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Downstream Demand Inference in decentralized supply chains

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ABSTRACT

For many years, the main objective of studying decentralized supply chains was to demonstrate that a better inter-firm collaboration could lead to a better overall performance of the system. The literature has demonstrated that collaborating by sharing information, even in a partial way, can lead to near-optimal solutions. In this context, many researchers have studied a phenomenon called Downstream Demand Inference (DDI), which presents an effective demand management strategy to deal with forecast problems. DDI allows the upstream actor to infer the demand received by the downstream actor without the need of information sharing. Recent research showed that DDI is possible with Simple Moving Average (SMA) forecast method, and was verified for an autoregressive [$AR(1)$] demand process, a moving average [$MA(1)$] demand process, and an autoregressive moving average [$ARMA(1, 1)$] demand process. In this paper, we extend the strategy's results by considering causal invertible [$ARMA(p, q)$] demand processes. We develop Mean Squared Error and Average Inventory level expressions for [$ARMA(p, q)$] demand under DDI strategy, No Information Sharing (NIS) and Forecast Information Sharing (FIS) strategies. We compute the Bullwhip effect generated by employing SMA method and we simulate the resulted improvement compared to employing MMSE method. We analyze the sensibility of the three performance metrics in respect with lead-time value, SMA and $ARMA(p, q)$ parameters. We compare DDI results with NIS and FIS strategies' results and we show experimentally that DDI generally outperforms NIS. Finally, we provide a revenue sharing contract as a practical recommendation to incite supply chain managers to adopt DDI strategy.

1. Introduction

A supply chain is two or more than two agents who integrate with each other, in order to create and deliver value to final customers. A decentralized supply chain is characterizing by independent agents with asymmetric information. In fact, in this form of supply chain, most of supply chain agents may not share information due to confidentiality policies, quality of information or different system's incompatibilities. Every actor holds its own set of information and try to maximize his objective (minimizing costs/minimizing inventory holdings) based on the available settings. Therefore, the agents control their own activities with the objective of improving their own competitiveness, which leads them to make decisions that maximize their local performance by ignoring the other agents or even the final consumer. These decisions are called myopic because they do not take into account the performance of all the partners to satisfy this consumer.

Over the last fifteen years, a major movement of business partner's integration to implement advanced and collaborative replenishment processes has emerged. Supply Chain Management (SCM) has thus emerged in the service and production sectors in order to identify and take advantage of new sources of improvement in the competitiveness of companies. SCM therefore proposes strategies and methods to reduce part costs whose origin is mainly due to poor coordination of operations. The observation of collaboration method implementation is very encouraging. Companies are able to better satisfy the consumer, by providing more availability of products, services and less delay, while being more efficient by having less stock, using the resources in a better way and procuring better return on used capital.

One of the common collaborative approach can be resumed by sharing information which described as a crucial key for overall supply chain performance (Asgari, Nikbakhsh, Hill, & Farahani, 2016; Ciancimino, Cannella, Bruccoleri, & Framinan, 2012). Indeed, in most industry sectors, final customer demand volatility need to be well considered by all supply chain actors, as demand is the first engine of benefits of whole supply chain. Forecasting customer demand can be the key for safe inventory levels and reducing inventory costs. Disney and Towill (2002) and

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Ireland and Crum (2006) have reported that inventory levels can be reduced to 50% and inventory costs reduced to 40% which leads to a competitive success. In recent years, numerous studies have emphasized the importance of information sharing within the supply chain (Barratt, 2004; Lambert & Cooper, 2000; Lau and Lee, 2000; Trkman, Groznik, & Koohang, 2006).

The question of our paper is motivated by the recently published work of Ali, Babai, Boylan, and Syntetos (2017), who studied three different strategies to examine the information sharing value in a two-level supply chain, under the hypothesis of an $AR(1)$ demand process. The first strategy, called No Information Sharing (NIS), is a decentralized demand management strategy where the demand information is not shared, and the upstream actor would simply base its forecasting on the orders received from the downstream actor. The second strategy, called Forecast Information Sharing (FIS), presents a centralized demand management strategy where the upstream actor has access to the demand at the downstream actor, and thus bases its forecast on the shared information. Between the NIS strategy, which presents sub-optimal solutions and FIS strategy, which presents optimal solutions, a third approach, called Downstream Demand Inference (DDI) strategy, allows to enhance the performance of the decentralized system to have near-optimal solutions. Instead of sharing demand information, the two supply chain actors infer the demand and the deduced customer's demand is using in the forecast. Ali and Boylan (2012) showed that DDI could not be applied with optimal forecasting methods, but only with Simple Moving Average (SMA) method, which is widely used in the literature.

