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Research Article

Demand Sharing Inaccuracies in Supply Chains: A Simulation Study

Salvatore Cannella,[1,2] **Roberto Dominguez**,[2,3] **Jose M. Framinan**,[2] **and Manfredi Bruccoleri**[4]

[1] *Management and Business Engineering Research Group, Department of Civil Engineering and Architecture (DICAR), University of Catania, Via A. Doria 5, 95131 Catania, Italy*
[2] *Industrial Management & Business Administration Department, School of Engineering, University of Seville, Seville, Spain*
[3] *Centre for Management Studies, Instituto Superior Técnico (CEG-IST), University of Lisbon, Lisbon, Portugal*
[4] *Department of Chemical, Management Software, and Mechanical Engineering, University of Palermo, Palermo, Italy*

Correspondence should be addressed to Salvatore Cannella; cannella@unict.it

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We investigate two main sources of information inaccuracies (i.e., errors and delays) in demand information sharing along the supply chain (SC). Firstly, we perform a systematic literature review on inaccuracy in demand information sharing and its impact on supply chain dynamics. Secondly, we model several SC settings using system dynamics and assess the impact of such information inaccuracies on SC performance. More specifically, we study the impact of four factors (i.e., demand error, demand delay, demand variability, and average lead times) using three SC dynamic performance indicators (i.e., bullwhip effect, inventory variability, and average inventory). The results suggest that demand error has a negative impact on SC performance, which is exacerbated by the magnitude of the error and by low demand variability scenarios. In contrast, demand delay produces a nonlinear behavior in the supply chain response (i.e., a short delay may have a negative impact and a long delay may have a positive impact), being influenced by the supply chain configuration.

1. Introduction

Information sharing is an effective collaboration strategy widely analyzed in the supply chain (SC) management-related literature, as it improves SC performance and reduces the noxious bullwhip effect [1–6]. This phenomenon can be defined as the amplification of order variability upstream in the SC, and it is known to cause excessive inventory, grossly inaccurate demand forecasts, low capacity utilization, and poor customer service level [3, 4]. Since the lack of market visibility has been traditionally identified as one of the main causes of the bullwhip effect, sharing market demand information to the upstream members of the SC becomes an effective strategy for bullwhip effect reduction [7].

Nevertheless, implementing information sharing (IS) in SCs presents some serious obstacles due to numerous barriers [8]. Perhaps one of the most severe barriers is the quality of the shared information, which can be defined as the degree to which the information exchanged between organizations meets the needs of the organizations [9]. Without reliability or validity, information has no value for the receiving partner [10, 11], since such information might be erroneous. While most of the studies about IS in SCs assume that the information shared between members is fully accurate, in practice, information is frequently distorted, either willfully or unintentionally, as it travels through the SC [12]. Therefore, unless each party can verify the authenticity of the other parties' information, SC members may spread false information for their own benefit [13].

Errors may be present in the transmission of market demand information and inventory levels, both of them having negative consequences on SC performance. Demand errors occur when the real market demand of a product differs from the level of sales recorded in the information system. As reported by Kwak and Gavirneni [14], the detrimental impact of errors in demand information outweighs the beneficial impact of IS when the variance of information errors exceeds the variance of end-customer demands. Inventory errors occur when the level of actual inventory of a product differs from that recorded in the information system. The value of transmitting inventory information to other SC partners may be undermined by these errors, which are often present in SCs [15]. In turn, the presence of inventory errors at downstream echelons causes demand information distortion and may undermine the expected benefit of IS and the effort in information technology investment [16].

In addition to the quality of the information, another important obstacle to IS implementation is the synchronization of the information transmission process. A bad synchronization leads to delayed information regarding market sales and/or inventory levels (i.e., the information transmitted upstream is received one or more periods later). The impact of such information delays on SC performance remains unclear in the literature; for example, Hoberg and Thonemann [17] state that the presence of unsynchronized processes or inadequate communication structures hinders the widespread availability of real-time information, thus harming the overall SC performance; Hosoda and Disney [18, 19] show that while the first level of a SC can benefit from shorter time delays, the benefit perceived by the second level of the SC is minor or even detrimental.

After a thorough review of the related literature, we notice that (1) the impact of transmitting erroneous demand information has not been addressed from a SC dynamic perspective, (2) the impact of demand information delay on SC performance presents contrasting results, and (3) most of the related literature focuses on two-echelon SCs. Motivated by these considerations, in this work, we aim to fill these gaps by analyzing the dynamics of a collaborative four-echelon SC where demand information is transmitted with errors and/or delayed. The SC is modelled using a system dynamics approach ([20], Syntetos 2011, [21, 22]). The results show that both the bullwhip effect and inventory variability are exacerbated in the presence of errors in market demand information, particularly for low demand variability scenarios. The impact of information delays depends on the magnitude of the delay, so the performance of the SC deteriorates for short delays and improves for long delays. Finally, we found that the impact on the average SC inventory of erroneous/delayed market demand IS is lower than on the bullwhip effect and inventory variability.

The remainder of the paper is structured as follows: in Section 2, we perform a systematic literature review. Then, we present the SC model in Section 3. In Section 4, we describe the design of experiments and show the results obtained. Section 5 summarizes findings and managerial implications, while Section 6 includes the conclusions of the research.

