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RFID-Enabled Shelf Replenishment with Backroom Monitoring in Retail Stores

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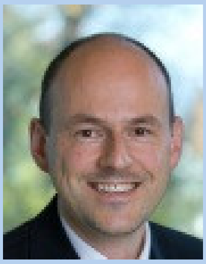

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Business Processes & Applications

Abstract

This contribution is concerned with the value of RFID for retail store operations, particularly the use of the technology to automate shelf replenishment decisions. We construct and test an inventory control policy based on RFID data with case-level tagging. Our model incorporates RFID hardware capable of detecting bidirectional product movements between a store's backroom and the sales floor. In contrast to prior research, we account for detection errors caused by imperfect RFID read rates. Furthermore, we propose and evaluate a simple heuristic extension to avoid some of the inherent downsides of fully automatic inventory control. We compare the performance of these policies under stochastic demand, lost sales, and shrinkage to the traditional scheme with periodic reviews in a simulation study. Our results indicate that RFID-based policies have the potential to improve cost efficiency and service levels. However, different sensitivities to cost factors and suboptimal read rates must be considered when choosing a policy.

Keywords. RFID; Retail; In-store Logistics; Inventory Management; Shelf Replenishment; Simulation.

1. Introduction

To establish a profitable and sustainable position in the market, retailers are required to operate at low cost while providing high product availability [24]. The extensive use of information technologies and industry initiatives such as "Efficient Consumer Response" (ECR) have traditionally been important means to achieve this objective. Automatic identification technologies, such as Radio Frequency Identification (RFID), are expected to further improve physical process efficiency and overall supply chain visibility [4,5,30]. RFID differentiates itself from the traditional barcode through its possibilities for bulk registration, identification without line of sight, unambiguous identification of each individual object, data storage on the object, and robustness toward environmental influences and destruction [39]. To leverage these potentials in their supply chains, Wal-Mart, Tesco, Metro, and other large retailers have recently issued mandates requiring hundreds of their suppliers to attach RFID transponders to their products. The expectation among these early adopters of RFID is that the technology will lead to unprecedented efficiency gains in manufacturing, distribution, store operations, and supply chain collaboration [44]. The corresponding benefit categories affect a variety of performance metrics, including lead times, personnel cost, asset utilization, product safety, product availability, customer satisfaction, and others [48]. The scope of RFID in logistics and supply chain management has been the subject of several recent review articles (e.g., [3,21,28,29,32,41]).

One potential logistical application of RFID that has attracted interest among retail practitioners is its use in the context of in-store processes such as shelf replenishment [42]. The underlying idea is to automate the monitoring of inventory and to trigger replenishments from the store's backroom to the sales floor based on RFID data in real time [11,50]. This process presents an alternative to having store employees visually inspect retail shelves by regularly walking the aisles. According to an ECR Europe study, it is at the 'last 50 yards' of the supply chain that most of the causes of stock-outs can be found [13]. Stock-outs affect sales in numerous ways. For example, consumers substitute one item for another, switch brands, delay the purchase, or buy the product at a different store [49,52], resulting in a reduction in profit of up to 10% [34] as well as long-term impacts on market share [2]. Gruen et al. [18] estimated that 25% of all stock-out situations are caused by inefficiencies in the shelf replenishment process so that products are in store but not on the shelf. Other causes include incorrect forecasts, suboptimal ordering decisions, and insufficient service levels in the upstream supply chain. Consequently, product availability in stores drops to an average of 91.7% in contrast to the 98 – 99% usually achieved at the manufacturer and the distribution center (DC). In another study among European retailers, Thonemann et al. [46] found that service levels range from 90%, in the worst case, to 98.7%, in the best case. In this survey, the responding retail executives also ranked current in-store logistics processes as the most promising area for improvement in the supply chain.

There has been little research investigating the use of RFID in the shelf replenishment process between a store's backroom and the sales floor. In practice, most companies may attempt to avoid store backroom inventory and favor so-called 'one-touch replenishment' policies [8]. Nevertheless, there are a number of reasons why retailers continue to keep backroom inventory: (a) more products can be stored per unit of floor space in the backroom compared with the sales floor; (b) backroom inventory can act as a buffer when deliveries are uncertain, lead times are long or deliveries are imperfect; and (c) for some bulky or high velocity products, there may not be enough shelf space available to unload all products directly onto the sales floor [50]. On the downside, the corresponding costs for inventory handling in stores add up to a large part of total supply chain costs [51]. Because retailers have thus far concentrated on the optimization of processes between the DC and the store by the introduction of automatic reordering systems, in-store processes are an attractive and untapped opportunity for efficiency improvements [12,33].

The present study aims to investigate the value of RFID as a means of optimizing shelf replenishment in a retail store under stochastic demand and shrinkage. Our contribution to the literature is threefold. First, we construct policies that use RFID data to eliminate manual inventory checks and, thus, to automate shelf replenishment decisions in stores. In contrast to the majority of prior work, which presumes that RFID is used to directly observe inventories at the item level on shelves, our approach relies on the detection of cases moving between the backroom and the sales floor. Given the substantial cost of RFID reading devices, the idea of having only one reader location seems far more realistic than the concept of RFID-enabled 'smart shelves' [9]. Second, we account for the fact that RFID is an error-prone identification technology whose performance is influenced by the physics of RF communications, the quality of hardware components, issues in the labeling and logistics processes, and other factors. We optimize control parameters for different read rates and explicitly consider the impact on costs and stock-outs. Third, we compare the performance of the new shelf inventory management strategy to a traditional process that relies on periodic inspections of product availability. We use a simulation to quantify the relative advantage of RFID-enabled replenishment, which allows us to draw a number of valuable conclusions regarding real-world implementations of RFID.

The remainder of the paper is organized as follows. In the next section, we provide a review of prior research on RFID in retail settings with a focus on in-store logistics. Section 3 provides an overview of the considered replenishment policies and the structure of our simulation model. In Section 4, we present and discuss numerical results from our simulation study, including a sensitivity analysis. The paper closes with a discussion of our main findings, limitations, and opportunities for further research.

2. Related Work

A number of models have recently been provided by the academic community to enable a realistic assessment of the value of RFID [27,38]. A comprehensive overview of the use of RFID-based information on inventory movements to expose and prevent inefficiencies in supply chain operations was provided by Lee and Özer [25]. With regard to RFID usage in retail, most researchers have focused specifically on the phenomenon of inventory inaccuracies that might be caused, for instance, by theft, product misplacements, or transaction errors.

Kang and Gershwin [20] studied the consequences of inventory record inaccuracies under a continuous review policy and determined that even small, undetected losses can lead to severe disruptions and stock-outs. They considered the adoption of an automatic identification technology one solution to mitigate the problem. Gaukler et al. [17] examined the benefits of item-level RFID on a vertically integrated supply chain, as opposed to a decentralized supply chain with one manufacturer and one retailer. They assumed that RFID could be used to improve the efficiency of the replenishment process in retail stores, measured by discrepancies between the shelf inventory available to satisfy customer demand and backroom inventory. The authors analyzed the benefits of full replenishment efficiency in the case of shrinkage, misplacements, and other execution errors and derived insights into the threshold cost at which RFID adoption would become profitable. De Kok et al. [22] studied an inventory system with periodic reviews in the presence of shrinkage due, for example, to theft. They considered RFID a technological means to partially prevent shrinkage. By comparing costs in the situation with RFID to costs without RFID, the authors derived an analytical expression for the break-even prices of a RFID tag. They showed that these break-even prices are highly related to the value of the items lost, the shrinkage fraction, and the shrinkage after implementing RFID. Rekik et al. [35] considered a newsvendor-type inventory model in which a manufacturer sells a single product to a retail store whose inventory is subject to errors, stemming from execution problems, that result in products lost in the backroom or products misplaced on other shelves of the store. In a first model, both parties know the extent of the execution errors at the retailer, and decisions about the ordering quantity are made by taking these into account. In a second model, RFID technology is deployed within the store to eliminate errors. The authors considered both centralized and decentralized scenarios and determined the best strategy depending on the structure of the supply chain and system parameters, such as error rate and technology costs. Similar investigations were presented in [36] and [37], which considered a retail store subject to inventory inaccuracies stemming from misplacements and theft, respectively.

