INVENTORY INACCURACY AND PERFORMANCE OF COLLABORATIVE SUPPLY CHAIN PRACTICES

by

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ABSTRACT

Purpose – This paper aims to explore the impact of inventory system inaccuracies on the benefits of collaborative supply chain practices under various supply chain scenarios. To achieve this purpose, two popular collaboration initiatives are considered in a four-stage supply chain. The first practice is a vendor managed inventory (VMI) program where the distributor takes the full responsibility of managing the retailer’s inventory. The second practice is a collaborative planning, forecasting, and replenishment (CPFR) program where all members work together to plan, forecast, and replenish the product.

Design/methodology/approach – The study utilizes Monte Carlo computer simulation in an experimental design.

Findings – The analysis suggests that while the inaccurate inventory records result in significant performance reductions for all supply chain configurations, their impact is substantially greater for the supply chains where members collaborate more closely on key supply chain management activities. In addition, we also realize that the adverse impact of inaccurate inventory information is stronger under the conditions where lead times are shorter and/or where demand uncertainty in marketplace is lower.

Practical implications – This analysis provides a means for practitioners to realize the importance of inventory accuracy to successful adaptation of collaborative supply chain practices. Moreover, this research also helps in understanding the supply chain conditions where the attempts of eliminating or reducing errors in inventory information are more crucial and more beneficial.

Originality/value – Although there is a range of research focusing on collaborative practices, none of these studies considered the errors in inventory information. This is the first study to investigate the impact of inaccurate inventory information on the benefits of collaborative practices.

Keywords – Supply chain management, Supply chain collaboration, Vendor relations, Inventory management, Simulation

Article Type: Research paper
1. Introduction

Shorter product life cycles, increased product variety, and better-informed customers have raised the competitive pressure in most industries. To excel in this competitive environment, companies must design and operate materials management and product distribution functions effectively. Literature on supply chain management (SCM) contains significant research studies on how a company can achieve effective management of these operations (see e.g. Faisal et al., 2007; Simchi-Levi et al. 2008, p.5). Indeed, all these works show that uncertainty inherent in procurement, manufacture, and distribution makes successful management of these operations extremely difficult. For example, we see that in spite of advances in communications and information technologies, nearly 50% of the inventory records at a leading retailer are inaccurate (Kang and Gershwin, 2005). Moreover, we also observe that with the contribution of the bullwhip effect (Lee et al., 1997a, b), a small variation in customer demand is propagated in an amplified form to the upstream stages of a supply chain. In return, companies realize great increases in production and inventory costs, as well as lead times, while realizing substantial decreases in profit margins and product availability (Metters, 1997; Chopra and Meindl, 2000, p.1363). Thus, various strategies are developed to create efficient order-delivery processes between suppliers, manufacturers, distributors, and retailers. Indeed, the main goal of these strategies is to minimize the uncertainty along the supply chain and provide fast, reliable reactions to changing customer demands.

SCM researchers are agreed that sharing of business information among trading partners and collaborating on key SCM-business processes are crucial elements to achieve the idea of “any product any time any place”. In the light of these studies, several supply chain collaborative practices, such as Efficient Customer Response (ECR), Vendor Managed Inventory (VMI), and Collaborative Planning, Forecasting and Replenishment (CPFR), have been implemented in various industries. For example, GlaxoSmithKline (Danese, 2004), Electrolux Italia (De Toni et al., 2005), Boeing and Alcoa (Micheau, 2005), Wal-Mart and Warner-Lambert (Foote and Krishnamurthi, 2001), Sears and Michelin (Steermann, 2003) have adopted some of these collaborative practices. Of course, each of these collaborative practices requires different levels
of collaboration among trading partners. That is, while some of them require sharing point of sales (POS) data only, some others include collaboration on key SCM-business processes.