2. Inaccuracy in Demand Information Sharing: Systematic Literature Review

In order to depict the state of the art on demand information sharing with errors and/or delays, we perform a systematic review of the literature, focusing specifically on studies that analyze the dynamic behavior of the SC. This systematic review is conducted according to the framework provided by Denyer and Tranfield [23], that is, (1) question formulation, (2) locating studies, (3) study selection and evaluation, (4) analysis and synthesis, and (5) result reporting. Therefore, in the first step, we define the following research question for the literature review: *how does erroneous/delayed demand information sharing impact on the dynamic of a multi-echelon SC?*

In the second step, in order to locate the relevant studies, we use three well-established scientific databases, that is, *Scopus*, *ABI/Inform Global*, and *Web of Science*. In each database, we perform an identical search with the following string: *"supply chain* " AND ("demand error* " OR "information error* " OR "false demand" OR "false information" OR "demand delay* " OR "information delay* ").*

The resulting queries provided a total of 34 different papers in the English language. Table 1 summarizes these papers, which are classified by scientific databases.

This third step concerns the explicit elucidation about the selection/exclusion criteria of the review. In the following, we report the exclusion criteria used in this review and the excluded articles:

(i) *Lack of specific insights*: articles [2], [3], [8], [9], [12], [20], [23], [26], [28], [29], [31], [32], and [33] are excluded from further analysis due to lack of specific insights on the potential impact of the *demand error* and the *demand delay* on the dynamics of SC.

(ii) *Nonrelated*: articles [13], [14], [15], [29], and [31] merely contain the search string's terms in the keywords, title, or abstract. However, they are not related to the research question in Step 1.

(iii) *Similar research results*: article [6] is excluded as it reports similar research results as in [5]. Thus, it does not contain additional contributions.

In Step 4, after the application of the exclusion criteria, the remaining 15 papers are reviewed in detail and cross-tabulated in order to identify their key features (Table 2). To this end, articles are categorized according to the following criteria: type of shared information, type of information distortion (i.e., demand error and/or demand delay), adopted methodology, number of echelons in the SC, customer demand patterns, replenishment policy, forecasting model, and indicator for SC dynamic performance (i.e., bullwhip effect, average inventory, and inventory variability).

By analyzing Table 2, in the following, we summarize the assumptions and observations arising from the literature gaps:

(i) The majority of the studies focuses on a two-echelon SC structure. Moreover, the three studies adopting a four-echelon structure (see, e.g., [37, 40, 45, 53]) do not provide specific insights on the dynamics of SC under demand information sharing with delays/errors (in the following, demand delays/errors).

Table 1: Literature review: paper selection.

Number	Authors (year)	SCOPUS	ABI	WOS	*Selected*	Reason for inclusion/exclusion
[1]	Kwak and Gavirneni (2015)	X	X	X	X	Insights on the impact of demand error
[2]	White and Censlive (2015)		X			Lack of specific insights
[3]	Ju et al. (2015)			X		Lack of specific insights
[4]	Hoberg and Thonemann (2014)	X	X	X	X	Insights on the impact of demand delay
[5]	Peng et al. (2014a)	X	X	X	X	Insights on the impact of demand delay
[6]	Peng et al. (2014b)	X	X	X		Similar insights to those in article [5]
[7]	Avrahami et al. (2014)			X		"Demand delay" is present only in the title
[8]	Yao and Ju-Qin (2013)	X				Lack of specific insights
[9]	Ikonen et al. (2013)	X				Lack of specific insights
[10]	Hosoda and Disney (2013a)	X		X	X	Insights on the impact of demand delay
[11]	Hosoda and Disney (2013b)	X		X	X	Insights on the impact of demand delay
[12]	Chung et al. (2011)	X	X	X		Lack of specific insights
[13]	Cheng et al. (2011)	X				"Demand delay" is present only in the keywords
[14]	Sundarakani et al. (2010)	X				"Demand delay" is present only in the abstract
[15]	Jaggi and Kausar (2010)	X				"Demand delay" is present only in the keywords
[16]	Kim (2010)		X	X	X	Insights on the impact of demand delay
[17]	Nachtmann et al. (2010)		X	X	X	Insights on the impact of demand error
[18]	Munoz and Clements (2008)	X	X		X	Insights on the impact of demand delay
[19]	Choi (2008)		X		X	Insights on the impact of demand error
[20]	Arcelus et al. (2007)	X	X	X		Lack of specific insights
[21]	Mishra et al. (2007)	X	X	X	X	Insights on the impact of demand error
[22]	Paik and Bagchi (2007)	X	X		X	Insights on the impact of demand delay
[23]	Leopoulos et al. (2006)	X				Lack of specific insights
[24]	Kim (2006)		X	X	X	Insights on the impact of demand delay
[25]	Zhang (2005)	X		X	X	Insights on the impact of demand delay
[26]	Ge et al. (2004)		X			Lack of specific insights
[27]	Angulo et al. (2004)		X		X	Insights on the impact of demand error and demand delay
[28]	Jayaraman and Baker (2003)	X	X	X		Lack of specific insights
[29]	Dutta and Roy (2003)		X			Lack of specific insights
[30]	Chen (1999)	X	X	X	X	Insights on the impact of demand delay
[31]	Jones and Riley (1985)		X			Lack of specific insights
[32]	Diedrichs et al. (2016)				X	Lack of specific insights
[33]	Asala et al. (2017)				X	Lack of specific insights
[34]	Lu et al. (2017)				X	Insights on the impact of demand error

(ii) The market demand structure adopted in studies on demand error is the normal distribution (iid), while the autoregressive model is the preferred demand pattern in works on demand delay.

(iii) The most used replenishment policy is the classical order-up-to, and the most used forecast policy is the exponential smoothing.

(iv) The erroneous demand is usually modeled as a percentage of the customer demand. Articles dealing with demand delays assume a constant and deterministic time delay.

Analogously, in the following, we provide a summary of the main findings related to the impact of demand and errors and delays on SC dynamics:

(1) *Impact on the bullwhip effect*: no work deals with the impact of the demand error on the bullwhip effect. In contrast, four studies focus on the demand delay and the bullwhip effect (see [17, 19, 40, 43]). However, the works report conflicting views on how demand delay affects SC performance.