These prior studies provide valuable insights into the potential of RFID, but they avoid detailed consideration of the actual shelf replenishment process. In fact, to ensure the mathematical tractability of the models, the modeling of RFID and its impact on in-store logistics is reduced to the technology's conjectured ability to completely eliminate misplacements and shrinkage. A first attempt to fill this gap in the literature was presented by Wong and McFarlane [50], who provided a qualitative analysis of opportunities for improvement using RFID at a more granular level of investigation. The authors first described the structure of the traditional replenishment process based on (a) a pull policy and (b) a push policy depending on whether the review is conducted in the backroom or on the sales floor, respectively. They subsequently discussed the main determinants of suboptimal replenishment performance, such as delayed reviews or outdated pick lists, and described an RFID-supported process characterized by automatic monitoring of stock levels and product movements as well as automatic compilation of pick lists on mobile devices.

Hardgrave et al. [19] analyzed Wal-Mart’s pilot project in 12 stores with varying store formats from February to September 2005. The company tagged 4,554 different products on the case level to allow any product movements to be monitored between the backroom and the sales floor. In this trial, the use of RFID led to a 16% reduction of stock-outs, on average, compared to a control group of 12 other stores. In the best case, a 62% reduction was observed for products with a daily demand of 6 to 15 units. The authors regard the ability to automatically generate pick-lists for store employees as the most important driver of this improvement, which eventually supersedes the need for manual reviews.

Lee et al. [26] used simulation models to investigate the effects of (a) the elimination of inventory inaccuracies, (b) the redesign of the shelf replenishment process, and (c) the exchange of inventory-level information between a supplier and retailer through the use of RFID. In the second case, the traditional process of inventory management based on periodic reviews was compared to continuous reviews through the use of RFID readers in the shelves. The authors argued that RFID allows for a replenishment process, which is better adapted to actual demand while necessitating lower stock levels on the shelves. However, the significance of their findings is limited because they chose arbitrary inventory policies to examine the performance of the different replenishment strategies instead of optimized policies. Additionally, the authors considered stock levels and stock-outs as the main performance indicators rather than cost.

Szmerekovsky and Zhang [43] studied the effect of RFID at the item level for a manufacturer and a retailer, relying on RFID in a vendor-managed inventory (VMI) system. They compared a system of continuous review using RFID and a non-RFID system of periodic review. The authors determined the optimal inventory policies in a centralized system and established conditions under which the RFID system was preferable to the system without RFID. Furthermore, they studied the decentralized system and showed how sharing the tag price can be used to coordinate the supply chain. The limitations of this single-period model include fixed shelf space, fixed review / replenishment intervals, and the fact that replenishment costs are not considered.

Çakıcı et al. [6] analyzed the incremental benefits of RFID technology over barcodes for managing pharmaceutical inventories. Based on a case study, the authors showed that inventory managers can benefit from RFID by leveraging automatic counting and continuous review and by tracking shrinkage actively. Using a mathematical model, they showed that the switch to continuous review achieves savings with regard to inventory holding, backorder, and ordering costs. Furthermore, they considered RFID in combination with an optimized replenishment process, which means that the fixed cost of ordering is reduced, shrinkage is eliminated, and an optimal continuous review order point-order quantity policy is used. The results indicate that the total cost savings of RFID combined with business process reengineering increase in all policy parameters except for cost per order under RFID.

As we argue in the following, a problematic simplification of most existing models is that RFID is regarded as an error-free identification technology [38,47]. However, in light of the many reports from real-world deployments of RFID, this assumption does not adequately reflect the factual limitations of the technology and diminishes the value of the respective models. The causes of suboptimal read rates are diverse and include dysfunctional tags, incomplete labeling of products, tags that are accidentally removed or destroyed by employees or customers, physical shielding by metals or liquids in the product or its packaging, shielding by other tags, and errors in the installation or the configuration of reader hardware and antennae [16]. Consequently, notwithstanding advances in the development of RFID tags and readers, read-rate issues are still common and are not limited to a small range of 'pathological' product types, which cannot be detected reliably even under near-perfect laboratory conditions [14,15].

The study by Thiesse et al. [45] is the only one we are aware of that explicitly investigates the impact of detection errors. The authors present a simulation study of a retail store operating under an RFID-based inventory control policy. They investigate the impact of suboptimal read rates on total cost and service level and compare their policy to the traditional process using manual shelf inspections. The fact that their model does not account for shrinkage is a major limitation of the study. As we show in the next section, shrinkage may lead to a 'replenishment freeze', which renders the RFID-based policy unfeasible in most practical settings. Moreover, the simulation model does not account for temporal delays between events.

The study by De Kok et al. [22] at least indirectly accounts for suboptimal RFID performance. The authors include a parameter α in their model, which denotes the fraction of theft that could be eliminated by the use of RFID. In their numerical evaluation, they consider different levels of α to illustrate the influence of RFID performance on break-even tag prices. However, the linkage between RFID detection rate and parameter α is beyond the scope of their research.

3. Model Development

3.1. General Framework

In this paper, we aim to fill the gap in the literature regarding the design of RFID-enabled replenishment policies in retail stores through the development of inventory control policies that account for detection errors in the RFID system. We consider a single-product model of a retail store with random demand and lost sales. The retailer's objective is to reduce costs while increasing service levels. We assume that the retailer’s practice of reordering from the distribution center is not a cause of out-of-stocks. Instead, we exclusively consider out-of-stocks as 'in stock but not on shelf' situations attributed to inefficiencies in the shelf replenishment process. Furthermore, we assume that the retailer already collects data on all ingoing and outgoing products at the store level using barcode scans or another identification procedure. Because the receipt and check-out of goods are technology-supported manual processes, we assume that the corresponding detection rates reach 100%. However, these data do not enable the retailer to distinguish between inventory in the backroom and on the sales floor because (s)he has no means to reliably observe if and when replenishments occur. Consequently, the retailer depends on an additional mechanism that allows him/her to make economical decisions on when and how many items to replenish.

The purpose of our model is to enable a rigorous comparison between two scenarios: (i) a traditional replenishment process and (ii) an RFID-enabled replenishment process. In the former scenario, the retailer conducts manual, periodic inventory counts on the sales floor to detect low levels of inventory. We refer to this as a periodic review (PR) policy. In the latter scenario, the retailer estimates the inventory levels on the sales floor by employing an RFID reader installed between the backroom and the sales floor, which is able to detect bidirectional product movement between the two areas. We refer to this as backroom monitoring (BM). This RFID-enabled scenario is characterized by higher-quality inventory information with regard to accuracy and timeliness as well as by new cost factors, such as hardware costs for RFID transponders. Furthermore, we analyze the impact of measurement errors induced by the technological limitations of RF communications on the value of RFID and optimize the control parameters for these effects.

We develop an event-driven simulation model to compare the two described classes of replenishment policies. Simulation is a well-established tool that allows the researcher to observe the impact of different operational decisions in inventory control systems and to avoid simplifications that are typically made in analytical modeling to achieve mathematical tractability [1,7]. We simulate a retail store consisting of a backroom of virtually unlimited capacity and a sales floor with a limited amount of shelf space for the considered product. We assume that sales items are stored and transported in cases with a fixed number of sales items per case. Any excess cases brought to the sales floor during replenishment are returned to the backroom; empty cases are collected for recycling in a trash compactor. Customer demand is modeled as a Poisson process with rate λ per day. All sold items are accurately identified at the point-of-sale (POS) and subtracted from the currently recorded inventory level. Our model also considers shrinkage (e.g., due to theft), which can be regarded as a form of invisible demand, with items leaving the system without being detected at the POS. The extent of shrinkage γ is expressed as a fraction of total demand. Within the simulation horizon, we observe various output parameters to calculate two performance metrics: (i) the retailer's total cost and (ii) the service level. An overview of our notation is given in Table 1.