The reports of DDI's results were consistent. First, FIS is in most of the cases the best strategy as actors behave optimally by sharing information and there is no need of inference. Second, DDI strategy improves on NIS by reducing Mean Squared Error (MSE) for higher values of autoregressive parameter (beyond a certain breakpoint), and reducing inventory costs for higher values of lead-time and SMA's order. The improvements on MSE and inventory costs were not proportional which confirmed the finding of Boylan and Syntetos (2006) who mention that accuracy implication (Inventory costs) is the end measure that must be taken into account, rather than accuracy itself (MSE). Information sharing values were evaluated especially when the demand followed an $AR(1)$, $MA(1)$ or $ARMA(1.1)$ processes. In this paper, we extend the results of the authors to situations where the demand follows an invertible causal $ARMA(p, q)$ process. We show through simulation, that DDI always outperforms NIS in terms of Average Inventory level ($\tilde{I}_t$), and for the most of cases in terms of MSE.

The rest of the paper is organizing as follows. Section 2 is devoted to the literature review. In Section 3, we derive the MSE and $\tilde{I}_t$ expressions, for an invertible causal $ARMA(p, q)$ demand process, under NIS, DDI and FIS strategies. We also present Bullwhip effect expressions with SMA and MMSE method and we propose an indicator of the performance separating the two methods. We simulate different $ARMA(p, q)$ processes, generalize MSE and $\tilde{I}_t$ behaviors for variable parameters under the considered strategies, and study the Bullwhip effect improvement in Section 4. In Section 5, we propose a revenue sharing contract as an incentive to adopt DDI strategy by supply chain managers. Finally, in Section 6, we present the conclusions and implications of the paper, as well as the natural avenues for future research.

2. Literature review

Information sharing among supply chain links can help achieve important benefits such as increased productivity, improved policy making and integrated services. Various papers (Chen, Drezner, Ryan, & Simchi-Levi, 2000; Lee et al., 2000) have shown that sharing demand information reduces the so-called "Bullwhip Effect". The Bullwhip effect is essentially the phenomenon of demand variability amplification along a supply chain, from the retailers, distributors, producer, and the producers' suppliers, and so on. Lee, So, and Tang (2000) characterize this phenomenon as demand distortion, which can create problems for suppliers, such as grossly inaccurate demand forecasts, low capacity utilization, excessive inventory, and poor customer service. Letting the upstream links have access to point-of-sales data, the harmful effect of demand distortion is improving. The most celebrated implementation of demand information sharing is Wal-Mart's Retail Link program, which provides on-line summary of point-of-sales data to suppliers such as Johnson and Johnson, and Lever Brothers (Gill & Abend, 1997). Indeed, demand information sharing between a downstream actor and his formal supplier can be viewed as the cornerstone of initiatives, such as Quick Response (QR) and Efficient Consumer Response (ECR). Often times, information sharing is embedded in programs like Vendor Managed Inventory (VMI) or Continuous Replenishment Programs (CRP). Major successes of such programs have been reported at companies like Campbell Soup (Clark, 1994) and Barilla SpA (Hammond, 1993).

Although it was accepted by academic researchers and industrial decision makers, that information sharing and managerial coordination generally lead to improved supply chain performance (La Londe, Ginter, & Stock, 2004), the potential weight of improvement and performance allocation through supply chain actors stay fuzzy. Cachon and Fisher (2000) report that information sharing benefits through different researches is varying between 0% and 35% of total costs. The large deviation of reported results appears, in some way, correlated to supply chains sectors, problems statements and models assumptions.

Sahin and Robinson (2005) analyses and identifies whether information sharing or coordination are the source of supply chain improvement, analyses benefits allocation across supply chain actors and study the relationship between environmental factors and cost decline. The authors reported a reduction of 47.58% in cost when adopting a centralized strategy.