Examination of SCM literature reveals the fact that there is still no consensus among the researchers as to which of the supply chain initiatives should be implemented across the supply chain. On one hand, we know that adaptation of higher levels of collaboration among members of a supply chain creates greater benefits for the supply chain. On the other hand, we also see that development and operational costs of a highly integrated collaboration is also higher. Thus, this trade-off between benefits and costs of the collaboration initiatives creates an urgent need for SCM practitioners to determine the right collaboration level for their supply chains. To the best of our knowledge, there have been very few research studies aiming to explore this dilemma. That is, a few research studies e.g. Raghunathan (1999), Aviv (2001, 2002, 2007), Ovalle and Marquez (2003), Disney et al. (2004), Cigolini and Rossi (2006), and Sari (2007a) represent most of the developments in this area. While some of these studies analytically investigated the problem with very restrictive assumptions for the sake of mathematical traceability (Raghunathan, 1999; Aviv, 2001; 2002; 2007), remaining others (Ovalle and Marquez, 2003; Disney et al., 2004; Cigolini and Rossi, 2006; Sari 2007a) performed simulation experiments to analyze the performance of various collaboration initiatives in more realistic supply chain environments. Although these studies provide valuable information to the SCM practitioners in determining the appropriate level of collaboration for their supply chains, none of them considered the inventory discrepancies in their models. That is, all these studies assumed that physical inventory levels of enterprises are perfectly known, and shared without errors in a collaborative relationship.

Indeed, there is an unfortunate reality that most of the enterprises experience inventory record problems. For instance, one empirical research indicates that about 50% of the inventory records at a leading retailer are inaccurate (Kang and Gershwin, 2005). Likewise, another research reports similar findings: more than 65% of the inventory records do not match the physical inventory at the store level of a leading retailer (Raman et al., 2001). Of course, significant studies are conducted to investigate this problem (see e.g. Angulo et al., 2004; Fleisch and Tellkamp, 2005; Kang and Gershwin, 2005; Waller et al., 2006). However, all these studies
examine the impact of inaccurate inventory information on the performance of individual enterprises or on the performance of a given supply chain configuration. Namely, we realize that the impact of inaccurate inventory information on the benefits of collaboration initiatives has not been analyzed. Therefore, this research aims to fill this gap in SCM literate. More specifically, in this research, we try to answer to the following two simple questions:

- How does inaccurate inventory information of supply chain enterprises influence the performance of supply chain collaborations? In other words, we would like to know whether or not the adverse impact of inventory discrepancies is stronger on the performance of more collaborative supply chains.

- Which factors are influential in answering the above question? Namely, is the impact of inventory discrepancies on the performance of collaboration initiatives different under different levels of manufacturing capacity, lead times or demand uncertainty?

This study, answering the above-mentioned questions, helps SCM practitioners to recognize the relationship between errors in inventory records and collaborative supply chain practices for their specific business conditions. In order to answer these questions, we have constructed a comprehensive simulation model. The simulation analysis is reasonably good approach to understand and analyze the complex systems in details. SCM researchers have been extensively used the simulation analysis in analyzing supply chain problems (e.g. Waller et al., 1999; Angulo et al., 2004; Lau et al., 2004; Sari, 2007a, b).

The remainder of this study is organized as follows. Section 2 clarifies the methodology and development of the simulation model. Setting of experimental design is identified in Section 3, followed by simulation results. Conclusions are in the final section.

2. The simulation model

The analysis tool chosen for this research is Monte Carlo simulation using Crystal Ball. Crystal Ball is a spreadsheet based risk analysis and forecasting program published by Decisioneering. The supply chain examined in this research consists of four echelons: a manufacturing plant, a warehouse, a distributor, and a retailer. The plant has limited manufacturing capacity and produces a single product. Each enterprise replenishes its inventory
from its immediate upstream enterprise. A realistic but simple cost structure is chosen for each facility in the supply chain. That is, we assume that the unit back-order costs per period for the plant, the warehouse, the distributor, and the retailer are $15, $25, $35, and $50, respectively. Moreover, the unit inventory costs per period for the plant, the warehouse, the distributor, and the retailer are $0.70, $0.80, $0.90, and $1.00, respectively.

According to different levels of collaboration among the supply chain, the relationship between supply chain members is described as one of the following three integration levels. The first structure is a traditionally managed supply chain (TMS) and the second structure is a supply chain model operated under a VMI program. Finally, the third structure is a supply chain model operated under a CPFR program. Here, the supply chain operated under TMS is included in the model as a benchmark. Namely, the benefits of the collaborative practices are obtained by comparing the performance of VMI and CPFR with that of TMS. In all three supply chain structures, an (R, S) inventory control policy is used for replenishment decisions. Here, R indicates the review interval and S indicates the order-up-to level. Review interval (R) is chosen as one period. Order-up-to level, however, is updated at the beginning of each period to reflect changes in demand patterns.