	Notation	Description
Parameters	r	Review interval
	s	Replenishment Threshold
	S	Shelf space
	τ	Inventory adjustment time threshold
	c_i	Cost of the manual inspection / review of shelf levels
	c_r	Cost of shelf replenishment
	c_a	Costs of shelf space allocation (per item)
	c_p	Penalty costs of lost sales (per item)
	c_t	Cost of RFID transponders
	c_m	Cost of the inventory adjustment
	d_R	Delay until shelf replenishment
	d_B	Delay until excess inventory is returned to backroom
	d_C	Delay until customer arrives at POS
	d_T	Delay until the box is trashed into the box crusher
	I_P	Physical inventory level
	I_R	Recorded inventory level
	y_c	Number of customer arrivals
	y_s	Number of sold units
	y_r	Number of shelf replenishments
	y_i	Number of manual shelf level inspections
	y_m	Number of manual inventory adjustments
	y_f	Number of stolen items
	T	Simulation horizon
	λ	Demand rate
	φ	Read rate of RFID hardware
	γ	Shrinkage rate
	u	Number of sales units per case
Functions	Π_{PR}	Total cost function under the PR policy
	Π_{BM}	Total cost function under the RFID-enabled policy
	β	Service level

Table 1. Notation overview

3.2. Replenishment with Periodic Reviews

The traditional process of shelf replenishment uses periodic reviews of the number of items on a shelf. We assume that demand manifests on the sales floor when a customer arrives at the shelf, puts an item into the shopping cart, and – after a time delay dC – goes to the POS, where the item is recorded and sold. The retailer may use POS data to keep track of his inventories at the store level, but these data do not allow the exact amount of items on the shelf to be determined. For this reason, every r time units, a store clerk visually inspects shelf levels. The shelf has a maximum capacity of S items. If the stock level reaches or goes below a threshold s, a replenishment is triggered. After a time delay dR, which includes the time to search, pick, and transport products from the backroom to the sales floor, the actual replenishment takes place. This procedure corresponds to the classical (r; s; S) policy, as described by Silver et al. [40]. However, an important characteristic of shelf replenishment is that the number of products moved to the shelf is not predetermined at the time of the inspection. Sales items are transported in cases with u items per case. The shelf is only refilled with complete cases; the number of items added to the physical shelf inventory during replenishment is always a multiple of u. The employee transports S/u cases from the backroom to the shelf and refills the shelf, returning excess cases to the backroom. This implies that for u > 1, the number of items on the shelf after replenishment will not necessarily equal S (see Figure 1).

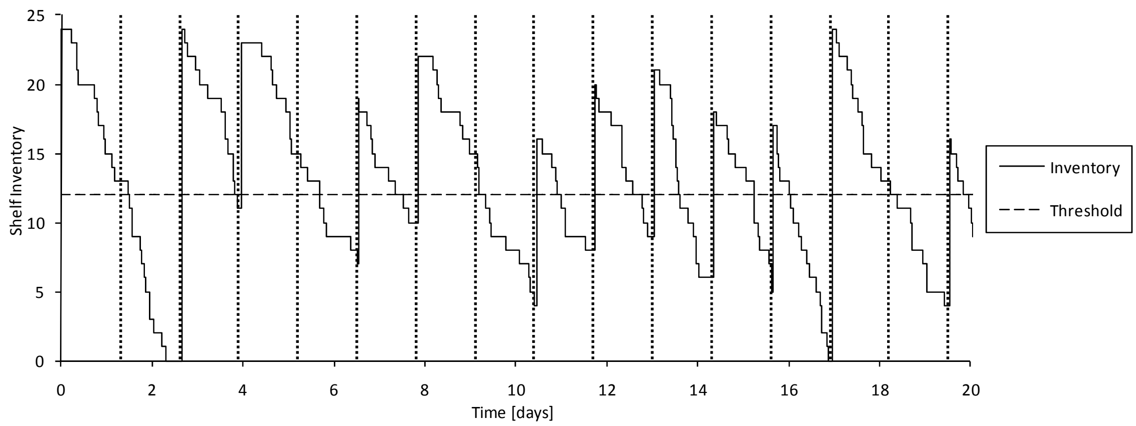

Figure 1. Inventory control under the PR policy (r=1.3; s=12; S=24; λ=10; u=12); dotted vertical lines indicate reviews

The retailer incurs shelf allocation cost ca per item, review cost ci per review, replenishment cost cr per replenishment, and penalty cost cp per lost sale in the event a customer faces an empty shelf. The output parameters recorded within the simulation horizon T include the number of customer arrivals yc, the number of sold units ys, the number of reviews yi, the number of shelf replenishments yr, and the number of thefts yf. The total cost function with periodic review ΠPR is then given by

$$\Pi_{PR} = c_i y_i + c_r y_r + c_a S \cdot T + c_p (y_c - y_f - y_s) \quad . (1)$$

The service level β is expressed as the fraction of fulfilled demand as compared to total demand excluding shrinkage:

$$\beta = \frac{y_s}{y_c - y_f} \quad . \qquad (2)$$

3.3. Replenishment with RFID-enabled Backroom Monitoring

The RFID-enabled replenishment process with backroom monitoring is intended to supersede most of the manual intervention required in the periodic review process through the automatic detection of product movements from the backroom to the sales floor and vice versa. We assume that the gate between the backroom and the sales floor is equipped with an RFID reader. As is common in many real-world implementations, readings are triggered by a complementary motion detector, which also allows the direction of product movements to be recorded. When cases are transported from the backroom to the sales floor, their contents (i.e., u items per case) are added to the recorded shelf inventory. Excess cases, returned to the backroom after replenishment, are subtracted from the recorded shelf inventory. Further, each sales transaction at the POS leads to a decrease of the recorded shelf inventory by 1. With such information at hand, the store's inventory management system can provide at any time t an estimate IR,t of the actual physical inventory IP,t. This recorded inventory will be the sole basis for triggering replenishments. The quality of this estimate is directly dependent on the read rate of the RFID infrastructure. We explicitly model this aspect in the form of a parameter φ, where φ ∈ [0, 1] is the probability of a product being detected by the RFID reader.

Imperfect read rates in combination with the fact that cases, but not the sales items themselves, are RFID-tagged introduces additional complexity to the model. Let t and t´ be the points in time immediately before and after a case brought to the sales room is detected by the RFID reader. The inventory estimate is then updated as IR,t´ = IR,t + u. If a case is not detected, IR remains unchanged. Items that are taken off the shelves by customers can only be detected at the POS when they are sold. However, because it is not possible to distinguish between items from previously detected and undetected cases, more items would be subtracted from IR in the long term than added. The retailer therefore requires a third data source that identifies empty cases taken off the shelf during replenishment and corrects the recorded shelf inventory accordingly if previously undetected cases are found. For this purpose, we assume that the store's trash compactor is equipped with an additional RFID reader. If this reader identifies a case that was not detected by the RFID reader between the backroom and the sales floor upon replenishment, the recorded shelf inventory is increased by u.

All described events in the store are separated from each other by temporal delays. First, we assume that when a replenishment has been triggered, backroom operations take some time dO until the cases reach the RFID gate. An additional time span dS passes until the cases arrive at the shelf. It should be noted that the total time for replenishment is the same as under the periodic review policy:
dO + dS = dR. After replenishment, excess cases return to the backroom after a delay dB. Empty cases are brought to the trash compactor after a delay dT. Items that are taken off the shelf by customers arrive at the POS after a delay dC. A schematic overview highlighting the logic of the model, including events, delays, and necessary data sources for backroom monitoring, is shown in Figure 2. The corresponding flow diagram of our simulation is given in Figure 3.