Based on a two-level decentralized supply chain, Yu, Yan, and Edwin Cheng (2001) illustrate the benefits of information sharing. From the comparison of cost savings and inventory reductions, the authors concluded that Pareto improvement is achieved with respect to the whole supply chain performance, but at the same time, the benefits of the producer are more valuable than the ones of the retailer. Hence, they recommend that partnership initiative must be taken by the producer and give some collaboration incentives such as sharing logistic costs or guarantying supply reliability.

Despite all the potential advantages and benefits procured by information sharing, the lack of availability of information systems is one of the most common barriers to information sharing (Ali et al., 2017). SCM World (Courtin, 2013) report that many companies are hampered by the high investment costs and system implementation issues associated with formal information sharing. Negotiation is the common issue to reduce supply chain parties' costs, as monetary losses remain the main reason for investment blockage (Klein, Rai, & Straub, 2007). Information systems costs are composed of the initial purchase costs and the time-implementation costs (Fawcett, Osterhaus, Magnan, Brau, & McCarter, 2007). Despite developers are constantly trying to find compatibility solutions, companies tend to resist change because of intra-organizational problems. Even when companies succeed in implementing information systems, the problem becomes a lack of trust and a lack of dialogue and sharing (Mendelson, 2000). Indeed, each partner is wary of the possibility of other partners abusing information and reaping all the benefits from information sharing (Lee & Whang, 2000). Hence, trust presents an important factor so that decision makers only share information with their trusted parties.

Besides these information-sharing inhibitors, even when information technology and trust exist between partners, another type of brakes can persist. It is firstly about information precision when decision makers do not trust shared information in terms of quality and estimate that error is relatively high (Forslund & Jonsson, 2007). Information leakage effect can also be a reason to frame information sharing. Managers always fear the fact that the shared information can be obtained or deduced by competitors who will react to the information sharing activity. As example, Ward (wardsauto.com) conducted a survey of 447 car suppliers in which 28% of survey respondents said their intellectual property was revealed by at least one Detroit car producer and 16% said their intellectual property was revealed by car producers (Anand & Goyal, 2009). As result, the reaction of the competitors may change the benefits among the parties involved in information sharing (Li, 2002). Wal-Mart announced that it would no longer share its information with other companies like Inc. and AC Nielson as Wal-Mart considers data to be a top priority and fears information leakage (Hays, 2004). Hence, many companies are conducting to control their information flows, which can lead to additional operational costs (Anand & Goyal, 2009).

In the midst of all these discussions, Downstream Demand Inference appears as topical subject in the scientific community. It is referring to a situation where the upstream actor of a supply chain, can infer the demand occurring at the downstream actor, without need of formal information sharing. A stream of papers, such as Raghunathan (2001) and Zhang (2004), demonstrate that received orders contain already demand information. Hence, they show that demand information can be mathematically concluded from the order history of the downstream actor.

Researchers on this stream of papers are based on two assumptions: The first one is the fact that orders received from the retailer already contain the customer's demand information. The second one is that the demand process and its parameters are known throughout all the supply chain. Hence, if this is always true, FIS is invaluable. In the paper of Ali and Boylan (2011), the authors present feasibility principles and show that inferring customer demand in a precise manner by an upstream member is impossible if model's hypotheses are strictly realistic. Thus, they conclude that FIS has value in supply chains. The authors showed also that DDI could not be applied with optimal forecasting methods but only with Simple Moving Average (SMA) method, which is widely used in the literature. This forecast method is based on the N most recent observations and in every future period, the oldest observation is dropped out and exchanged by the last observation. As Ali and Boylan (2012) showed that, if a downstream actor accepts to use SMA method for his forecasts, the upstream actor will be able to infer the actual downstream customer demand, Ali et al. (2017) applied DDI on real sales data and discussed the practical implications. The authors showed that DDI outperforms NIS in terms of forecast *MSE* and inventory costs under the assumption of an $AR(1)$ demand model and for high values of autoregressive coefficient. They also studied the sensibility of DDI with regard to SMA's order N and lead-time L and found that DDI is valuable for high values of N and relatively low values of L. As future works, it was proposed to extend research on DDI strategy by considering a more generalized $ARMA\ (p,\ q)$ demand model.

Thus, we present in Table 1 recent and relevant works, which are related to our research field, ordered by date of publication over the last two decades.