We model the inaccuracy of inventory records in each supply chain member by inserting an error factor in each period’s actual inventory position. Namely, we multiply the true values of inventory and sales (in case of the retailer), inventory and shipment quantity (in case of the distributor and the warehouse), and inventory, production quantity, and shipment quantity (in case of the plant) by random numbers generated from a uniform distribution in the range of from 1-IAC to 1+IAC. Here, IAC denotes the percentage error observed in inventory information through the supply chain. In fact, a very similar form of random numbers is also used by Angulo et al. (2004) and Waller et al. (2006) to represent the inaccuracies on inventory information. In this study, we represent the inaccuracies in inventory information in five different levels for comparison purposes. That is, five different levels of inventory discrepancies are represented by assigning the following values of IAC: 0.00, 0.05, 0.10, 0.15, and 0.20.
2.1. Retailer’s demand structure

Demand for the retailer is generated by using the formula 1. In fact, a very similar form of time series is also used by Zhao et al. (2002) and Bayraktar et al. (2007).

\[ D_t = base + season \times \sin \left( \frac{2\pi}{SeasonCycle} \times t \right) + noise \times \text{normal}() \]  

In formula 1, \( D_t \) is the demand in period \( t \) and \( \text{normal}() \) is a standard normal random number generator. \( Base \) and \( SeasonCycle \) are common parameters, and assigned the values of 100 and 7, respectively. The others (\( season, noise \)) are the characteristic parameters of demand structure and represent different magnitudes of demand uncertainty. In order to evaluate the performance of various supply chain scenarios under different levels of demand uncertainty, two types of demand structures are used in this research. These are the demand structure with low level of uncertainty (LDU) and the demand structure with high level of uncertainty (HDU). For \( season \) and \( noise \), respective values of 0 and 10 are assigned under LDU. On the other hand, under HDU, both of these parameters take the value of 30. Here, the specific values of demand parameters are determined very carefully in such a way that uncertainty inherent in LDU is increased to higher levels in HDU. Namely, while there is no seasonality in LDU, there is a seasonal swing in the size of 30% of average demand in HDU. Similarly, \( noise \) factor of HDU is three times greater than that of LDU. Indeed, in this research, we insert two types of uncertainty (i.e. uncertainty resulting from seasonality and random factor) into the customer demand. That is, while the uncertainty caused by seasonality can be resolved by better forecasting, the uncertainty caused by \( noise \) factor can not be eliminated.

2.2. The Supply Chain Operated under TMS

Under TMS, each member strives to develop strategies for optimizing its own organization without considering the impact of these strategies on the performance of other members. Moreover, since no information is shared between members, upstream stages are unaware of actual demand information at the market place. That is, while creating demand forecasts and inventory plans, supply chain members use only replenishment orders placed by their immediate
downstream member. Therefore, each member of the supply chain replenishes his own inventory by following an installation-based (R, S) policy. Under an installation-based (R, S) policy, each member considers his local inventory position. The sequence of events followed by a supply chain member operated under TMS is outlined as follows:

i) The member receives the delivery from its immediate upstream member, which was ordered $L$ periods ago (the lead-time is $L$ periods). If the member is the plant, $L$ is the production lead time.

ii) The member observes the order placed by its immediate downstream member. If the member is the retailer, the order is the market demand.

iii) The member fulfils the customer orders (plus backorders if there are any) by on-hand inventory, and any unfulfilled customer orders are backordered. The member analyzes the historical replenishment orders placed by its immediate downstream member for forecasting. Based on this demand forecast, the member updates its order-up-to point. If the member is the retailer, historical market demand data is analyzed. The order-up-to point of the member at stage $k$, $S^k$, estimated from the observed demand as indicated in formula 2 (Simchi-Levi et al., 2008, p.46).