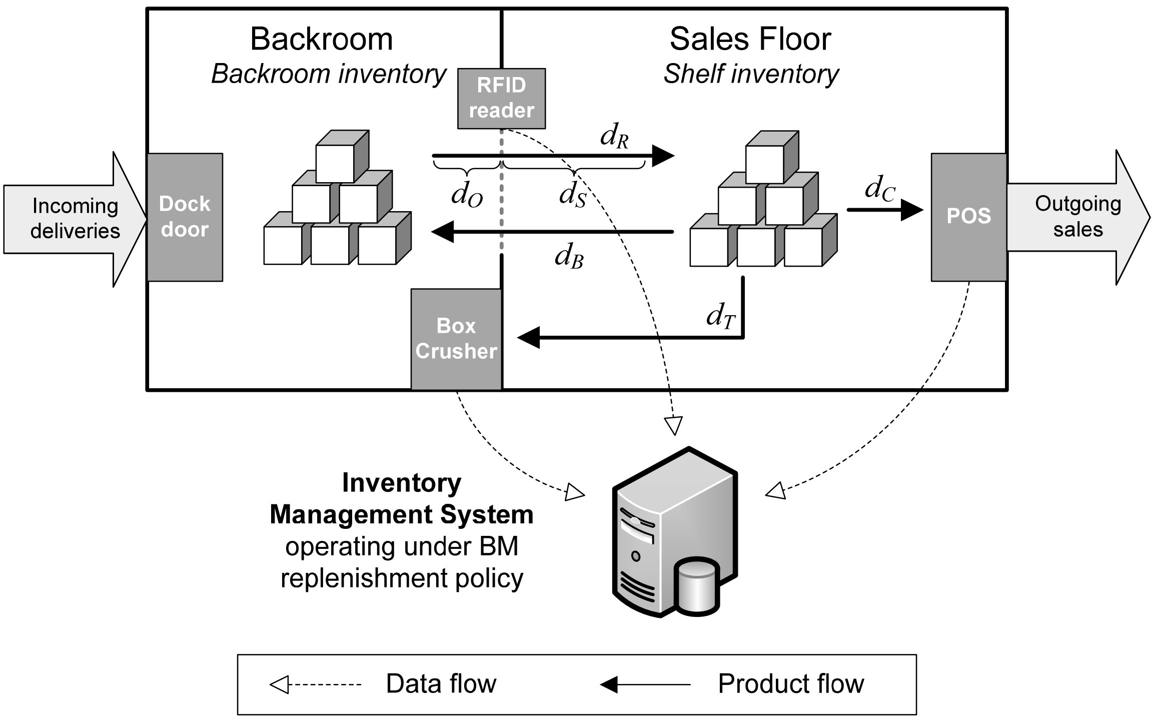

Figure 2. RFID-enabled replenishment with backroom monitoring

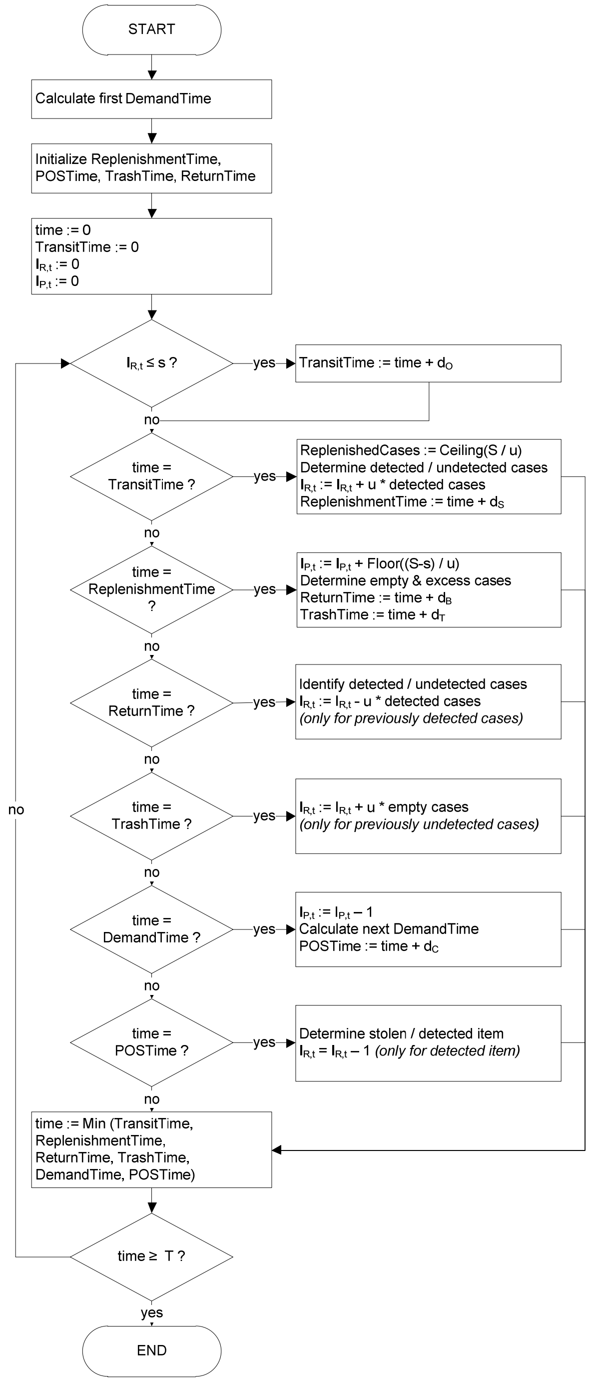

Figure 3. Flow diagram of the event-driven simulation model under the RFID-enabled backroom monitoring policy

A further issue associated with backroom monitoring arises in the form of replenishment freezes. Due to the imperfect read rate, it may happen that excess cases are first detected on their way to the sales floor but not on their way back. This situation poses a second source of inventory inaccuracies, in addition to cases that are not detected upon entering the sales floor. If the resulting error increases over time, it may eventually reach a point where IR > s, while IP = 0. No replenishment is triggered then because the recorded inventory will not decrease further; consequently, a state of permanent out-of-stock is reached. Replenishment freezes can also be caused by shrinkage. Acting as a source of invisible demand, shrinkage leads to errors in the recorded inventory as items leave the system without being detected at the POS.

To prevent replenishment freezes, the retailer might continually analyze POS data for exceptional decreases in sales. After each sale recorded at the POS, the retailer will set a time offset τ after which, if no further sale took place, the retailer needs to take corrective action. Threshold τ denotes the point in time when the probability of an undetected stock-out (i.e., a replenishment freeze) is higher than the probability of no customer demanding the product. After τ has elapsed, the store manager then inspects the shelves and counts (e.g., with a mobile RFID reader) all cases and their contained items currently on display on the shelf. Finally, (s)he corrects the error of the recorded inventory from the information system by setting it to the value of the physical inventory. We assume that such an activity implies inventory adjustment cost cm. Figure 4 depicts an example of an inventory adjustment addressing a replenishment freeze caused by an imperfect read rate.

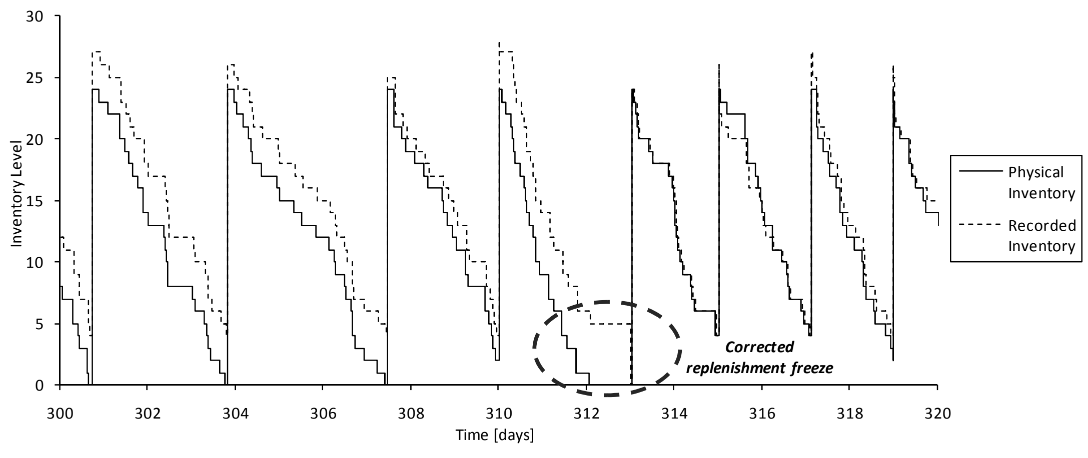

Figure 4. Inventory control under RFID-enabled backroom monitoring policy with a corrected replenishment freeze (φ=0.9; s=5; S=24; τ=0.92; λ=10, u=1)

