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The Impact of Inventory Inaccuracy on Retail Supply Chain Performance: A Simulation Study

Elgar Fleisch, Christian Tellkamp

AUTO-ID CENTER UNIVERSITY OF ST. GALLEN, INSTITUTE OF TECHNOLOGY MANAGEMENT, UNTERSTRASSE 22, CH-9000 ST. GALLEN, SWITZERLAND

ABSTRACT

Inventory inaccuracy is a main issue in businesses dealing with physical assets. The aim of this paper is to examine the relationship between inventory inaccuracy and performance in a retail supply chain. We simulate a three echelon supply chain with one product in which end-customer demand is exchanged between the echelons. In the base model, without alignment of physical inventory and information system inventory, inventory information becomes inaccurate due to low process quality, theft, and items becoming unsaleable. In a modified model, these factors that cause inventory inaccuracy are still present, but physical inventory and information system inventory are aligned at the end of each period. The results indicate that an elimination of inventory inaccuracy can reduce supply chain costs as well as the out-of-stock level. Auto-ID technologies can be one means to achieve inventory accuracy.

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Biography

Prof. Dr. Elgar Fleisch
Research Director

Elgar Fleisch is Professor for Technology and Information Management at the University of St. Gallen, Director of the Institute of Technology Management at the University of St. Gallen, Research Director of the Mobile and Ubiquitous Computing Lab (M-Lab) as well as of the Auto-ID Center at the University of St. Gallen.

Christian Tellkamp
PhD Student

Christian Tellkamp is PhD student at the Institute of Technology Management at the University of St. Gallen and Research Assistant for the M-Lab and the Auto-ID Center at the University of St. Gallen. Previously, Christian worked as Project Manager for an internet consultancy and as analyst in the equity research division of a leading European bank. He holds a master's degree in industrial engineering and management from the University of Karlsruhe. His work for the Auto-ID Center focuses on assessing the business impact of Auto-ID technologies.

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1. INTRODUCTION

Even if information technology (e.g. EDI) is used within a supply chain to share information on end-customer demand and inventory levels, there is still often a discrepancy between the data on customer demand or inventory levels in information systems, and the real physical flow of products. This discrepancy frequently stems from media breaks and the missing real-time or near real-time alignment of both data and the physical flow of goods. The result is inaccurate inventory information.

The phenomenon of inventory inaccuracy is well-known. Raman et al. [1] found in a case study that for more than 65% of SKUs in retail stores, information on inventory in the inventory management system was inaccurate (i.e. the information system inventory differed from physical inventory). The difference was on average 35% of the target inventory. In a second case study, the authors found that a median of 3.4% of SKUs were not found on the sales floor although inventory was available in the store. In the first case, inventory inaccuracy reduced profits by 10 %, in the second case, misplaced items reduced profits by 25%.

Reasons why information system inventory records are inaccurate include external and internal theft [2], unsaleables (e.g. damaged, out-of-date, discontinued, promotional, or seasonal items that cannot be sold any longer), incorrect incoming and outgoing deliveries [1,3], as well as misplaced items [1].

There is some empirical evidence on the magnitude of these factors that cause inventory inaccuracy. Based on survey data, internal and external theft, administrative errors and vendor fraud accounted for an estimated 1.8% of sales in the US retail industry in 2001, costing US retailers USD 33 billion [4]. For US supermarkets, the NSRG survey [5] estimates that internal and external theft, receiving errors, damage, accounting errors and retail pricing errors amount to 2.3% of sales. These figure only take into account the item value, but not any process-related costs (e.g. for handling of damaged items).

2. RELATED WORK

In our paper, we draw on two areas of research: (a) research on the bullwhip effect, and (b) previous studies on the effect of inventory inaccuracy on performance.

The bullwhip effect has been studied intensively in recent years (e.g. [6,7]). It has been shown that the sharing of information on end-customer demand can lead to a significant reduction of the bullwhip effect [8]. However, there is also evidence that using information technology to improve the physical flow of products through the supply chain (e.g. by reducing lead times and batch sizes) can be more beneficial than the sharing of demand and inventory data [9]. Simulation studies on the bullwhip effect have been conducted e.g. by Joshi [10] and Simchi-Levi et al. [7].