(2) *Impact on average inventory*: four studies, using different methodological approaches and modelling assumptions, prove that demand errors increase the average inventory level for all SC members (see [14, 36, 38, 45]). According to these studies, demand errors increase forecast errors, which leads to the need of holding higher safety stocks in order to achieve the target service level. Analogously, two studies agree on the fact that demand delays increase

Table 2: Literature review: selected papers.

Authors	Demand	Information	Error	Delay	Unwilled	Willed	Methodology	Number of echelons	Demand structure	Replenishment policy	Forecasting technique	Error model	Delay model	Impact on Bullwhip effect	Impact on average inventory	Impact on inventory variability
Lu et al. [52]	x		x		x		Analytical model and numerical analysis	2	AR (1)	Order-up-to	MMSE	iid	NA	NA	NA	↑↓
Kwak & Gavirneni [14]	X		X		X		Analytical model and numerical analysis	2	iid	Order-up-to	NA	Percentage	NA	NA	Echelon 2: ↑	NA
Hoberg and Thonemann [17]	X			X	X		Control theory	2	iid	Order-up-to	Exponential smoothing	NA	Constant (1–4 days)	↑↓	NA	NA
Peng et al. [26]		X		X	X		System dynamics simulation	2	NA	Order-up-to	Exponential smoothing	NA	Stochastic (negative exponential function)	NA	Echelon 2: ↑	NA
Hosoda and Disney [19]	X			X	X		Analytical model and numerical analysis	2	AR (1)	Order-up-to	Conditional expectation (echelon 1): (a) sub-optimum (b) optimum	NA	Constant	(a) ↓ (b) ↑	NA	(a) Echelon 1: ↑ (a) Echelon 2: ↓ (b) Echelon 1: ↑ (b) Echelon 2: ↑
Hosoda and Disney [18]	X			X	X		Analytical model and numerical analysis	1	AR (1)	Order-up-to	Conditional expectation	NA	Constant (1 day)	NA	NA	Echelon 1: ↑
Kim [35]	X			X	X		Analytical model and numerical analysis	2	AR (1)	Order-up-to	NA	NA	Constant	NA	NA	Echelon 2: ↑
Nachtmann et al. [36]	X		X		X		Simulation model and statistical analysis	1	iid (gamma)	Order-up-to	Exponential smoothing (alpha = 0.1)	Percentage	NA	NA	Echelon 1: ↑	NA
Munoz and Clements [37]		X		X	X		Discrete event simulation	4	Triangular random distribution	NA	NA	NA	Constant (1–4 weeks)	NA	NA	NA
Choi [38]	X		X		X		Simulation model	2	iid	Order-up-to	NA	Additive	NA	NA	Echelon 2: ↑	NA
Mishra et al. [13]		X	X			X	Analytical model and numerical analysis	2	iid	NA	NA	NA	NA	NA	NA	NA
Paik and Bagchi [40]		X		X	X		Simulation model and statistical analysis	4	Step	Order-up-to	NA	NA	Constant (1–4 weeks)	↑	NA	NA
Kim [42]	X			X	X		Analytical model	2	AR (1)	Order-up-to	NA	NA	Constant	NA	NA	Echelon 2: ↑
Zhang [43]	X			X	X		Analytical model	1	AR (1)	Order-up-to	MMSE	NA	Constant	↓	NA	NA
	X		X		X							Percentage	NA	NA	(b) Echelon 2: ↑	NA
Angulo et al. [45]	X			X	X		Discrete event simulation and statistical analysis	4	Poisson process: (a) Stationary (b) Nonstationary	Order-up-to	Moving average	NA	Constant (2 days)	NA	(a) Echelon 1: ↑ (a) Echelon 2: ↑ (b) Echelon 1: ↑ (b) Echelon 2: ↓	NA
Chen [48]		X		X	X		Analytical model	N	iid	Order-up-to	NA	NA	Constant	NA	NA	NA

the inventory level of the echelons. The only exception is represented by Angulo et al. [45], where the average inventory level of the upstream echelon decreases in the presence of demand delay under a nonstationary customer demand.

(3) *Impact on inventory variability*: the work of Lu et al. [52] provides some insights on the impact of demand error on inventory variability, which may increase or decrease depending on the demand shock, on information reliability and if errors occur during or before the replenishment. Moreover, four studies [18, 19, 35, 42] show that demand delays increase inventory variability.

As a summary, the impact of demand errors on SC dynamic performance is almost unknown. On the other hand, the effect of demand delays has not received particular attention in terms of the inventory variance ratio. Furthermore, these few related studies present conflicting results.

3. Supply Chain Model

In this section, we present the main assumptions and the mathematical formalization of the SC model. To perform a structured analysis, we adopt the information sharing SC model presented by Cannella [21] via system dynamics simulation (Syntetos et al. 2001) and extend it to the case of delayed or erroneous customer demand information. More specifically, in contrast to the classical SC, in which the information flow consists of the mere upstream transmission of members' orders, in the information exchange SC, the information flow consists of the upstream transmission of members' orders and on sharing the market demand information. Consequently, a member receives data regarding the replenishment from the downstream adjacent member and regarding the forecast on the market demand [21]. The following assumptions are adopted in the SC model:

(i) In a single-product, K-stage production-distribution serial system, each echelon in the system has a single successor and a single predecessor. The generic echelon's position is represented by index i. Echelon $i = 1$ denotes the manufacturer and $i = K + 1$ the final customer.

(ii) In the nonnegative condition of order quantity, products delivered cannot be returned to the supplier.