$$S^k = \hat{D}^{L+R}_t + z\hat{\sigma}^{L+R}_t$$

where $\hat{D}^{L+R}_t$ is an estimate of the demand during an interval of $L+R$ periods realized by the member at stage $k$, $\hat{\sigma}^{L+R}_t$ is an estimate of the standard deviation of the $L+R$ period forecast error, and $z$ is a constant chosen to meet a desired service level. It should be noted that $z$ is also known as the safety factor. Since there exits seasonal swings in demand structure modeled in formula 1, winter’s method for forecasting is employed in the simulation model. This is because among others winter’s method performs good estimates for seasonal demand structures. For interested readers, more detailed information on this forecasting method is provided in Abraham and Ledolter (1983, p.170).
iv) The member decides how many units to order from its immediate upstream member. The quantity of the order is equal to the difference between the order-up-to level and “system inventory position”. We use “system inventory position” term here because the member may not know its actual inventory position depending on the degree of error rate (IAC) in inventory information. Here, if the member is the plant, a production order is placed. The plant, because of its limited manufacturing capacity, cannot always produce enough to bring its inventory position up to the updated value of $S_i^k$. In these cases, the plant makes full capacity production by backordering the remaining requirement. This modification of order-up-to policy for the case of limited production capacity provides an optimal solution for uncertain demands (see e.g. Gavirneni et al., 1999; Federgruen and Zipkin, 1986a, b).

2.3. The Supply Chain Operated under VMI

Under VMI, the retailer provides the distributor with access to its real-time inventory level as well as POS data. In return, the distributor takes the responsibility of managing the inventories at the retailer. That is, under VMI, the distributor does not only need to take its own inventories into account while making inventory plans, but also the inventories of the retailer. Therefore, under this structure, the distributor follows an echelon-based policy in its replenishment planning. Under the echelon-based policy, the distributor considers its own inventory position plus the inventory position of the retailer, instead of its local inventory position only. For a discussion of installation and echelon policies, see Clark and Scraf (1960), Axsäter and Rosling (1993). All other echelons of the supply chain (the plant and the warehouse), on the other hand, are operated in the same way as in TMS. In this supply chain again, members adopt winter’s forecasting model in order to update their order-up-to levels.

2.4. The Supply Chain Operated under CPFR

Under CPFR, inventory levels, POS data, promotion plans, sales forecasts, and all other information that are influential on the market demand are shared between trading partners. Consequently, a single joint demand forecast is created by the contribution of each member.
Here, there is no doubt that demand forecasts created with the joint contributions of all supply chain members are more accurate than the ones created by the individual organizations (e.g. demand forecasts created by the supply chains operated under TMS or VMI). Indeed, it is very possible at the end of the collaborative forecasting process the parameters of the market demand distribution are predicted. Therefore, in the simulation model, we assume that under CPFR, distribution parameters of the market demand are predicted by contribution of each member. This assumption does not mean that at the end of the collaborative forecasting process, the members can know exactly what the customer demand is, but rather they can know what the parameters of the underlying demand distribution are (i.e. if the customer demand is normally distributed, mean and standard deviation of the customer demand is known only). Indeed, this assumption makes it sure that the promise of CPFR is realized. That is, the large amounts of information available with CPFR are effectively used to minimize the uncertainty along the supply chain. Of course, in practice, as the model of Disney et al. (2004) also indicates, it might possible that bulk of information available with CPFR result in confusion of supply chain managers, which can result in poor of supply chain performance. Therefore, the benefits of CPFR obtained in this study are valid only if CPFR is properly implemented. Moreover, under this collaboration mode again, an echelon-based (R, S) inventory policy is used for entire supply chain. That is, inventory positions and inventory costs of all members are taken into account in production and replenishment decisions.

2.5. Verification and validation of the simulation

In order to verify that the simulation program performs as intended, the conceptual model is divided into three parts: Demand generation and determination of total manufacturing capacity, Forecasting and production/inventory planning, and Order fulfillment and reporting. Each part is designed separately so that more efficient and effective debugging is made possible. Moreover, the combined simulation model is also traced and tested with the results calculated manually.

Later, in order to validate the simulation output, the random demand variables generated in the simulation model are plotted on a scatter diagram. Then, it is validated that the intended
demand structure is generated. The supply chain model is simulated for 518 periods. The initial parameters of the forecasting model is estimated with the first 98 periods of simulation run, which is removed later from the output analysis to eliminate the warm up period effect. Moreover, in order to eliminate the terminating effect, last 20 periods of the simulation run are also removed from the output analysis. Therefore, the rest of the data from 99th period to 498th period (400 periods) are used for effective simulation output analysis. In order to reduce the impact of random variations, the same random numbers are used to simulate all three systems. That is, same customer demand is generated for all types of supply chain systems. In addition to this variance reduction technique, fifteen replications for each combination of the independent variables are conducted. Interested readers can see Bank et al. (1996, p.429) for a discussion of techniques to reduce the impact of random variations and also output analysis considerations.