To our knowledge there is a limited amount of research that has been carried out to study the effect of inventory inaccuracy on supply chain performance. Ganeshan et al. [11] simulate the impact of forecasting error (among other parameters) on supply chain performance, but do not consider inaccurate inventory data. We are only aware of two papers that study MRP (Material Requirements Planning) systems, but have not seen any research that addresses this issue for a multi-echelon supply chain. Both papers use simulation as research method. Brown et al. [12] simulate the effect of inventory inaccuracy in a MRP environment. They look at frequency of error, magnitude of error, and location of products. Frequency of error refers to the number of time periods with inventory inaccuracy. Magnitude of error measures the percentage deviation of physical inventory from information system inventory. Location of goods takes into account that errors can occur at different points in the production process, e.g. at the beginning of the production process or closer to the end. The authors conclude that frequency of error has a consistent and dominant impact on the performance measures that they used. (The performance measures are percentage of late units and inventory cost.) However, location and magnitude of error can also impact performance depending on the supply chain configuration. Krajewski et al. [13] assess the impact of several factors on the performance of a MRP system and compare this with the performance of a Kanban system. Inventory inaccuracy is introduced to the system by incoming and outgoing deliveries. A certain percentage of deliveries is assumed to be inaccurate. The magnitude of error is normally distributed. Inventory inaccuracy is eliminated by inventory counts which are conducted in regular time intervals. The authors use the amount of labor needed, inventory level, amount of past due demand, and percentage of late orders as performance measures. Krajewski et al. [13] conclude that inventory inaccuracy had less impact on the performance than anticipated. A reduction in batch sizes combined with shorter setup times had the single most important impact on performance of the factors considered.

The results of previous research on the bullwhip effect are used to determine the configuration of the supply chain model. Our supply chain configuration is similar to the one used by Joshi [10] and Simchi-Levi et al. [7], except that we eliminated one echelon, the wholesaler, to reduce complexity. A three echelon supply chain was e.g. used in the original Forrester production-distribution system [14].

The work on inventory inaccuracy in a MRP environment provides the basis for modelling the specific factors that cause inventory inaccuracy.

Our analysis extends the above mentioned research in two respects: (a) Simulation studies of the bullwhip effect frequently focus on showing the benefit of sharing information on end-customer demand in a multi-echelon supply chain. We assume that this is already done, and introduce inventory inaccuracy into the analysis. Inventory inaccuracy has so far only been studied in a production environment. (b) Both Brown et al. [12] and Krajewski et al. [13] use only a low and high setting for each independent variable (with one exception where also a middle setting is used). This has the drawback that the selection of the high and low setting can determine whether a variable has a significant impact on performance or not. For example, by increasing the difference between the high and low setting, a variable which previously had no significant effect can become significant. In our approach, we make incremental changes to each variable in order to determine the critical value at which a significant change in supply chain performance accrues.

3. RESEARCH QUESTION

In our research we want to answer the question: How does supply chain performance change when inventory inaccuracy is eliminated? Our focus is not on changing the physical flow of products. We look at improving supply chain performance through more accurate information, given the existing flow of products.

We start with a discussion of the research method, followed by an overview of the simulation model. We continue with a description of the performance measures that we use to determine supply chain performance. Then, the simulation results are analyzed. The article finishes with a summary, our conclusions and directions for further research. We also discuss managerial implications in the light of recent advances in technology.

4. RESEARCH METHOD

We use simulation as research method. This allows us to study the impact of several factors that cause inventory inaccuracy on a number of supply chain performance measures within a dynamical system. Simulation models are often used when certain characteristics of the supply chain can not easily be modeled with analytical models or when stochastic variables are to be incorporated [15]. They are useful to understand complex systems. Simulation models do not optimize a supply chain. Instead, they allow to determine the performance of a given supply chain configuration [7].

Our simulation model uses discrete and constant time intervals. Demand, orders and other variables related to the physical flow of products are continuous variables. In the base case, we set up a supply chain where information on end-customer demand is available to all echelons in real-time, and inventory inaccuracy is caused by various factors which are discussed below. We then modify the model so that physical inventory and information system inventory are aligned in each time period which eliminates inventory inaccuracy, and compare the two models.

Each simulation runs for 200 time periods. We start with the calculation of the performance measures in time period 11 in order to avoid a bias from starting conditions. Initially, demand is stable, and there is no inventory inaccuracy. A similar procedure is also used by Brown at al. [12]. For each specific setting of the supply chain, we perform 20 runs in order to get robust results as proposed by Swaminathan et al. [16].

There are a number of stochastic variables included the model: End-customer demand is normally distributed. Theft, one factor that causes inventory inaccuracy, follows an uniform distribution. Another factor called incorrect deliveries is influenced by an uniformly distributed variable for the magnitude of error and a binary variable for frequency of error. The default values for the factors that cause inventory inaccuracy are derived from industry sources. This is described below.