(iii) In each echelon, the backlog will be fulfilled as soon as on-hand inventory becomes available. Thus, orders not fulfilled in time are backlogged so that inventory remains a positive or null value.

(iv) Production-distribution capacity is unconstrained. No quantity limitations in production, buffering, and transport are considered.

(v) Customer demand is assumed to be independent and identically distributed (*i.i.d*).

(vi) Each member generates the order quantity on the basis of the available data about incoming orders and received information on market demand and according to its own ordering parameters (i.e., inventory level and in-transit orders).

(vii) In line with related studies (see, e.g., [14]), demand error is modelled by a multiplicative error structure, since the magnitude of the error may depend on the quantity requested.

(viii) Analogously, according to the related literature, demand delay is modeled as a shift in the time dimension of the information about market demand.

(ix) The replenishment rule employed is a periodic-review order-up-to (R, S) [54]. More specifically, each member adopts a specific typology of order-up-to named Automatic Pipeline, Variable Inventory, and Order-Based Production Control System (APVIOBPCS) [2].

(x) Products delivered cannot be returned to the supplier. By adopting this assumption, we implement a more reliable modelling assumption for the bullwhip effect analysis [1].

The mathematical nomenclature is reported in Table 3. The full model is reported in Table 4.

4. Experiment and Simulation Output

In this section, we discuss the design of experiments, the experimental factors (independent variables), and the outcome of the experiments (dependent variables), as well as the parameters of the model and simulation conditions. Then, we present a statistical analysis of the output data using ANOVA.

4.1. Design of Experiments. To infer on the dynamics of a multiechelon SC, we consider a serial system composed of four echelons ($K = 4$), that is, retailer ($i = 4$), wholesaler ($i = 3$), distributor ($i = 2$), and manufacturer ($i = 1$). The experimental factors of our experiment are (1) the level of demand error (measured as a percentage of the market demand), (2) the demand information delay (measured in time periods), (3) the average lead time, and (4) the standard deviation of customer demand. We test the statistical significance of the impact of these experimental factors by performing a full factorial set of experiments.

The demand error factor is represented by three levels (0%, ±10%, and ±20%). The first level, that is, 0%, emulates the situation where the members receive in each period nonerroneous data on the observed customer demand. The other two levels emulate erroneous demand information, where the percentage of error changes every time period according to a uniform distribution. Analogously, demand delay is set to three levels and varies from 0 periods (it is equivalent to a scenario where customer demand information is timely shared among partners) to

Table 3: Model nomenclature.

Variables	
B	Order backlog
C	Units/orders delivered
d	Market demand
$\hat{d}$	Market demand forecast
I	Inventory
W	Work in progress
O	Replenishment order quantity
Parameters	
α	Forecast smoothing factor
η	Customer demand error factor
ϕ	Customer demand delay time
i	Echelon in the serial system
K	Total number of echelons
T	Time horizon
ε	Safety stock factor
λ	Estimated pipeline time
β	Order policy proportional controller
p	Position of ith echelon
Statistics	
σ_d^2	Variance of the market demand
σ_I^2	Variance of the inventory
σ_O^2	Variance of the order quantity
μ_d	Market demand mean

2 and 5 periods. The standard deviation of customer demand is characterized by two levels (i.e., 10 and 30 units of product), as well as the average lead time (i.e., 2 periods and 5 periods). Thus, we analyze a total of 36 ($3 \times 3 \times 2 \times 2$) scenarios [55].

As both demand error and delay may produce a polyhedral impact on the behavior of the whole supply chain, we adopt three complementary performance metrics for evaluating three different dimensions of the internal process efficiency of the SC at systemic level. By using the bullwhip slope (BwSl) (*), we may assess the dynamics of the members' orders. Using the inventory variance slope (InvSl) (**), we may assess the dynamics of inventories, and finally, using the systemic average inventory (SAI) (***), we can assess the impact on inventory requirements. A reduction in all three metrics reflects improved cost effectiveness of members' operations. Table 5 provides more details on the performance metrics adopted [56].

The values adopted for the parameters of the model are common values used in SC dynamics literature (see, e.g., [20, 57]). Table 6 shows the summary of the experimental design.

We determine the simulation parameters (i.e., run length, number of replications, and warm-up period) by analyzing the results of a pilot test. As a result, we use a simulation time of 1000 periods with a warm-up of 200 periods. In order to obtain the consistency of the estimations in terms of the width of confidence intervals, we perform 30 replications of each experiment. The SC is modelled and simulated using Vensim PLE [58], a widely used system dynamics software tool, running on a PC with Intel Core i7 CPU @ 2.00 GHz and 8 GB memory. The simulation output is obtained by adopting the Euler-Cauchy method with the order of accuracy $\Delta t = 0.25$.

4.2. Statistical Analysis (ANOVA). We present here the results of the experiments by performing an ANOVA on the simulation output using the statistical software Minitab. Only information regarding the main effects and first-order interactions is presented. Tables 6–8 show the results of the ANOVA for each one of the three performance measures. Table 8 reports the percentual variations in the performance indicators for demand error and demand delay when shifting from the condition of perfect and timely shared customer demand to the different levels of erroneous/delayed demand. Additionally, percentual variations due to the interactions between demand delay and demand error with demand variability and lead time are also reported in Table 9. Finally, Figure 1 shows the main effects of demand error and demand delay on the performance measures.

Results show that all the main factors are statistically significant at the 95% confidence level ($p < 0.05$). Regarding the first order interactions, they are all significant except the interaction between demand error and demand delay for the inventory metrics ($p = 0.076$ for the average inventory level and $p = 0.484$ for the inventory variability).