3. Experimental design

Five independent factors are considered in the experimental design. These are; error rate in inventory information (IAC), type of supply chain (SCTYPE), available production capacity of the plant (CAP), uncertainty in market demand (DU), and lead times (L). The number of levels of these variables and their values are listed in Table I.

Take in Table I here

Factor IAC indicates the degree of inaccuracies in the inventory information of the supply chain enterprises. The factor SCTYPE refers to the way the supply chain is operated. Specifically, this factor indicates whether the supply chain is operated under TMS, VMI, or CPFR. The factor CAP is expressed as the ratio of the plant’s total capacity to the total market demand. Total capacity of the plant is distributed to each period, equally. The factor L denotes the replenishment lead times between each member of the supply chain. Finally, the factor DU indicates the level of demand uncertainty observed in market place.

Two factors are used as dependent variables in the experimental design in order to evaluate impact of inaccurate inventory information on the benefits of VMI and CPFR. These factors are
total cost for the entire supply chain (TSC) and customer service level of the retailer (CSL). TSC is the sum of the inventory holding costs of all members in the supply chain and backorder cost of the retailer. Here, we include the back order cost of the retailer only, because all other back order costs are internal costs within the entire supply chain and they are not actually incurred. Factor CSL is the percentage of customer demand satisfied by the retailer through the available inventory.

4. Simulation output analysis

The output from the simulation experiments are analyzed using MANOVA (multivariate analysis of variance) procedure of the Minitab. MANOVA is a statistical procedure that is used to determine if a set of predictor variables can explain the variability in a set of response variables. Indeed, it is simply an ANOVA (analysis of variance) with several dependent variables. In addition, it considers the correlation between dependent variables in the experimental design. Since in the experimental design of this research includes more than one dependent variable (i.e. TSC and CSL), MANOVA is chosen here as an analysis tool. For more detailed information about MANOVA, see Hair et al. (1998, p.331). Selected MANOVA results are presented in Table II.

**Take in Table II here**

Indeed, our experimental results can also be used to evaluate the benefits of supply chain collaboration practices under different operational and environmental conditions. However, in this study, we mainly focus on measuring the impact of inaccurate inventory information on the performance of collaborative practices.

MANOVA results in Table II indicate that at 5 percent significance level inaccurate inventory information has significant impact on the performance of VMI and CPFR. This indicates that the benefits of collaborative supply chain practices significantly influenced from inventory record problems. Moreover, the results in Table II also show that this impact exhibits different behaviours under different market demand structures and lead times. Namely, the
impact of inaccurate inventory information on the performance of VMI and CPFR are not the same for different levels of customer demand uncertainty and lead times. On the other hand, MANOVA results presented in Table II also shows that negative impact of inventory discrepancies on the performance of supply chains does not change significantly with different manufacturing capacity levels at the plant (p value <0.05). That is, whether the manufacturing capacity level of the plant is high or low, the adverse impact of inventory record errors on the performance of supply chains does not differ significantly.

In the light of these initial findings, in subsequent sections, we further discuss and extend the results presented in Table II.

4.1. The impact of IAC on benefits of VMI and CPFR

MANOVA results in Table II shows that at 5 percent significance level, the interaction effect between IAC and SCTYPE has significant impacts on both dependent variables. This means that inaccurate inventory information has a significant influence on the performance of VMI and CPFR for both performance measures.

Taken Figure 1 here

Figure 1 shows the relationship between inaccurate inventory information and cost reduction gained from VMI and CPFR, as well as customer service levels achieved in each collaboration mode. Here, while calculating the cost reduction obtained from VMI or CPFR, we consider the total supply chain cost of TMS as a benchmark. Namely, Formula 3 is used to get the total cost reduction achieved from VMI or CPFR.

\[
\text{Reduction in TSC} \ (%)=\left(1-\frac{\text{TSC of TMS}}{\text{TSC of VMI or CPFR}}\right)\times100
\]  

(3)

Examination of Figure 1 reveals that the while the cost reduction gained from CPFR, as well as the customer service level achieved, substantially decrease with inaccurate inventory information, the performance of VMI is not affected that much great. In other words, Figure 1
shows that the influence of inaccurate inventory information is not at the same strength for both collaborative practices. That is, we observe that CPFR is substantially more sensitive to the errors in inventory information in terms of cost savings and customer service level achieved. For example, we see that as error rates in inventory records (IAC) increase from 0% to 20%, the cost reduction gained from CPFR dramatically drops from 45.2% to 12.2%. Similarly, we also see that the customer service level achieved by CPFR decreases from 95.9% to 82.1%. On the other hand, when the other collaboration initiative is considered, we observe that the performance decrease realized in VMI due to inaccurate inventory information is comparatively small. That is, the savings achieved in supply chain cost decrease from 10.36% to 7.24% and the customer service level achieved decreases from 95.9% to 87.4%.