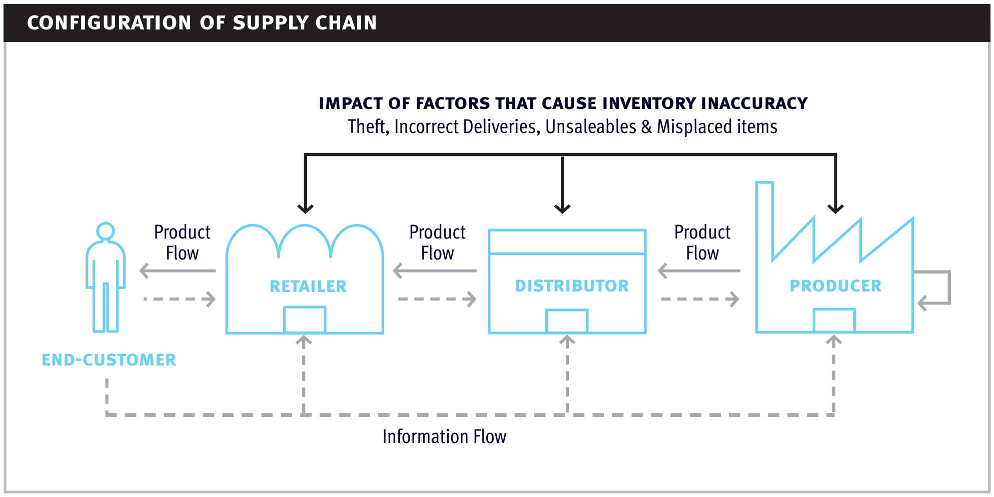
The data is analyzed using variance analysis in order to determine the critical value for a factor at which supply chain performance changes significantly. Firstly, we examine the base case without alignment of physical inventory and information system inventory at the end of each period. In this model, inventory inaccuracy can occur. We vary each factor and compare the resulting performance with the performance when the default value is used. Secondly, we compare performance in the base case with the performance of a modified model in which physical and information system inventory are aligned at the end of each period. Finally, we extend our second analysis by assuming that the factors that cause inventory inaccuracy improve at the same time as inventory inaccuracy is eliminated.

5. SIMULATION MODEL

A number of parameters need to be estimated and several relationships between variables and parameters have to be defined when building a simulation model. We have tried to find reasonable estimates for the parameters and relationships, and are not aware that our conclusions would change due to a variation in any of the parameters or relationships (e.g. lead times, batch sizes). However, more research in this area is needed. In this paper we can only present a broad description of the model. A formal description of the simulation model is available on request.

For our model, we assume a high value CPG (consumer packed goods) product that is sold in supermarkets. The supply chain consists of a single retailer, distributor and producer. Each time interval is assumed to be one week. There are no capacity constraints. Figure 1 illustrates the configuration of the supply chain used for simulation purposes and shows the various factors that cause inventory inaccuracy as well as the flow of products and information.

Figure 1: Configuration of supply chain for simulation, impact of factors that cause inventory inaccuracy, and flow of products and information



End-customers demand a certain quantity of a SKU from the retailer each week. Demand consists of two components, real demand plus returns of unsaleable items that are detected by the end-customer.

The retailer can fulfill customer demand as long as items are in stock. It is assumed that end-customers whose orders could not be fulfilled immediately are prepared to wait for next week's delivery. These orders enter the order backlog. This assumption is somewhat idealistic for the retailer as customers react in different ways to stock-outs [17]. They can buy a different SKU, buy the SKU elsewhere, came back later, or decide not to be the product at all.

The retailer places an order every week, taking into account end-customer demand, available inventory (based on information system inventory, adjusted for any alignments with physical inventory), and the incoming delivery (adjusted for any detected missing or unsaleable items). By placing an order, the retailer has to consider batch size constraints which are determined e.g. by the amount of items in a case.

The information on the number of available items in the inventory and the incoming delivery may differ from the physical inventory level respectively the real number of items in the incoming delivery due to various factors that cause inventory inaccuracy.

The retailer shares the information on real customer demand and cover orders with the distributor. Cover orders are those orders which result from inventory inaccuracy. They occur when (a) an inventory count is conducted and a difference between information system inventory and physical inventory is detected, or (b) unsaleable items are detected by either the retailer or the end-customer. The concept of cover orders is mentioned e.g. by Towill [14] who looks at the demand amplification occurring in a supply chain (the bullwhip effect). He sees the separation of real customer demand and cover orders and sharing of this information throughout the supply chain as a means to significantly smooth demand amplifications.