4.3. Interpretation of the Results. We start by analyzing the impact of the demand error on SC performance. In Figure 1, it can be seen that each performance metric analyzed shows a growing trend as the demand error increases. More specifically, *BwSl* and *InvSl* show a quasilinear trend with the level of demand error. Instead, the trend of *SAI* is different and does not appear to be linear. Such trend is characterized by an almost horizontal stretch (for the error in the range from 0% to 10%) and another stretch with a higher slope (from 10% to 20%). However, as we can see in Table 8, the overall impact of demand error on *SAI* is almost insignificant (the percentage variation of *SAI* is very low with demand error, not exceeding 0.4% on average). This result is confirmed by the low F value obtained from the ANOVA (Table 7). Regarding the interaction of demand error with demand variability, we can notice in Table 8 that the impact of the error on *BwSl* and *InvSl* is much stronger when demand variability is lower. In this case, the percentage variations of *BwSl* and of *InvSl* are +79.4% and +68.4%, respectively. Instead, when demand variability is high, these are only +6.6% and +5.6%. We interpret these results as the demand variability masks the impact of demand error on both performance metrics. In fact, when demand variability is low, both *BwSl* and *InvSl* remain low as well. As such, in this scenario, the introduction of an additional source of uncertainty (such as the demand error) is more noticeable, having a significant impact on both indicators. On the other

Table 4: Mathematical model.

Order quantity placed by retailed ($i = K$)	$O_K(t) = \widehat{d}_K(t) + \beta(\lambda \widehat{d}_K(t) + \varepsilon \widehat{d}_K(t) - W_i(t) - I_i(t))$
Order quantity placed by upstream echelon ($i = 1, \ldots, K-1$) under delayed demand	$O_i(t) = \widehat{d}_K(t-\eta) + \beta(\lambda \widehat{d}_i(t) + \varepsilon \widehat{d}_i(t) - W_i(t) - I_i(t))$
Order quantity placed by upstream echelon ($i = 1, \ldots, K-1$) under erroneous demand	$O_i(t) = (1-\phi)\widehat{d}_K(t) + \beta(\lambda \widehat{d}_i(t) + \varepsilon \widehat{d}_i(t) - W_i(t) - I_i(t))$
Work in progress	$W_i(t) = W_i(t-1) + C_{i-1}(t) - C_{i-1}(t-\lambda)$
Inventory	$I_i(t) = I_i(t-1) + C_{i-1}(t-\lambda) - C_i(t)$
Backlog	$B_i(t) = B_i(t-1) + O_{i+1}(t) - C_i(t)$
Orders delivered	$C_i(t)=\min\{O_{i+1}(t)+B_i(t-1); I_i(t-1)+C_i(t-\lambda)\}$
Demand forecast	$\widehat{d}_i(t) = \alpha O_{i+1}(t-1) + (1-\alpha)\widehat{d}_i(t-1)$ $O_{K+1}(t) = d(t)$
Nonnegativity condition of order quantity	$O_i(t) \geq 0$
Unlimited raw material supply	$C_{i-1}(t) = O_1(t), \quad i = 1$

Table 5: Performance metrics.

The BwSl is a concise measure of the bullwhip propagation in a given multiechelon structure. Essentially, the BwSl is the slope of the linear interpolation of the set of bullwhip values for a given SC. It provides information on potential unnecessary costs for suppliers, such as lost capacity or opportunity costs and overtime working and subcontracting costs of the whole SC.	$\text{BwSl} = \dfrac{K\sum_{i=1}^{K} p_i \sigma_{O_i}^2/\sigma_d^2 - \sum_{i=1}^{K} p_i \sum_{i=1}^{K} \sigma_{O_i}^2/\sigma_d^2}{K\sum_{i=1}^{K} p_i^2 - \left(\sum_{i=1}^{K} p_i\right)^2}{}_{*}$
Similar to the BwSl, the InvSl is the slope of the linear interpolation of the set of the inventory variance ratio values for a given SC. It measures the net stock instability, as it quantifies the fluctuations in inventory. An increased inventory variance results in higher holding and backlog costs, inflating the average inventory cost per period.	$\text{InvSl} = \dfrac{K\sum_{i=1}^{K} p_i \sigma_{I_i}^2/\sigma_d^2 - \sum_{i=1}^{K} p_i \sum_{i=1}^{K} \sigma_{I_i}^2/\sigma_d^2}{K\sum_{i=1}^{K} p_i^2 - \left(\sum_{i=1}^{K} p_i\right)^2}{}_{**}$
The SAI is the sum of the average inventory values of all nodes, that is, the mean of tier's inventory values over the interval T. This metric provides concise information on inventory investment.	$\text{SAI} = \sum_{i=0}^{K} \sum_{t=0}^{T} \dfrac{I_i(t)}{T}{}_{***}$

Table 6: Experimental design.

Independent variables	L_1	L_2	L_3
Demand error factor ϕ	0	±10%	±20%
Demand delay time η	0 period	2 periods	5 periods
Lead time mean λ	2 period	5 period	—
Demand St. Dev σ_d	10	30	—
Dependent variables	*BwSl*	*InvSl*	*SAI*
Model parameters			
Customer demand mean μ_d		$N(100, \sigma_d)$	
State variables at $t = 0$		$[W_i(0), I_i(0), B_i(0)] = [\lambda d(0), \varepsilon d(0), 0] \quad \forall i$	
Safety stock factor ε		3	
Demand smoothing forecasting factor α		0.33	

hand, when the demand variability is high, the *BwSl* and *InvSl* are also high. In this scenario, the negative consequences of introducing the additional source of uncertainty are less noticeable than in the previous scenario. Therefore, the impact of demand error on *BwSl* and *InvSl* is still present in the scenario with high demand variability, but its relative impact is lower. Regarding the interaction of demand error with lead time, we observe a weak interaction, since the impact of the demand error on *BwSl* and *InvSl* is very similar for the different levels of lead time.