4.2. The interaction between DU, SCTYPE and IAC

MANOVA results in Table II show that at 5 percent significance level, the interaction effect between DU, SCTYPE, and IAC has significant impacts on both dependent variables. This means that the impact of inaccurate inventory information on VMI and CPFR is significantly different under different levels of uncertainty in market demand.

**Taken Figure 2 here**

Examination of Figure 2 reveals the following facts for VMI and CPFR under different levels of demand uncertainty and various levels of inaccurate inventory information:

- First, we observe that the compared to high level of demand uncertainty (DU=HDU), influence of inventory discrepancies on the benefits of CPFR is substantially greater under low level of demand uncertainty (DU=LDU). For example, we see that, when the demand uncertainty is low (DU=LDU), the cost reduction achieved by CPFR dramatically drops from 56.16% to -1.35% as inventory discrepancies increase from 0% to 20%. On the other hand, we also observe that, when the demand uncertainty is high (DU=HDU), the same amount of increase in inventory discrepancies does not produce that much performance reduction in
CPFR. For example, we see that even when the error rate is in its highest level (IAC=20%), CPFR still produces 25.69% reduction in supply chain cost.

- Second, we realize that the response of VMI to the inaccurate inventory records is very similar to that of CPFR. However, the strength of this adverse impact is relatively small. For example, we observe that when the demand uncertainty is low (DU=LDU), the total cost savings of VMI reduces from 9.85% to 0.26% as inventory discrepancies increase from 0% to 20%. On the other hand, when the demand uncertainty is high (DU=HDU), we cannot see any significant reduction in the total cost savings of VMI. Furthermore, when we consider the customer service level achieved by VMI, again we see that the impact of inaccurate inventory records is stronger under low level of demand uncertainty. That is, while there is a great reduction (from 95.1% to 81.2%) in the customer service level under low level of demand uncertainty (DU=LDU), we realize only a slight decrease (from 95.8% to 93.5%) in case of high level of demand uncertainty (DU=HDU).

- Finally, when we take the performance of both collaboration initiatives into consideration together, we see that either VMI or CPFR does not provide any significant benefit to the supply chain where error rate in inventory information is in its highest level (IAC=20%) and where demand uncertainty is low (DU=LDU). In addition, we also observe that the gap between the performance of VMI and CPFR falls to its lowest level when the error rate in inventory information is in its highest rate (20%). In other words, we understand that additional performance increase provided by CPFR over VMI is smallest when the error rate in inventory records is high.

4.3. The interaction between L, SCTYPE and IAC

MANOVA results in table 2 show that at 5 percent significance level, the interaction effect between L, SCTYPE and IAC has significant impacts on both performance factors. This means that the impact of inaccurate inventory information on VMI and CPFR is significantly different under different levels of replenishment lead times.

Taken Figure 3 here
Examination of Figure 3 reveals the following facts for VMI and CPFR under different levels of demand uncertainty in market place and various levels of inaccurate inventory information:

- First, we observe that compared to the longer lead times, the impact of inventory discrepancies on the benefits of CPFR is more crucial under shorter lead times. This is because we see that, when the lead times are short (L=1) and when the error rate in inventory information is in its highest level (IAC=20%), the reduction in supply chain cost provided by CPFR falls to a negligible level. On the other hand, we see that, in case of long lead times (L=5), the performance of CPFR is influenced in lower amounts from inventory discrepancies. That is, although the customer service level achieved by CPFR greatly decreases, it still produces nearly 23% of reduction in supply chain cost when the error rate in inventory records are at its highest rate (IAC=0.20).