Although the mathematical expression for calculating the service level is evidently the same as under the PR policy, the retailer's cost function is different. On the one hand, the RFID-enabled policy with backroom monitoring does not lead to any manual inspection cost. On the other hand, two new cost factors must be taken into account: (i) RFID transponder cost ct per case associated with u different items in that case and (ii) inventory adjustment cost cm for each of the ym observed adjustments of the recorded inventory triggered by the aforementioned strategy. The total cost ΠBM is then given by

$$\Pi_{BM} = c_r y_r + c_a S \cdot T + c_p (y_c - y_f - y_s) + c_m y_m + \frac{c_t (y_f + y_s)}{u} \quad (3)$$

3.4. Extensions to the BM Policy

Imperfect read rates not only cause replenishment freezes; they may also negatively impact replenishment efficiency in another way. As explained previously, if cases are not detected on their way to the sales floor, IR is not increased and does not appropriately reflect IP. Consequently, the inventory management system may eventually assume the presence of a stock-out situation and repeatedly trigger replenishments although they are, in fact, unnecessary. To counter this problem, we propose to extend the original BM policy by a heuristic based on (i) the ability of the RFID infrastructure to detect when cases are being transported to the sales floor and (ii) the POS data. The heuristic relies on the assumption that a replenishment event always increases IP above the base stock threshold s and that a certain number of items must be sold before any further replenishment makes sense. Accordingly, when at least one case is read upon transit to the sales floor, the system begins counting the sales registered at the POS. A replenishment is not triggered unless at least X sales transactions have been observed. This simple extension of the BM policy prevents unnecessary replenishment cost, but this advantage might come with the downside of a higher risk of replenishment freezes. With shrinkage, the shelf inventory may be depleted before X sales are recorded and the system encounters an unobserved stock-out situation. However, this issue is eventually corrected by the previously described inventory record adjustments.

In our simulations, we investigate two different variants with regard to control parameter *X*. First, we set *X* := 1 to prevent replenishments unless at least one item has been sold. This setting is obviously sufficient to keep the system from triggering successive replenishments. Replenishment freezes could only occur if all items on the shelf left the system undetected. Second, we might decide to choose a higher value for *X.* Based on the characteristics of the shelf replenishment process with cases, we may assume that there are at least S – u + 1 items on the shelf after each replenishment. We know that there should be at most s items on the shelf when a new replenishment is triggered and that a shrinkage rate γ is present in the system. We can therefore set to $X := \lfloor (1-\gamma)(S-u+1-s) \rfloor$ further reduce unnecessary replenishment cost, while encountering a replenishment freeze only if the extent of shrinkage in the respective replenishment cycle exceeds γ. We refer to the two improved backroom monitoring policies as BM+1 and BM+X, respectively. The corresponding total costs and service levels are computed in the same way as for the original backroom monitoring policy.

4. Simulation Results

4.1. Experimental Design

Our simulation model was implemented on a standard PC (Pentium 3.0 GHz, 4GB memory) using C#, a widely used object-oriented programming language. For computing performance reasons and due to the limited complexity of our model, we refrained from using a specialized simulation software package. We collected simulation output data in a relational database and analyzed them using a statistical software package.

We began our simulation study with a base case that corresponds to a daily consumer demand of λ = 10 units, a product that can be regarded as neither a typical fast-moving nor slow-moving good. We assume an in-store logistics cost of ci = $0.5 for review, cr = $2 for replenishment, and cm = $2 for adjustment, respectively. The shelf allocation cost is reckoned at ca = $0.1 per item per day with a penalty cost for each lost sale of cp = $1. Furthermore, based on our observations of actual processes in a retail store, we assume delays between events dO = dS = 15 min (i.e., dR = 30 min), dC = 15 min, dB = 15 min, and dT = 15 min. The case size is u = 12 items. We consider a store that is open 10 hours per day and simulate over a horizon of T = 1000 days per run. Each setting of the control parameters was simulated with 300 different replications. The shrinkage rate is assumed to be γ = 2% of the total demand.

4.2. Replenishment with Periodic Reviews

To determine the optimal values for r, s, and S under periodic review, we simulated all parameter settings for $0 \leq s \leq S \leq 160$ and $0 < r \leq 3$ days. Although the use of a simple search algorithm would have been less computationally expensive, we chose complete enumeration to facilitate subsequent analyses of the data, particularly sensitivity analysis and analyses of optimal solutions under additional constraints. Our simulation results under periodic review, including performance metrics and confidence intervals at 95% significance levels (CI), are given in Table 2. For the cost-optimal parameter setting, we see that the service level of the simulated store is within a range of 96 – 97%. Note that in our model, product availability is only determined by the replenishment process. Other factors that are relevant in reality (forecasts, ordering decisions, etc.) are beyond our scope.

r	s	S	y_c	y_s	y_r	y_i	y_f	Π		β	
								Mean	CI	Mean	CI
1.3	13	24	10007.95	9515.89	674.39	769	193.6	4431.67	±30.71	0.9696	±0.0031

Table 2. Numerical results under periodic review

4.3. Replenishment with RFID-enabled Backroom Monitoring

For the RFID-enabled processes, we simulated the same parameter settings for s and S and for the entire possible range of read rates $0.1 \le \varphi \le 1$ (step size 0.1) as previously. Furthermore, for each read rate, we optimized the adjustment threshold τ. Overly small or overly large values for τ both cause suboptimal behavior. With a small τ, adjustments are triggered more often than needed, whereas with a large τ, the occurrence of out-of-stocks is unnecessarily prolonged. The range on which we simulated τ depended on the respective policy. It appeared that at optimality, BM and BM+1 show a preference for lower thresholds, whereas BM+X tends towards higher ones. The adequate range eventually proved to be $0.2 \le \tau \le 0.7$ days for BM and BM+1 and $0.2 \le \tau \le 1.5$ days for BM+X. Figure 5 shows how total cost under the BM policy reaches its minimum within the simulated threshold domain for intermediary read rates. The choice of τ for extremely low and high (perfect) read rates will be further explained following a discussion of the simulation results.

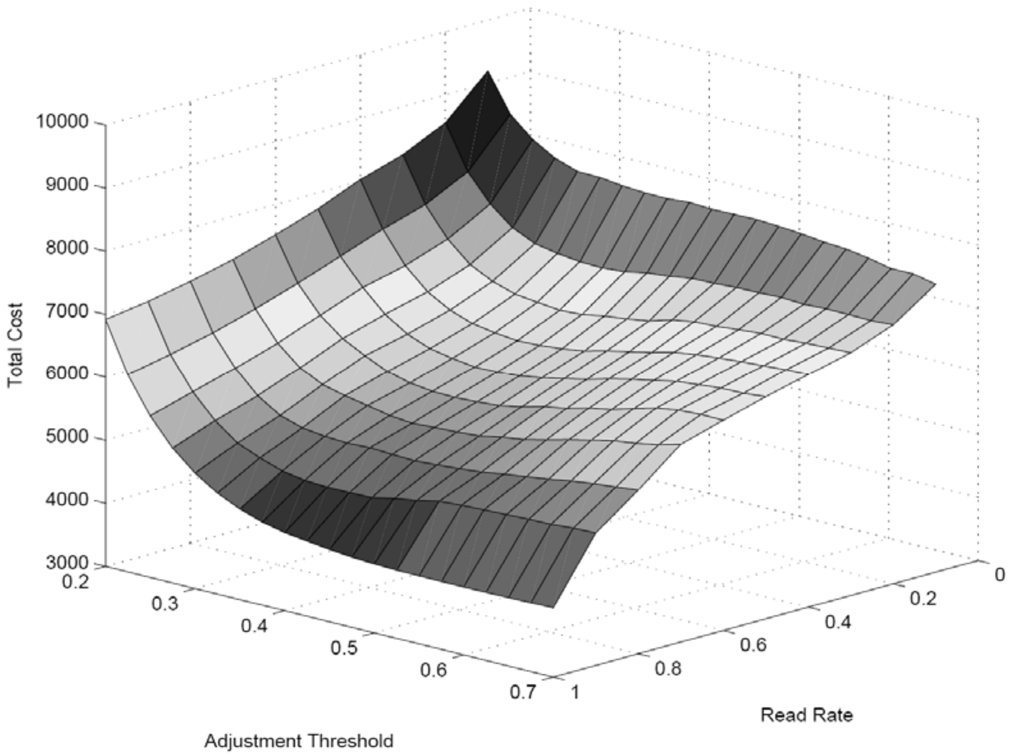

Figure 5: Optimization on the adjustment threshold τ for the BM replenishment policy