Now, we continue the analysis by focusing on the impact of demand delay on SC performance. In Figure 1, we can see a particular trend of all the performance metrics with the increase of the demand delay. Such trend is characterized

Table 7: ANOVA results for the bullwhip slope.

Source of variation	SS	DF	MS	F	p
Delay	9.570	2	4.785	49.140	0.001
Error	23.187	2	11.593	119.057	0.001
Demand variability	19.211	1	19.211	197.282	0.001
Lead time	662.124	1	662.124	6799.581	0.001
Delay ∗ demand variability	1.184	2	0.592	6.077	0.002
Delay ∗ error	1.426	4	0.356	3.660	0.006
Delay ∗ lead time	6.997	2	3.499	35.930	0.001
Error ∗ demand variability	18.142	2	9.071	93.152	0.001
Demand variability ∗ lead time	11.961	1	11.961	122.836	0.001
Error ∗ lead time	14.067	2	7.034	72.230	0.001
Error	50.636	520	0.097		
Total	818.505	539			

Table 8: ANOVA results for the inventory variance slope.

Source of variation	SS	DF	MS	F	p
Delay	47.846	2	23.923	17.854	0.001
Error	268.951	2	134.476	100.362	0.001
Demand variability	678.410	1	678.410	506.310	0.001
Lead time	8958.670	1	8958.670	6686.024	0.001
Delay ∗ demand variability	11.628	2	5.814	4.339	0.014
Delay ∗ error	11.421	4	2.855	2.131	0.076
Delay ∗ lead time	45.333	2	22.667	16.916	0.001
Error ∗ demand variability	226.667	2	113.334	84.583	0.001
Demand variability ∗ lead time	538.603	1	538.603	401.970	0.001
Error ∗ lead time	179.289	2	89.644	66.903	0.001
Error	696.753	520	1.340		
Total	11663.572	539			

by an increasing stretch (from a demand delay of 0 periods to a demand delay of 2 periods) and a decreasing stretch (from a demand delay of 2 periods to a demand delay of 5 periods). Moreover, a decrease of each metric is experienced when moving from a demand delay of 0 periods to a demand delay of 5 periods. As we can see in Table 8, *SAI* does not change much (in percentage) with the increase in demand error. Nevertheless, the percentage variations of *BwSl* and *InvSl* are much larger. Regarding the interaction of demand delay with demand variability, we notice that the impact of the delay on *BwSl* and *InvSl* is stronger when demand variability is lower. Instead, in the case of high demand variability, the impact of demand delay on such performance indicators is lower. Following a line of reasoning similar to that for the demand error, it seems that demand variability masks the effect of delayed information on both performance metrics. When the demand variability is low, both *BwSl* and *InvSl* are also low. As such, in this scenario, the positive/negative impact of delayed demand information on both performance metrics (measured as the relative decrease/increase of the indicator) is more significant than in the scenario with high demand variability, where both performance metrics have high values regardless of the presence of delayed information. Regarding the interaction of demand delay with lead time, we notice that the impact of short delays on *BwSl* and *InvSl* is stronger when lead time is shorter; nonetheless, long delays have a stronger impact on these performance indicators when lead time is longer.

5. Discussion

5.1. Findings. From the analysis of the simulation outcome, a number of insights on the impact of demand error/delay on the dynamics of SCs have been identified. More specifically, in general, demand error causes an increase in the amplification of orders and inventory variability upstream in the SC, leading to a decrease of the SC performance. This is due to the fact that, in the presence of errors, the forecasts and the orders are based on market demand data characterized by a larger variability. Thus, the variability of the forecasts and the orders increases as well, amplifying the bullwhip effect and inventory variability. In practice, demand errors add another source of uncertainty to the system, increasing the

Table 9: Detailed percentual variations of main effects and interactions.

Factors	Level shifting	BwSl	InvSl	SAI
Demand error	$L_1 \rightarrow L_2$	+15.4%	+15.6%	0.0%
	$L_2 \rightarrow L_3$	+24.4%	+21.9%	+0.4%
	$L_1 \rightarrow L_3$	+43.6%	+40.8%	+0.4%
Demand error ($\sigma_d : L_1$)	$L_1 \rightarrow L_2$	+22.8%	+20.7%	0.0%
	$L_2 \rightarrow L_3$	+46.1%	+39.5%	0.0%
	$L_1 \rightarrow L_3$	+79.4%	+68.4%	0.0%
Demand error ($\sigma_d : L_2$)	$L_1 \rightarrow L_2$	+7.7%	+9.0%	+0.1%
	$L_2 \rightarrow L_3$	−1.1%	−3.1%	+0.8%
	$L_1 \rightarrow L_3$	+6.6%	+5.6%	+0.8%
Demand error ($\lambda : L_1$)	$L_1 \rightarrow L_2$	+11.8%	+8.9%	0.0%
	$L_2 \rightarrow L_3$	+33.1%	+28.0%	0.0%
	$L_1 \rightarrow L_3$	+48.7%	+39.4%	0.0%
Demand error ($\lambda : L_2$)	$L_1 \rightarrow L_2$	+15.8%	+16.3%	+0.1%
	$L_2 \rightarrow L_3$	+23.5%	+21.3%	+0.8%
	$L_1 \rightarrow L_3$	+43.0%	+41.0%	+0.8%
Demand delay	$L_1 \rightarrow L_2$	+14.4%	+8.0%	+0.5%
	$L_2 \rightarrow L_3$	−20.9%	−13.6%	−0.6%
	$L_1 \rightarrow L_3$	−9.5%	−6.7%	−0.1%
Demand delay ($\sigma_d : L_1$)	$L_1 \rightarrow L_2$	+17.1%	+10.2%	0.0%
	$L_2 \rightarrow L_3$	−24.4%	−16.3%	−0.1%
	$L_1 \rightarrow L_3$	−11.5%	−7.7%	0.0%
Demand delay ($\sigma_d : L_2$)	$L_1 \rightarrow L_2$	+10.9%	+4.5%	+0.9%
	$L_2 \rightarrow L_3$	−16.1%	−9.2%	−1.2%
	$L_1 \rightarrow L_3$	−7.0%	−5.1%	−0.2%
Demand delay ($\lambda : L_1$)	$L_1 \rightarrow L_2$	+38.5%	+29.6%	+0.1%
	$L_2 \rightarrow L_3$	−15.1%	−4.7%	−0.2%
	$L_1 \rightarrow L_3$	+17.6%	+23.5%	−0.1%
Demand delay ($\lambda : L_2$)	$L_1 \rightarrow L_2$	+12.2%	+6.2%	+0.9%
	$L_2 \rightarrow L_3$	−21.6%	−14.5%	−1.0%
	$L_1 \rightarrow L_3$	−12.0%	−9.2%	−0.2%