The procedure for the distributor and producer is similar. The distributor tries to fulfil the incoming order if possible. Orders that could not be fulfilled enter the order backlog. The distributor places its order, based on end-customer demand (not the incoming order), cover orders (its own and the retailer's), its inventory level, and the information on the incoming delivery, while taking batch size constraints into account. The information regarding the cover order is shared with the producer. As for the echelons downstream, the producer tries to fulfil the incoming order from the distributor if possible. Orders that could not be fulfilled enter the order backlog for production. The producer produces according to customer demand, any cover orders (its own, the distributor's, and the retailer's), its inventory as well as last week's production, now available for shipment. Batch size constraints also exist for production. Batch sizes increase upstream in the supply chain.

As mentioned above, physical inventory and information system inventory can differ. In our model, the difference results from the following factors: incorrect deliveries, misplaced items, theft, and unsaleables. Incorrect deliveries in our model are deliveries in which less items are physically delivered than shown in the delivery records. This happens from time to time with varying degrees of error magnitude. Sometimes, the receiver detects that the delivery is incorrect when inspecting the delivery. If the error is not detected, incorrect data on the number of items is used to update the information system inventory of both the customer and the supplier, and both information system inventory records become inaccurate. Misplaced items are items that are stored in a location where they cannot be found and therefore are not available for sale. These items may reappear after a while (at latest when a physical inventory count is conducted). Theft reflects theft by employees in case of the distributor and the producer, and by employees and customers in case of the retailer. Unsaleable items are items that e.g. have been damaged during the handling process or are out-of-date. We assume that unsaleable items are not detected unless they are to be shipped. In some cases, unsaleable items are even shipped to customers.

There are two events in which physical inventory and information system inventory are aligned. The first one are periodical inventory counts, the second one is when the product is not available any longer. In our model, this is assumed to happen when real inventory falls below one item. The out-of-stock situation is then detected, and the information system inventory is adjusted.

Figure 2 shows the development of physical inventory and information system inventory for one specific simulation run and 50 time periods in the base case. The figure shows that when no out-of-stock instances occur over a certain period of time, inventory inaccuracy can built up.

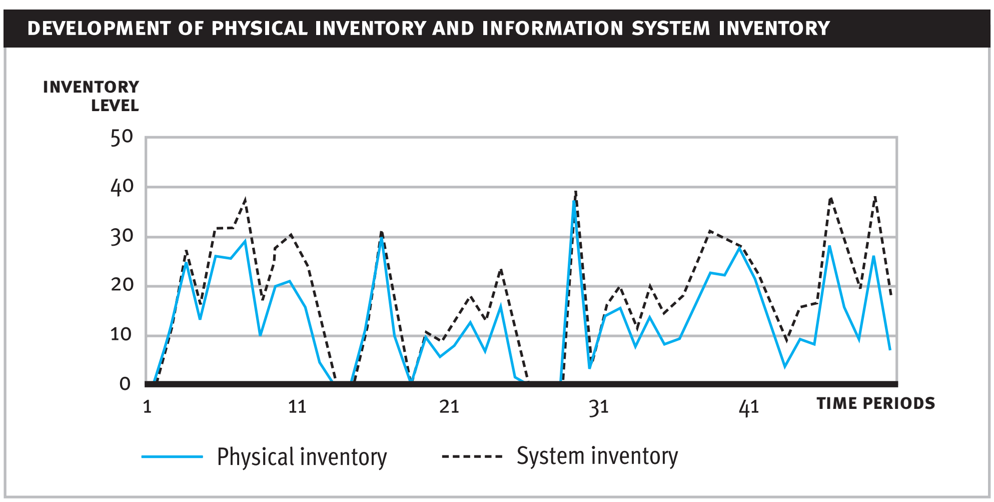


Figure 2: Example for development of physical inventory and system inventory over a selected period of time in the base case

In general, physical inventory tends to be below information system inventory. Theft and items becoming unsaleable reduce the physically available inventory, but do not effect the information system inventory. The net effect of process quality in a specific period can vary. For example, if the incoming delivery is correct, but less items are physically shipped than shown in the delivery records, physical inventory decreases less than information system inventory. Assuming theft and unsaleables as zero and an accurate inventory at the beginning of the period, this would result in a physical inventory at the end of the period which is higher than the information system inventory.