Valuable insights can be gained by taking a closer look at the detailed output data for RFID-enabled policies in Table 3. First, we observe that the replenishment efficiency drops drastically even for slightly worsening read rates. If φ decreases, all policies show a tendency to (i) allocate more shelf space and (ii) increase the number of replenishments. This is a direct consequence of the fact that the probability of the recorded inventory IR dropping and then staying below s is greater with low read rates. The inventory management system then begins triggering many more replenishments than are actually necessary to eliminate apparent stock-out situations. The resulting growth in total cost is substantial. However, the erroneously numerous replenishments triggered to counter the hypothetical stock-outs guarantee a high service level. Consequently, β is higher for low read rates, which initially seems counterintuitive. This argument also explains the choice of τ for low read rates. In such a case, policies perform best with a high τ, which allows them to save, at least, on adjustment costs. For high (perfect) read rates, the optimal threshold again tends to be higher because, as a matter of principle, it is not possible to encounter replenishment freezes due to detection rate inaccuracies. Shrinkage remains the sole reason why τ is still needed in this case.

φ	τ	s	S	y_c	y_s	y_r	y_m	y_f	Π		β	
									Mean	CI	Mean	CI
BM												
0.1	0.700	1	48	9992.01	9717.34	1305.85	19.24	198.19	7567.98	±341.77	0.9921	±0.0018
0.2	0.375	1	36	9997.94	9551.61	1197.32	292.84	195.13	6872.14	±153.25	0.9743	±0.0030
0.3	0.375	1	36	10007.64	9546.10	946.00	294.42	195.53	6387.46	±126.65	0.9728	±0.0030
0.4	0.375	1	36	9995.12	9527.22	789.96	295.81	194.13	6085.81	±116.29	0.9720	±0.0029
0.5	0.375	1	36	10003.29	9520.51	662.27	299.66	194.50	5852.62	±108.56	0.9706	±0.0031
0.6	0.400	1	36	9997.18	9492.63	597.83	246.93	193.74	5640.69	±116.75	0.9682	±0.0031
0.7	0.400	2	36	9997.52	9631.31	581.54	220.80	197.35	5414.49	±109.32	0.9827	±0.0024
0.8	0.450	2	36	10000.92	9565.69	494.81	154.91	196.21	5179.14	±92.627	0.9756	±0.0029
0.9	0.400	1	24	10003.59	9217.06	581.39	284.84	186.58	4771.59	±131.49	0.9388	±0.0042
1.0	0.575	3	24	9991.61	9387.35	530.97	79.97	192.10	4073.96	±37.69	0.9579	±0.0036
BM+1												
0.1	0.700	1	48	10003.93	9730.51	1263.40	19.20	198.65	7481.35	±303.54	0.9923	±0.0019
0.2	0.375	1	36	9991.83	9543.31	1123.97	292.93	195.45	6727.48	±133.95	0.9741	±0.0028
0.3	0.400	1	36	10002.84	9545.72	930.58	238.25	194.64	6240.74	±124.50	0.9732	±0.0030
0.4	0.400	2	36	10000.76	9683.91	866.06	214.46	198.00	5921.07	±123.74	0.9878	±0.0020
0.5	0.400	2	36	9996.19	9666.19	734.91	217.19	196.71	5678.59	±104.99	0.9864	±0.0022
0.6	0.425	2	36	9997.61	9636.56	661.03	178.02	197.14	5482.98	±105.35	0.9832	±0.0025
0.7	0.375	1	24	9992.91	9336.51	862.60	324.47	191.35	5278.89	±140.20	0.9525	±0.0037
0.8	0.400	1	24	10008.15	9278.06	720.11	277.82	188.46	4976.95	±118.96	0.9448	±0.0041
0.9	0.425	2	24	9999.49	9455.62	710.11	200.90	192.63	4613.46	±112.57	0.9641	±0.0032
1.0	0.575	3	24	9996.84	9392.27	531.28	80.12	191.26	4076.04	±36.18	0.9578	±0.0037
BM+X												
0.1	0.950	1	36	10009.34	9701.95	1215.43	10.92	196.92	6204.42	±117.15	0.9887	±0.0020
0.2	0.875	1	36	9998.88	9676.47	775.09	14.36	196.11	5346.34	±54.20	0.9871	±0.0025
0.3	0.775	1	36	9999.63	9658.89	597.44	20.55	197.02	5020.76	±41.99	0.9853	±0.0028
0.4	0.850	1	36	9990.59	9613.12	505.45	20.83	196.89	4874.04	±37.44	0.9815	±0.0033
0.5	0.750	2	36	9988.14	9605.36	467.55	27.93	195.90	4818.68	±36.69	0.9809	±0.0032
0.6	0.475	2	24	10001.78	9490.75	840.33	139.63	192.54	4718.76	±52.84	0.9675	±0.0034
0.7	0.475	2	24	10000.34	9459.47	751.53	143.47	193.08	4578.01	±45.15	0.9645	±0.0034
0.8	0.475	2	24	10002.04	9427.54	667.30	145.66	191.39	4449.10	±49.12	0.9609	±0.0037
0.9	0.500	2	24	9996.35	9362.73	582.71	130.27	190.38	4309.01	±47.96	0.9548	±0.0040
1.0	0.550	3	24	9994.10	9419.41	539.00	86.61	192.50	4073.46	±37.95	0.9610	±0.0035

Table 3. Numerical results under RFID-enabled replenishment with cost optimization

Figure 6 shows the influence of φ on minimal cost for all RFID-enabled policies. We used periodic review as the benchmark for our newly developed policies. The backroom monitoring, in its pure form, outperforms the traditional periodic review process only for high read rates (beyond approximately. 95%). However, the optimized variants of backroom monitoring make this policy perform better for read rates starting at approximately 80%. Remember that under the PR policy, the execution of replenishments is unobservable to the retailer. In contrast, the RFID infrastructure allows replenishments to be identified by detecting items in transit from the backroom to the sales floor, which provides the foundation for implementing BM+1 and BM+X. The results indicate the importance of utilizing RFID data not only for estimating inventory levels but also for monitoring in-store logistics processes.