inherent uncertainty cause of a stochastic demand, and thus the SC performance worsens.

Another important finding about the demand error is the fact that its impact on orders and inventory variability is much stronger when the demand variability is low. This is because, when demand variability is low, an important part of the total variability of orders/inventory is caused by demand errors. Instead, when demand variability is high, demand errors slightly impact on the total variability of orders/inventory.

Regarding the demand delay, we found that a long delay decreases in the variability of the orders and the inventory, leading to a better performance of the SC. This observation is in line with the analytical results of Zhang [43], who demonstrates that, in the presence of delays, forecasts are characterized by a smaller variability because they are less sensitive to changes in demand and so they tend to gravitate closer to the average market demand. Consequently, the orders are also characterized by a smaller variability and thus a decrease of bullwhip effect and inventory variability is obtained. However, this behavior is observed for a long demand delay. Instead, for a short delay, the results obtained are very different. In fact, in this case, the introduction of the delay causes increments in order variability and inventory variability, decreasing the SC performance.

Interestingly and perhaps in contrast to intuition, demand delay may cause either an increase or a decrease of SC performance. Although we do not have a conclusive explanation, it might be due to the fact that, under the conditions of this study, the impact of the forecast variability reduction provided by the short delay (see [43]) is not enough to compensate the impact of the forecast error. A possible further reason behind this nonlinear behavior may lie in the assumptions adopted and the design of experiments (e.g., different combinations of delay with lead time). Note that this nonlinear behavior caused by different demand delays has been previously noticed by Hoberg and Thonemann [17]. Using control theory, they study the dynamics of several configurations of a two-stage inventory system subjected to information delays and observe a mixed picture regarding the impact of the length of information delay. More specifically, in terms of order amplification, longer information delays do not seem to necessarily imply a performance deterioration as compared to shorter delays, but their impact depends on the setup of the SC. Interestingly, although our work greatly differs from the analysis of Hoberg and Thonemann [17] regarding the adopted methodological approach (i.e., control theory versus system dynamics simulation), modelling assumptions (e.g., two-echelon versus four-echelon), and metrics (e.g., order amplification at echelon level versus bullwhip slope), we have noted a similar counter-intuitive effect of demand delay on the SC dynamics. In line with Hoberg and Thonemann [17], we may consider that this counter-intuitive effect depends on the SC setting. However, we acknowledge that further focused studies need to be developed for better understanding the nature of this interesting behavior, as it may have important implication in real-life SC.

5.2. Insights for the Industry. Following the above considerations, we report next some brief recommendations for SC managers in the scenario of a collaborative multiechelon SC with market demand information sharing facing information errors and/or delays. First, as the demand error increases, the dynamic performance of the entire SC deteriorates. SC managers should work on eliminating or at least reducing these errors, mainly emphasizing the prevention of inaccuracies caused by human actions at the point-of-sale stage. Second, the negative impact of demand error on the dynamic performance is more noticeable when the demand variability is low. Therefore, error reduction can be more important in markets with relatively stable demand (as in the case of basic hardware, grocery, or pharmaceutical goods). However, the inventory levels may be more sensitive to demand error in turbulent markets and in SCs characterized by high lead times, making important to control these errors also in such