We compare the performance of this supply chain with a modified supply chain in which inventory inaccuracy is eliminated. The factors that cause inventory inaccuracy are still present in this supply chain.

We draw on data from two industry sources to select appropriate default values for incorrect deliveries, theft, and unsaleables [4,5]. The data is based on surveys of supermarkets in the US. We derived the following default values: 0.25% of items in deliveries for incorrect deliveries, 1.5% of inventory for theft, and 0.2% of inventory for unsaleables. The surveys do not contain a figure for misplaced items. As mentioned above, Raman et al. [1] found for one retailer that a median of 3.4% of SKUs could not be found on the sales floor although they were available in the store. To be conservative, we chose the ratio of misplaced items at 2% of deliveries. To our knowledge, there are no sources which provide comparable data for distributors and producers. Therefore, we decided to use the same data for these echelons although there is a risk that these figures overestimate the problem. For example, as batch sizes increase, the risk of incorrect deliveries or wrong storage may decrease.

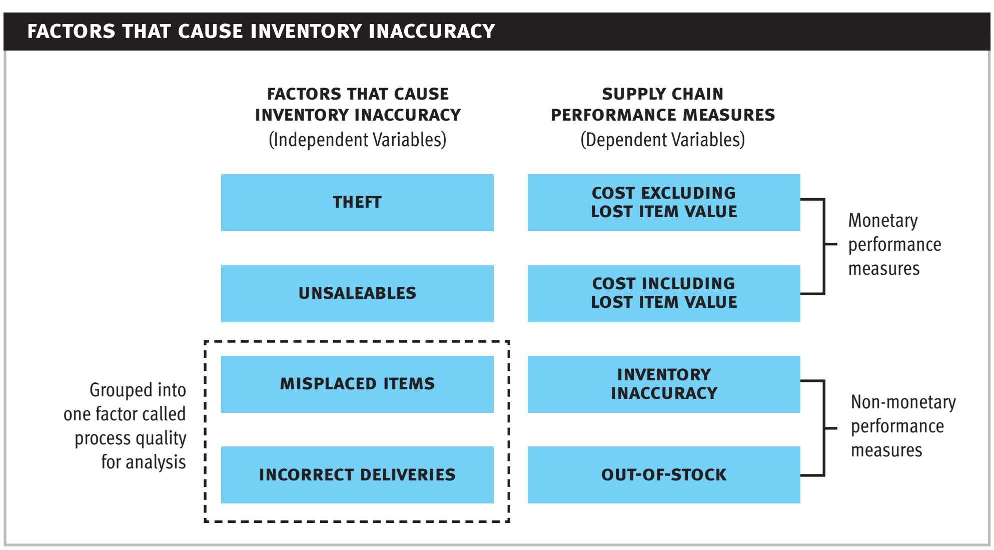
For our analysis, we have grouped the factors incorrect deliveries and misplaced items into one factor called process quality. Process quality also takes accidental shipment of unsaleable items to customers into account. The factors incorrect deliveries and misplaced items are similar as they deal with problems that are inherent to the current process of physically handling the product (i.e. receiving, storing, picking, and shipping).

6. SUPPLY CHAIN PERFORMANCE MEASURES

Performance measures are used in supply chain management to determine the efficiency or effectiveness of a given supply chain. One can distinguish qualitative and quantitative measures [16,18]. Quantitative measures based on monetary data include measures of cost, sales, profit, inventory investment, and return on investment. Quantitative measures based on non-monetary data include fill rate, customer response time, and lead time [18].

In order to determine supply chain performance, a number of performance measures are used. We examine the direct effect of the factors that cause inventory inaccuracy on each of the supply chain performance measures. This is illustrated in figure 3.

Figure 3: Factors that cause inventory inaccuracy and supply chain performance measures



We use two monetary and two non-monetary quantitative measures to determine supply chain performance. They are based on the performance measures suggested by Beamon [18]. The measures we selected were chosen because of their appropriateness to measure the effect of inventory inaccuracy for our supply chain configuration. For example, measures such as customer response time or lead time are not used because they are more suitable for different production and distribution processes, e.g. make-to-order.

The first non-monetary performance indicator measures the fraction of time items are out-of-stock, assuming a linear trend of outgoing deliveries in each period.

The second non-monetary performance is inventory inaccuracy. Inventory inaccuracy is defined as the absolute difference between physical and information system inventory, divided by the average physical inventory . For both performance measures, the value is calculated as the average over the three echelons and over the entire simulation time.