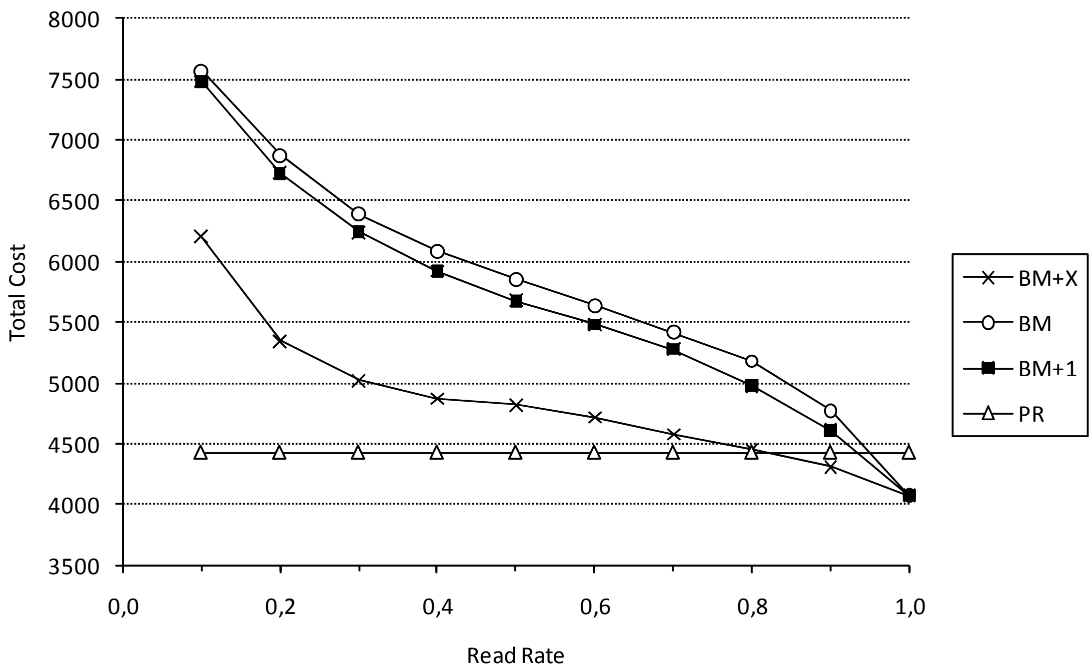

Figure 6: Comparison of PR, BM, BM+1, and BM+X replenishment policies

As mentioned in the introduction, the deployment of RFID technology in retail settings is motivated not only by cost considerations but also by reductions in stock-outs. However, our simulation data show that cost optimization under RFID-based inventory control does not necessarily lead to an increase in service levels. To investigate the performance of the RFID policies with the constraint that the retailer wants to achieve a service level greater than the 98% usually achieved in the distribution center, we ran an analysis of a subset of our simulation output data limited to those parameter settings that achieve this objective (see Table 4). We observe that total cost is only weakly affected by the additional constraint, with an increase of less than 1%, compared to the results given in Table 3. Thus, the RFID-enabled policies hold the potential to optimize both cost and stock-out rates simultaneously.

AUTO-ID LABS

φ	r	s	S	y_c	y_s	y_r	y_m	y_f	Π Mean	Π CI	β Mean	β CI
BM												
0.1	0.700	1	48	9992.01	9717.34	1305.85	19.24	198.19	7567.98	±341.77	0.9921	±0.0018
0.2	0.375	2	36	9996.77	9703.48	1352.34	265.43	198.41	6971.67	±184.39	0.9903	±0.0017
0.3	0.375	2	36	10003.59	9703.16	1095.25	266.16	198.55	6465.96	±151.65	0.9896	±0.0017
0.4	0.375	2	36	10006.93	9697.53	928.44	265.37	198.36	6139.89	±135.21	0.9886	±0.0018
0.5	0.375	2	36	9988.62	9671.91	799.27	270.29	195.76	5901.18	±121.60	0.9876	±0.0019
0.6	0.400	2	36	9992.89	9646.96	718.47	218.92	197.43	5664.31	±129.15	0.9848	±0.0023
0.7	0.400	2	36	9997.52	9631.31	581.54	220.80	197.35	5414.49	±109.32	0.9827	±0.0024
0.8	0.375	2	36	10000.46	9627.81	443.36	278.69	197.61	5260.10	±63.37	0.9821	±0.0024
0.9	0.450	3	36	9999.79	9623.93	455.08	145.44	196.24	5021.57	±83.06	0.9816	±0.0026
1.0	0.700	6	24	10006.96	9623.19	690.75	47.70	195.28	4106.30	±30.76	0.9807	±0.0028
BM+1												
0.1	0.700	1	48	10003.93	9730.51	1263.4	19.20	198.65	7481.35	±303.54	0.9923	±0.0019
0.2	0.375	2	36	10000.85	9711.71	1257.87	265.62	198.43	6778.99	±153.34	0.9907	±0.0017
0.3	0.400	2	36	9997.88	9694.44	1034.83	212.36	197.27	6241.78	±145.73	0.9891	±0.0019
0.4	0.400	2	36	10000.76	9683.91	866.06	214.46	198.00	5921.07	±123.74	0.9878	±0.0020
0.5	0.400	2	36	9996.19	9666.19	734.91	217.19	196.71	5678.59	±104.99	0.9864	±0.0022
0.6	0.425	2	36	9997.61	9636.56	661.03	178.02	197.14	5482.98	±105.35	0.9832	±0.0025
0.7	0.425	2	36	9998.52	9614.31	552.63	181.56	195.98	5297.50	±82.14	0.9807	±0.0025
0.8	0.475	3	36	10005.63	9628.82	574.58	120.39	197.26	5210.43	±102.79	0.9816	±0.0026
0.9	0.450	3	36	10001.88	9619.39	432.56	146.3	197.77	4983.34	±51.73	0.9811	±0.0027
1.0	0.650	7	24	10005.14	9614.73	699.53	36.28	196.34	4106.57	±27.90	0.9802	±0.0027
BM+X												
0.1	0.950	1	36	10009.34	9701.95	1215.43	10.92	196.92	6204.42	±117.15	0.9887	±0.0020
0.2	0.875	1	36	9998.88	9676.47	775.09	14.36	196.11	5346.34	±54.20	0.9871	±0.0025
0.3	0.775	1	36	9999.63	9658.89	597.44	20.55	197.02	5020.76	±41.99	0.9853	±0.0028
0.4	0.850	1	36	9990.59	9613.12	505.45	20.83	196.89	4874.04	±37.44	0.9815	±0.0033
0.5	0.750	2	36	9988.14	9605.36	467.55	27.93	195.90	4818.68	±36.69	0.9809	±0.0032
0.6	0.675	3	36	9998.59	9611.78	446.71	37.45	196.04	4799.96	±32.51	0.9805	±0.0029
0.7	0.700	4	36	9999.11	9609.34	441.97	34.06	194.83	4787.87	±30.92	0.9801	±0.0029
0.8	0.675	5	36	9998.82	9616.67	438.69	36.47	196.24	4777.12	±28.01	0.9810	±0.0027
0.9	0.375	3	24	9997.05	9612.06	699.85	283.27	196.59	4595.52	±43.63	0.9807	±0.0023
1.0	0.650	7	24	10004.04	9611.91	699.27	36.13	196.55	4107.25	±29.21	0.9800	±0.0025

Table 4. Numerical results under RFID-enabled replenishment with β > 0.98

4.4. Sensitivity Analysis

In the previous sections, our analysis was limited to a base case that was defined by a number of model parameters assumed to be constant. However, in reality, cost and time factors may vary significantly depending on the store format, assortment, location, geographic region, etc. For this reason, this section investigates the impact of changing parameter values on total cost and service levels. All cost- and time-related parameters are varied by factors of 0.25, 0.5, 2.0, and 4.0. Again, we compare the periodic review policy to the RFID-enabled policies with backroom monitoring, fixing φ = 0.9. The detailed results of our sensitivity analysis are given in Table 5. We find that the most influential factors under all policies are shelf allocation cost ca, demand rate λ, replenishment cost cr, case size u, and the cost of lost sales cp. Compared to these factors, the influence of time-related factors seems negligible. Furthermore, the much-scrutinized cost of technology appears to have a modest influence, ranging from -0.011% to +0.024% for the extremes of our tag cost variation range. This is a consequence of our assumption that tags are attached only to cases, not to individual sales units.