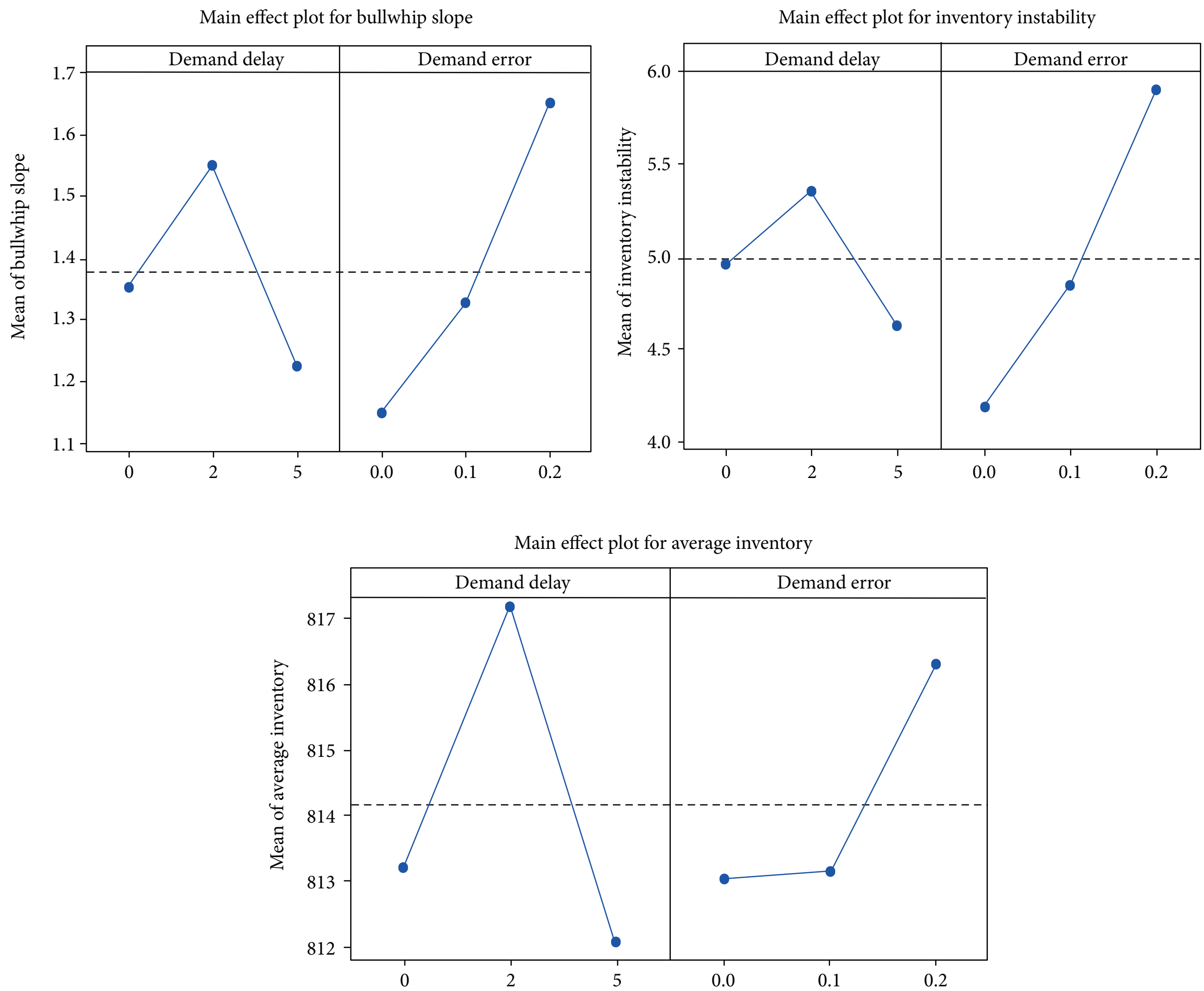

Figure 1: Main effect plots.

markets and SC settings, especially when the inventory holding costs are high.

In contrast, the impact of demand delay on performance may depend on its length. While a short delay has a negative impact on performance, a long delay may have a positive impact on performance. Under both circumstances, managers should try to identify the length and causes of these inaccuracies and consider tuning the inventory control parameters for stabilizing the dynamics of the SC. Furthermore, the impact of demand delay may depend on the SC setting (e.g., lead time); thus, it may be relevant for SC managers to consider this potential error when the SC is characterized by high lead times.

6. Conclusions and Limitations

In this work, we have investigated the main aspects of inaccuracies (errors and delays) in demand information sharing along the SC. In particular, we analyze their causes and consequences, using previous studies and different research methodologies like simulation and statistical analysis. We have carried out a systematic literature review on inaccuracy in demand information sharing and its impact on SC dynamics. We have detected that the impact of demand errors and demand delay in the dynamics of SCs has been not specifically addressed and that more explorative studies were needed. Thus, we have used systems dynamics to develop a simulation model to assess the impact of such information transmission inaccuracies on SC performance. Through a factorial design of experiments, we have studied the impact of four factors (i.e., demand error, demand delay, demand variability, and average lead time) on three SC dynamic performance indicators (i.e., bullwhip effect, inventory variability, and average inventory). We have statistically analyzed the results obtained, from which we have extracted some findings and related managerial implications. More specifically, our simulation output suggests that demand error has a negative impact on SC performance and that its impact increases with its magnitude of the error; moreover, it has a higher impact when the market demand is stable. On the other hand, the impact of demand delay on SC performance depends on the length of the delay. In our study, a short delay may have a negative impact while a long delay may have a positive impact. However, the final impact may also depend on the SC configuration.

This work is limited by several assumptions, and therefore, it might be interesting for future works to extend it with different hypotheses or to investigate different aspects not covered in our paper. As previously stated, we believe that the impact of demand delay deserves more research to understand which factors—endogenous or exogenous to the SC—may produce the counter-intuitive effect observed in this work and, under different assumptions, also observed by Hoberg and Thonemann [17]. In this fashion, the adoption of analytical models, which may consider the uncertainty of the demand delay for different SC configurations and market demand, may shed light on this peculiar behavior. As the demand delay may produce better SC dynamics with respect to sharing timeless information on market demand, it can be particularly relevant to explore the causes of such behavior, as sharing demand delay can also be converted in an ad hoc bullwhip-dampening method. A starting point can be represented by structurally analyzing the interaction between the lead-time variability and demand delay.

Further research should also focus on the impact of sharing timely erroneous data on customer demand. Our work, in line with other studies, reasserts that demand errors affect the internal process efficiency of the whole SC. However, our model does not take into account the intrinsic variability of several processes in SC, such as the delivery lead-time, neither other market scenarios nor SC configurations characterized by higher structural complexity (i.e., divergent and/or convergent SC).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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