We used two specifically designed monetary performance measures. They include only those cost components that are effected by the factors that cause inventory inaccuracy and exclude cost such as fixed order costs or transportation costs. The first monetary performance indicator measures the costs which are directly related to inventory inaccuracy, excluding the item value of stolen or unsaleable items. The cost components are (a) cost for out-of-stock items, (b) inventory holding cost, (c) additional inventory holding cost for misplaced items, (d) handling cost for detected missing or unsaleable items, and (e) cost for not-detecting missing or unsaleable items in the incoming delivery.

If the echelon downstream, the receiver, does not detect that items are missing or are unsaleable in the delivery, the echelon upstream, the supplier, can realize a profit. We have refrained from including these profits in our cost measures because this would effectively represent an incentive for the supplier to constantly deliver less than ordered or to ship unsaleable items, hoping that this will not detected by the receiver. Conceptually, one can argue that the profit for the echelon downstream is offset by an equal amount of cost at this echelon, e.g. due to loss of business or higher transaction costs in the future.

The second monetary performance measure includes two additional cost components which measure the lost item value due to theft and items becoming unsaleable. (For the latter, this means only the part of the cost that is not already included in the first cost measure.) The two cost components are not directly influenced by reductions in inventory inaccuracy or improvements in process quality. (Indirectly, however, increased process quality helps the receiver to detect more unsaleable items in the delivery which affects the second cost component.) We include these cost components as process changes or new technology that helps to increase inventory accuracy might not only eliminate inventory inaccuracy, but reduce theft and the amount of items becoming unsaleable at the same time.

7. ANALYSIS OF SIMULATION RESULTS

7.1. Base Case: No Periodic Inventory Alignment

We first wanted to determine whether the factors that cause inventory inaccuracy have an impact on supply chain performance in the base case (i.e. without inventory alignment in each period). This was done by successively lowering the level of theft and unsaleables, and increasing the level of process quality, respectively. The results of the variance analysis are shown in table 1. The performance measures show significant improvements if the level of theft is decreased from 1.5% to between 1.3% and 1.1%. Changes in performance become significant first for the cost measure which takes the lost item value into account. The reason for this is that the cost of stolen items account for more than 50% of cost in this cost measure and fall directly if the level of theft decreases.

For unsaleables, the cost measure that includes the lost item value improves significantly. As for theft, this is due to the direct impact of a decrease in unsaleables on the lost item value cost component. The other performance measures do not show significant improvements. This can be attributed to the low default value for unsaleables compared to theft.

Table 1: Values of factors at which performance measures differ significantly from default values in the base case

INDEPENDENT VARIABLE	VALUE	DEPENDENT VARIABLE	F-VALUE	SIGNIFICANCE
Theft (default value: 0.015)	0,011	Inventory inaccuracy	7,597	0,009*
	0,012	Out-of-stock	5,319	0,027*
	0,011	Cost excluding lost item value	8,360	0,006**
	0,013	Cost including lost item value	24,152	0,000**
Unsaleables (default value: 0.002)	0	Inventory inaccuracy	0,178	0,675
	0	Out-of-stock	0,003	0,954
	0	Cost excluding lost item value	2,039	0,161
	0	Cost including lost item value	15,966	0,000**
Process Quality (default value: 0)	0,6	Inventory inaccuracy	4,415	0,042*
	1	Out-of-stock	1,918	0,174
	0,2	Cost excluding lost item value	18,032	0,000**
	0,4	Cost including lost item value	9,948	0,003**

* Significant at 95% level
** Significant at 99% level

For an increase in process quality, both inventory accuracy and the two cost measures improve significantly, but not the out-of-stock level. The cost measures show significant improvements before the change in inventory inaccuracy becomes significant. (A value of zero for process quality corresponds to a process where process quality is equal to the default values, a value of 1 to a process with no quality problems. A process quality of e.g. 0.4 means that the level of misplaced items decreases from a default value of 2% to 1.2%, the level of detected unsaleable items in a delivery increases from 60% to 76% at the customer and from 40% to 64% at the supplier. Furthermore, incorrect deliveries decrease from an average of 0.5% of items to 0.3%, and the level of detected incorrect deliveries at the customer increases from 50% to 70%.) The result indicates that, although significant costs may be saved when process quality is improved, the improvement has comparably little impact on inventory inaccuracy and hardly any impact on the out-of-stock level.