Variation factor		PR		BM		BM+1		BM+X	
		Π	β	Π	β	Π	β	Π	β
Base Case		4431.67	0.9696	4771.59	0.9388	4613.46	0.9641	4309.01	0.9548
λ	.25	2230.63	0.8418	2955.74	0.9570	2414.80	0.9451	2880.46	0.9655
	.5	3307.43	0.8094	3535.88	0.9364	3470.29	0.9427	3354.96	0.9615
	2.0	6027.73	0.9823	6321.58	0.9750	6269.50	0.9700	5915.74	0.9789
	4.0	8128.50	0.9947	8627.78	0.9792	8620.51	0.9794	8185.88	0.9841
u	.25	3876.00	0.9779	3821.49	0.9778	3808.14	0.9741	3731.99	0.9764
	.5	4077.03	0.9788	4146.45	0.9714	4134.88	0.9686	3953.35	0.9652
	2.0	5199.86	0.8825	6160.46	0.9677	5809.06	0.9400	5875.93	0.9764
	4.0	6627.43	0.9195	8607.14	0.9765	7074.18	0.9682	8560.19	0.9756
d_R	.25	4423.50	0.9719	4759.50	0.9419	4605.21	0.9497	4335.79	0.9621
	.5	4423.36	0.9713	4757.65	0.9429	4595.47	0.9419	4321.39	0.9575
	2.0	4443.63	0.9649	4726.89	0.9599	4536.35	0.9501	4320.27	0.9637
	4.0	4457.60	0.9750	4605.08	0.9443	4524.75	0.9460	4335.74	0.9399
d_H	.25	n/a		4759.32	0.9393	4606.50	0.9599	4314.17	0.9522
	.5			4771.48	0.9384	4604.71	0.9601	4300.03	0.9617
	2.0			4725.41	0.9245	4562.68	0.9611	4305.44	0.9546
	4.0			4700.36	0.9335	4506.01	0.9604	4306.09	0.9578
d_T	.25	n/a		4722.77	0.9310	4583.42	0.9573	4296.07	0.9574
	.5			4715.54	0.9395	4560.95	0.9602	4313.48	0.9574
	2.0			4763.23	0.9334	4620.23	0.9680	4309.07	0.9501
	4.0			4753.78	0.9388	4615.69	0.9672	4315.27	0.9535
d_C	.25	4428.36	0.9695	4714.60	0.9357	4587.81	0.9638	4295.36	0.9584
	.5	4427.00	0.9700	4698.44	0.9394	4599.40	0.9658	4299.72	0.9544
	2.0	4436.86	0.9691	4775.53	0.9320	4605.64	0.9618	4310.14	0.9510
	4.0	4441.50	0.9683	4879.66	0.9400	4653.28	0.9584	4335.57	0.9467
γ	.25	4430.36	0.9704	4406.41	0.9627	4261.06	0.9592	4049.47	0.9585
	.5	4431.63	0.9699	4532.50	0.9523	4430.16	0.9504	4169.91	0.9691
	2.0	4435.00	0.9686	4950.93	0.9386	4754.02	0.9487	4480.22	0.9498
	4.0	4425.36	0.9680	5163.05	0.9101	4970.14	0.9426	4677.64	0.9298
c_t	.25	n/a		4742.20	0.9388	4583.31	0.9641	4279.15	0.9548
	.5			4752.00	0.9388	4593.36	0.9641	4289.10	0.9548
	2.0			4810.77	0.9388	4653.66	0.9641	4348.81	0.9548
	4.0			4889.14	0.9388	4734.07	0.9641	4428.42	0.9548
c_t	.25	4129.03	0.9788	n/a					
	.5	4233.15	0.9788						
	2.0	4802.30	0.9588						
	4.0	5428.84	0.9761						
c_r	.25	3357.88	0.9885	3594.53	0.9622	3487.85	0.9716	3232.09	0.9764
	.5	3731.34	0.9864	4041.37	0.9622	3896.22	0.9608	3658.23	0.9645
	2.0	5624.15	0.9696	5731.56	0.9706	5694.65	0.9707	5444.84	0.9289
	4.0	7038.20	0.9539	7062.43	0.9505	7036.40	0.9499	6865.50	0.9645
c_a	.25	2110.97	0.9866	2162.93	0.9812	2154.67	0.9861	2010.56	0.9875
	.5	3010.97	0.9866	3183.85	0.9654	3155.70	0.9766	2946.27	0.9796
	2.0	6715.22	0.8191	7171.59	0.9388	7013.46	0.9641	6709.01	0.9548
	4.0	9115.22	0.8191	11971.59	0.9388	9713.11	0.9072	11509.01	0.9548
c_p	.25	3456.07	0.6195	4275.48	0.9313	4137.91	0.9300	3926.82	0.9171
	.5	4194.21	0.9238	4443.97	0.9313	4309.60	0.9300	4086.97	0.9527
	2.0	4595.32	0.9923	5201.19	0.9816	4944.61	0.9710	4669.77	0.9710
	4.0	4713.57	0.9957	5488.19	0.9892	5420.43	0.9887	5132.25	0.9899
c_m	.25	n/a		4209.69	0.9553	4146.37	0.9512	4026.76	0.9701
	.5			4450.74	0.9467	4366.18	0.9468	4145.74	0.9634
	2.0			5184.38	0.9707	4938.90	0.9549	4524.34	0.9486
	4.0			5393.55	0.9688	5333.10	0.9692	4728.87	0.9631

Table 5. Sensitivity analysis

5. Summary and Conclusions

This study aimed to analyze the characteristics of RFID-based shelf replenishment policies in retail stores and to compare them with the traditional procedure of periodic reviews using computer-based simulations. Our conclusions on the benefits of the technology are also relevant to practitioners planning to implement RFID systems. First, we showed that the RFID-enabled redesign of in-store processes holds the potential to increase process efficiency in terms of total cost and service levels, depending on data quality. Other influential factors requiring special consideration include the cost of lost sales, demand rate, shelf allocation cost, and case size. Second, we found that the possibility of utilizing RFID as a means of monitoring in-store logistics processes has fundamental consequences on the performance of the replenishment policies. As we observed, the value of RFID-based estimates of shelf inventories using pure backroom monitoring is severely influenced by imperfect read rates, which makes this policy acceptable only under optimal reader performance. In contrast, RFID-based policies employing a heuristic to eliminate unnecessary replenishments are considerably less sensitive to reader performance. These policies are able to outperform the traditional process even with moderate read rates. Third, we conclude from the data that the maximum benefits of RFID may only be achieved if the retailer is willing and able to make parallel decisions on optimal shelf space allocation and to implement replenishment processes that are not performed periodically but are flexibly adapted to customer demand by the inventory management system. Fourth, we conclude that RFID does not allow for full automation of the replenishment process in the presence of shrinkage. As pointed out in the development of our policies, the presence of shrinkage leads to inventory inaccuracies that cannot be detected by RFID alone and thus undermine the concept of fully automatic inventory control. Consequently, the retailer does not avoid having to adjust the recorded inventory to the physical inventory manually from time to time.

As with other studies of this kind, our research is not without limitations. In particular, our model relies on a number of simplifications. First, as mentioned in the introduction, determinants of shelf availability other than replenishment issues (e.g., forecasts and ordering decisions) are beyond the scope of the present study. This constraint does not diminish the value of our research, but it should be taken into account when interpreting our numerical results. Second, we did not consider stochastic influences on lead times and the quality of manual activities. For instance, similar to the RFID-based process, periodic reviews and replenishments might be imperfect, influencing the relative differences between the two considered classes of policies. Third, we concentrated on stock-outs and did not consider consumer reactions to different shelf inventory levels. For example, supermarkets often hold more inventory on the shelves than apparently necessary in the hope that product visibility will drive demand. Some apparel retailers, in contrast, try to achieve similar results by keeping the availability of a specific item low. These and other psychological factors are beyond the scope of the current paper. Further, our model is limited to a single product and does not account for dependencies between the replenishment of different product types. For this reason, we did not include infrastructure implementation costs in our model because these costs cannot be attributed to single product categories. These limitations should be regarded as opportunities for future research in this area. Moreover, we propose that the improvements made possible by RFID-enabled policies should not only be compared to the traditional process with periodic reviews. For example, it might be interesting to analyze the extent to which more sophisticated policies can compete with RFID (e.g., [23]). Finally, we see great potential in the combination of RFID with machine-learning techniques for the detection of stock-outs (e.g., [10,31]).

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