLIER DEMAND AND MODEL FACTORS

Response Variable	Outlier = no Model = 1		Outlier = no Model = 2		Outlier = yes Model = 1		Outlier = yes Model = 2	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
avgstinv	2,877	361.7	847	262.3	2,753	407.3	752	236.3
avgDCinv	2,197	27.1	2,209	27.2	2,074	53.3	2,104	38.8
numorders	2,142	923.7	2,103	887.0	2,221	903.2	2,200	879.5
DCsodays	105	41.3	108	44.8	235	92.6	200	73.7
ServLev	100	0.00	99.89	0.064	99.88	0.170	97.35	1.098

Reason: Regardless of whether or not there is outlier demand, Model 1 carries a significantly higher average store inventory which results in a higher service level. This is due to the higher ROP amount which is better able to account for demand spikes.

Managerial Insights: Outlier demand was the only scenario that resulted in a service level below 98% for Model 2 (97.35%). This is due to the significantly lower average inventory held at the stores in Model 2. To better manage and prepare for outlier demand, an alert should be sent to the warehouse if daily demand reaches a set multiple of average demand or if a single consumer purchases a quantity at or above a specified amount.

VI. SUMMARY AND CONCLUSIONS

The primary purpose of this paper is to provide an example demonstrating how timely and relevant data collection with RFID could be applied to supply chain analytics. Our research used a simulation study of a two-echelon system of a retail store and a distribution center to model an inventory replenishment policy that examines the value of using RFID. The simulation study examined the difference between two inventory replenishment policies: Model 1 is based on a periodic inventory review policy which is consistent with a typical retail store and Model 2 that is based on a periodic review policy that is facilitated using RFID. A full factorial experimental design is used with main treatment factors and environmental factors that resulted in 192 experimental scenarios. Each scenario was replicated 50 times, yielding a total of 9,600 observations for analysis.

The results illustrate that while new operational techniques provide different options for businesses, performance trade-offs must be balanced. Of all the factors investigated in this experiment, the choice of inventory replenishment model has the greatest impact on supply chain performance. As seen in Table 4, the minor reduction in actual store service levels using Model 2 is offset by a substantial reduction in average inventory at the stores, with little impact on average inventory at the DC and number of store orders. As previously noted, the performance of Model 1 is influenced by the amount of shelf space allocated to each product. Nevertheless, valuable insight can be gained by examining the performance changes with each model as inventory management policies and parameters vary. By using Model 2, retail stores should be able to free up a significant amount of shelf space that can become available for additional product offerings.

Examining the average store inventory levels for Model 2 in Table 6 suggests that even more shelf space can be freed up if smaller case pack sizes are utilized. As noted earlier, retailers are already embracing smaller pack sizes. However, smaller case pack sizes also result in more store orders and slightly lower customer service levels. Thus, stores must determine the best balance for their local markets. More frequent deliveries with Model 2 also helped to substantially reduce average store inventory levels. But again, this was at the expense of more store orders and a slight reduction in customer service levels.

One important finding of this research is that with the improved inventory record accuracy that RFID technologies provide, grocery stores can take advantage of more efficient reordering policies. By using a policy like Model 2, average inventories can be substantially reduced, with only small reductions in customer service levels. Average inventories can be further reduced by going to smaller case pack sizes and by having more frequent deliveries. Reducing average store inventories is important because this allows stores to make more room on the shelves for additional product varieties, giving customers more choices, and providing a competitive advantage.

The basic economical analysis for minimizing cost theoretically involves the reduction in average inventory, the number of orders placed at the retail store, and service level (e.g., the need for carrying safety stock). By comparison, the reduction in average inventory in Model 2 suggests a sizeable cost reduction in holding costs without a significant loss to service level. The number of orders placed by the retail store is also slightly reduced, which is a small saving in ordering cots. Overall, for Model 2, this implies that high service levels can still be obtained with a significant cost reduction in holding cost and a small reduction in ordering costs.

In the supply chain environment studied here, the grocery store was assumed to place the orders. However, with RFID technology and the inventory models that were investigated, the store orders could just as easily be placed by the DC instead of the stores. This has direct impacts on the management of grocery chains, including:

- The use of RFID tags gives the DC better real-time visibility of store inventories to allow for better managing DC inventories. RFID tags also provide better inventory record accuracy for the inventory stored at the DC.
- Real-time store inventory visibility at the DC allows the possibility for ordering to be done by the DC rather than by the store manager. This frees time for the store manager and allows them to focus more on customer service and employee engagement.
- After real-time inventory information is in place at the stores and the DC, the next step is to allow the manufacturers to see certain inventory data at the DC, which would give manufacturers a real-time view for better planning.

The actual implementation of RFID in grocery stores is not without challenges. Prater *et al.* (2005) noted that accurate data entry by store clerks is required and that each item should be individually scanned at checkout. Pramatari (2007) identified three challenges to RFID: technical, organizational, and multi-party coordination. Cost, technical issues, and privacy have been cited as concerns by Gaukler *et al.* (2007) and Reyes *et al.* (2016), while shrinkage and product misplacement have been discussed by Condea *et al.* (2012), and Thiesse and Buckel (2015).

Beyond the commonly cited challenges, Jones *et al.* (2005) how retailers will want to indicate their abilities to handle and make effective use of the data captured by the RFID systems. Leung *et al.* (2014) report on multiple case studies and caution the adoption process because of *'misalignment'* and the *'bandwagon effect'* and that the RFID adoption should be aligned with the supply chain strategy based on product characteristics and marketplace. Doss *et al.* (2020) examined the cybersecurity vulnerabilities for secure attribute-based search in RFID-based inventory control systems.

To conclude, future research opportunities in this area should focus on assessing the impact of the new management options that RFID provides. This includes developing an approach to determine the best shelf space allocations if Model 2 is used in the stores. Also, an investigation of how to balance lower inventories in the stores with reduced service levels can provide guidelines for setting appropriate safety stock levels. This can be in conjunction with an optimal delivery frequency to the stores and optimal case pack sizes that allow for better utilization of resources. Additional research into possible substitution strategies can prove useful as researchers continue to develop tools and methods to handle uncertainty and better meet the ever-changing demands of its customers.

While we did provide a short discussion to the basic economic analysis in section six (summary and conclusion), we acknowledge that this to be a limitation of this study. We did not assess inventory holding, ordering and stockout costs in the models as this would have added a significant number of scenarios to the experimental design. Holding and stockout costs would have to be calculated for the ten retail stores and the DC. Future research could investigate a range of costs for several of the experimental design factors in Table 3, such as case pack size, delivery frequency and artificial outlier.

Finally, our simulated supply chain model represented a scaled-down version of the type of grocery supply chains currently operated by national grocery store chains in the U.S. and was limited to five products within one category. This research could be then be extended to include complementary products across two or three additional categories. As such, a sensitivity analysis on the different parameters with additional options for each parameter would enhance the strength of our RFID model based on a continuous review policy.

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