7.2. Comparison of Base Case and Modified Model

Secondly, we looked at the change in supply chain performance when inventory inaccuracy is eliminated in the modified model. This is done by assuming that physical inventory and information system are aligned at the end of each period. For the default values, an elimination of inventory inaccuracy significantly improves all performance measures. In order to better understand at which level the improvements become significant, we varied each factor starting with the best case (i.e. with perfect process quality, no theft and unsaleables). This gives an indication of the required magnitude for each factor that causes inventory inaccuracy before supply chain performance deteriorates significantly, assuming that the other sources are not present. The results are shown in table 2. Since inventory inaccuracy is eliminated, we exclude this performance measure.

Table 2: Values of factors at which performance measures in the modified model differ significantly from the base case

* Significant at 95% level
** Significant at 99% level

INDEPENDENT VARIABLE	VALUE	DEPENDENT VARIABLE	F-VALUE	SIGNIFICANCE
Theft	0,005	Out-of-stock	11,956	0,001**
	0,005	Cost excluding lost item value	9,880	0,003**
	0,005	Cost including lost item value	13,538	0,001**
Unsaleables	0,005	Out-of-stock	0,174	0,679
	0,005	Cost excluding lost item value	2,942	0,094
	0,005	Cost including lost item value	2,726	0,107
Process Quality	0	Out-of-stock	3,433	0,072
	0,4	Cost excluding lost item value	6,290	0,017*
	0,4	Cost including lost item value	6,290	0,017*

Eliminating inventory inaccuracy leads to significant improvements in all performance measures if theft is the source of inventory inaccuracy. The improvements become significant if the level of theft reaches 0.5%, i.e. one third of the default value.

Up to the default level of 0.2% for unsaleables, there is no significant change in the performance measures. We increased the level of unsaleable items to 0.5%, but even at that level we do not find any significant impact. This is in contrast to the results above for theft and can be explained by the fact that in our model most items are shipped by the producer and distributor or sold by the retailer in the same time period in which they are received. The effect is that, in contrast to theft, most unsaleable items are detected (either by the supplier or customer) within the time period in which they become unsaleable, and information system inventory is adjusted.

If inventory inaccuracy is due to low process quality, eliminating inventory inaccuracy only has a significant impact on the cost measures, but not on the out-of-stock level. The effect on cost measures occurs if process quality is 0.4. The results in our model indicate that if there are problems with process quality, eliminating inventory inaccuracy can be beneficial from a monetary perspective even if the out-of-stock level does not change significantly.

7.3. Comparison of Base Case and Modified Model with Improvements in Factors

The previous analysis does not take into account the fact that procedures or technologies to eliminate inventory inaccuracy might have the potential to improve process quality and reduce the level of theft and unsaleables. In our final analysis, we vary the modified model and assume that, at the same time as inventory inaccuracy is eliminated, the relevant factor that causes inventory inaccuracy improves as well. Specifically, we assume that each factor improves by approximately 80% compared to its default value. This means that process quality improves to 0.8, theft decreases to 0.2% and unsaleables to 0.1%. The results of the variance analysis are shown in table 3.

Table 3: Values of factors at which performance measures in the modified model differ significantly from the base case, assuming improvements in factors

INDEPENDENT VARIABLE	VALUE	DEPENDENT VARIABLE	F-VALUE	SIGNIFICANCE
Theft	0,004	Out-of-stock	7,217	0,011*
	0,004	Cost excluding lost item value	7,217	0,011*
	0,003	Cost including lost item value	38,002	0,000**
Unsaleables	0,005	Out-of-stock	4,218	0,047*
	0,005	Cost excluding lost item value	3,450	0,071
	0,002	Cost including lost item value	43,925	0,000**
Process Quality	0,4	Out-of-stock	4,457	0,041*
	0,6	Cost excluding lost item value	15,223	0,000**
	0,6	Cost including lost item value	15,223	0,000**

* significant at 95% level
** significant at 99% level

With one exception, we see significant changes in the performance measures already at lower factor values, compared to the previous analysis.

The results for stolen and unsaleable items highlight the impact of changes in the level of theft and unsaleables on the cost measure that includes the lost item value. Here, significant improvements are reached first. For unsaleables, the cost measure which excludes item cost is the only one that does not improve significantly. Improvements in process quality first show in the cost measures and only later in the out-of-stock level. This is consistent with the results above.