- Second, when we consider VMI, we realize that, under longer lead times, inaccurate inventory information is not very important for the supply chain performance. Namely, we see that there is no statistical evidence that the cost reduction achieved by VMI adversely affected from inaccurate inventory information. Instead, there exists a reduction in the customer service level only. On the contrary, when the lead times are short (L=1), we see that there is a substantial decrease in cost saving of VMI, that is from 15.75% to 6.70%, as the inventory discrepancies increase from 0% to 20%.

- Finally, when we take the performance of both collaboration initiatives into consideration together, we observe that, under both lead times, the performance decrease realized in CPFR is greater than that of VMI. Moreover, we also observe that both collaborative practices are influenced from inaccurate inventory information in greater amounts when the lead times are short (L=1).

5. Conclusions

This paper investigates the impact of inaccurate inventory information on the benefits gained from VMI and CPFR in a four-stage supply chain under different environmental and
operational factors by means of a simulation study. Through comprehensive simulation experiments and subsequent statistical analysis of the simulation outputs, we make the following two important observations:

• First, we observe that inaccurate inventory information significantly influence the performance of both collaboration initiatives. However, we also observe that the magnitude of this impact is not the same. That is, while errors in inventory records tremendously drop the performance of the supply chain operated under CPFR, the reduction realized in the performance of VMI is not that much great. Thus, we realize that the negative impact of inaccurate inventory information on the supply chain performance substantially increases as the trading partners collaborate more closely throughout the supply chain.

• Second, we realize that both collaborative supply chain practices are more sensitive to the inaccurate inventory information under the conditions where customer demand uncertainty is low and/or when lead times are short. That is, we observe that errors in inventory records may drop the benefits of VMI and CPFR to negligible levels if demand uncertainty in market place is low and/or lead times are short.

Indeed, the main findings of this research are not surprising for us and can be explained intuitively as follows. Consider a business environment where members of a supply chain collaborate closely on key SCM activities. That is, they share sales and forecast information as well as inventory levels in order to coordinate manufacturing and distribution functions. Thus, this collaborative practice among trading partners greatly reduces the lead times, demand forecast errors, and consequently the bullwhip effect. Of course, under this system, the members require substantially lower safety stocks. Moreover, we also know that as the level of collaboration among the supply chain members increase, the safety stock levels throughout the supply chain will be lower. Indeed, it is not very surprising for us that this supply chain with lower levels of safety stocks is more responsive or more sensitive to uncertainty or ambiguity inherent in inventory, sales, or production. Similarly, this reasoning also explains why the impact of inaccurate inventory information is stronger on the benefits of collaboration initiatives under low levels of demand uncertainty and/ or when the lead times are short. That is, in both of these cases, the safety stock levels of the supply chain enterprises are lower.
The managerial implications of this research are significant. Namely, this research provides a framework for SCM practitioners in understanding the impact of inaccurate inventory information on the benefits of collaborative supply chain practices under various conditions. By means of this study, SCM practitioners can recognize the importance of inventory accuracy for successful management of supply chain operations. Furthermore, they can also understand the conditions under which elimination of errors in inventory records are more crucial and important for successful collaborative practices. Indeed, this research shows the significance of attempts in eliminating or reducing the errors in inventory records. At this point, SCM practitioners can consider implementation of an advanced data capture technology such as the radio frequency identification (RFID) in order to reduce errors in inventory records. This is because many industry applications in various sectors show that if properly implemented, RFID can provide more accurate information of the available inventories and its position throughout the supply chain.

Finally, we have to state that there are some limitations of this study. First, we consider a serial supply chain structure with one member at each echelon. This supply chain structure is only a simplified case and in future research studies, modelling more realistic supply chain structures may better explain and extend the results obtained from this research. Second, we assume that the members in the supply chain apply (R, S) policies to make their production/inventory decisions; however, we know there are other types of inventory/production policies that can be included in the simulation model. Third, the cost structure used in the simulation model only represents one special case.
References


### Table I: Independent factors of the experimental design

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<th>Independent Factors</th>
<th>Description</th>
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<td>IAC</td>
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Table II: Selected MANOVA results

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<th>CSL</th>
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Note: * Based on residual analysis, log transformation of TSC was made to satisfy the assumptions of MANOVA
Figure 1: The impact of inaccurate information on the performance of VMI and CPFR
Figure 2: The interaction between DU, SCTYPE, and IAC
Figure 3: The interaction between $L$, SCTYPE, and IAC