8. SUMMARY AND CONCLUSIONS

To our knowledge, this is the first study that simulates the impact of inaccurate inventory information on supply chain performance. We have studied how process quality, theft and unsaleables affect inventory inaccuracy, the out-of-stock level, and the cost related to inventory inaccuracy. Our results indicate that eliminating inventory inaccuracy can reduce supply chain cost as well as reduce the level of out-of-stock, even if the level of process quality, stolen and unsaleable items remains unchanged. Supply chain performance increases further if, at the same time as inventory inaccuracy is eliminated, improvements in the factors that cause inventory inaccuracy (i.e. process quality, stolen and unsaleable items) can be achieved. These results are achieved in a supply chain in which information on customer demand is already exchanged.

The impact of inventory inaccuracy on supply chain performance varies by factor that causes inventory inaccuracy.

Inventory inaccuracy caused by theft appears to have the biggest impact on supply chain performance compared to inventory inaccuracy caused by unsaleables or low process quality. Eliminating inventory inaccuracy caused by theft reduces the level of out-of-stock and supply chain cost. The impact increases when theft is reduced at the same time as inventory inaccuracy is eliminated.

In our model, inventory inaccuracy caused by unsaleable items does not have an impact on supply chain performance. This can mainly be attributed to the fact that the level of unsaleables is small compared to theft and that most unsaleable items are detected early. Only when the level of unsaleables is reduced at the same time as inventory inaccuracy is eliminated, we can observe a change in the cost measure that takes the lost item value into account.

Process quality consists of two factors, incorrect deliveries and misplaced items. Eliminating inventory inaccuracy caused by low process quality reduces supply chain cost, but does not have an impact on the out-of-stock level. Supply chain cost improve further if process quality improves at the same time as inventory inaccuracy is eliminated. With improvements in process quality, we also notice a decrease in the out-of-stock level.

Our research is limited to a one-product supply chain configuration with specific parameter estimates, e.g. for lead time, demand variability, among other things, and default values for the factors that cause inventory inaccuracy. In our model, inventory inaccuracy caused by theft had a substantial effect on supply chain performance, in contrast to inventory inaccuracy caused by unsaleables. However, for other products such as food and grocery products the level of unsaleables is estimated at around 1% of sales [19], five times the 0.2% that we derived as an average for a product sold in supermarkets. Further studies of other supply chains are needed in order to understand under which circumstances it is worthwhile to attack the problem of inventory inaccuracy. Case studies based on real data should be conducted to study the impact of inventory inaccuracy in relation to total supply chain cost. In these case studies, one may also compare the benefits of eliminating inventory inaccuracy with the associated cost of process changes or the introduction of new technologies.

Our research suggests that it can be useful for companies that face high levels of inventory inaccuracy to examine procedures or technologies to eliminate (or at least reduce) inventory inaccuracy. To give some guidance, the results of our model indicate that an elimination of inventory inaccuracy can reduce supply chain cost and decrease the out-of-stock level when inventory inaccuracy is initially as low as 2%.

There are different ways in which the problem of inventory inaccuracy can be tackled. We can distinguish approaches that use technology from those that do not rely on technology. Non-technology approaches include benchmarking, awareness building, and process improvements [1]. These steps mainly focus on, and can help to reduce, e.g. the amount misplaced items. However, they offer less potential for detecting theft or incorrect deliveries which also cause inventory inaccuracy. There are different ways in which the problem of inventory inaccuracy can be tackled. Raman et al. [1] do not explicitly advocate the use of new technology, but stress the relevance of POS (point of sale) data or automatic replenishment systems which rely on accurate data.

Auto-ID technologies are an additional means in order to improve inventory accuracy. Benefits of RFID technology being discussed include reductions in stolen and unsaleable items, labour cost savings, and a reduction in out-of-stock items (e.g. [20]). RFID technology has some advantages over conventional barcode technology (e.g. non-line-of-sight and automatic identification), but also some drawbacks (e.g. tag cost, potential technical limitations) [3,21]. Eliminating inventory inaccuracy relies on frequent checks of physical inventory against information system inventory. To detect stolen or unsaleable items in a store, for example, individual items on a shelf need to be identified which can not be achieved with a barcode-based solution.

When RFID technology is solely to be used to achieve inventory accuracy, it seems most appropriate for high value items, due to the cost of tags. The results of our model indicate that it might be used for a wider range of products if improvements in process quality, a reduction in theft or in unsaleable items can be achieved. Furthermore, there are potential benefits of Auto-ID technologies that have not been considered in our model (e.g. increased efficiency in the receiving, picking and shipping process) which may additionally support the use of RFID.

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