Considering more realistic assumptions into demand models remains one of the most important directions in inventory theory (Graves, 1999). Many researchers have investigated the dependence of the value of sharing information on the time-series structure of the demand process using an Autoregressive Moving Average (ARMA) methodology. It has been argued that demands over consecutive time periods are rarely statistically independent (Graves, 1999; Kahn, 1987; Lee et al., 2000). Therefore, it would be appropriate to model the demand (tourism, fuel, food products, machines, etc.) process as auto-correlated time series as they are long lifecycle goods. Based on these recommendations, we move on to next section in order to assess DDI performance under a more realistic and generalized $ARMA(p, q)$ demand model, in comparison with NIS and FIS strategies.

3. Framework model assumptions

We base our modeling framework on the works of Lee et al. (2000) and Ali et al. (2017). We consider a simple two-level supply chain formed by a producer and a retailer. We thus consider the same model's assumptions, except the time-series demand structure. As in above mentioned works, it is assumed that replenishment policy follows a periodic review system, where downstream actors place their orders at upstream actors after examining their respective inventory levels. Indeed, at time period t, demand D_t is realized at the retailer who observes his inventory level and then places and order Y_t before the end of the period. The producer prepared the required quantity order Y_t, and ships it to the retailer, who will receive it at period $t+L+1$. Here, L presents the replenishment time of both production and shipment. On one hand, it is assumed that there is no order cost. On the other hand, unit inventory holding cost and shortage cost are fixed and denoted respectively by h and s. It is also assumed that both producer and retailer adopt Order-Up-To policy, which minimizes the total costs over infinite time horizon (Lee et al., 2000).

We assume that demand arriving at the retailer is an invertible causal $ARMA(p, q)$ process (see properties 1 and 2 stated below). Let D_t be the $ARMA(p, q)$ demand process at the retailer, such as:

$$D_t = c + \sum_{j=1}^{p} \phi_j D_{t-j} + \xi_t + \sum_{j=1}^{q} \theta_j \xi_{t-j} \tag{1}$$

Where $c \geq 0$ determines the unconditional mean of the process D_t, $\phi_j \in [-1, 1]$ are Autoregressive coefficients $(j = 1, \ldots.., p)$, $\theta_j \in [-1, 1]$ are Moving Average coefficients $(j = 1, \ldots.., q)$ and $\xi_t \sim N(0, \sigma_\xi^2)$ are independent and identically distributed $\forall t \in [0, +\infty[$. Please note that for consideration of all $ARMA(p, q)$ models, we do not exclude cases where $q = 0$ or $p = 0$. In the case where $q = 0$, we consider causal $AR(p)$ demand processes, and in the case where $p = 0$, we consider invertible $MA(q)$ demand processes.

3.1. Mean squared error generalization and demand amplification under ARMA(p, q) demand model

First, we focus on establishing the *MSE* expressions under DDI, FIS and NIS strategies whose proofs are stated in Appendix A. We note here that, on one hand, we used causality and invertibility $ARMA(p, q)$'s properties, Ψ-weigths of Infinite Moving Average Representation (IMAR) of $ARMA(p, q)$ models (see Shumway & Stoffer, 2011). On the other hand, we follow standard time-series methods by defining d_t as the mean-centered demand process. *MSE* under DDI, FIS and NIS are, respectively, expressed by Eqs. (2)–(4).

$$\boldsymbol{MSE^{DDI}} = (\boldsymbol{L}+1)\boldsymbol{\gamma}_0 + 2\sum_{\boldsymbol{j}=1}^{\boldsymbol{L}} \boldsymbol{j}\ \boldsymbol{\gamma}_{\boldsymbol{L}+1-\boldsymbol{j}} + (\boldsymbol{L}+1)^2 \left[\frac{\boldsymbol{\gamma}_0}{\boldsymbol{N}} + \frac{2}{\boldsymbol{N}^2} \sum_{\boldsymbol{j}=1}^{\boldsymbol{N}-1} \boldsymbol{j}\ \boldsymbol{\gamma}_{\boldsymbol{N}-\boldsymbol{j}} \right] - \frac{2(\boldsymbol{L}+1)}{\boldsymbol{N}} \sum_{\boldsymbol{j}=1}^{\boldsymbol{L}+1} \sum_{\boldsymbol{k}=0}^{\boldsymbol{N}-1} \boldsymbol{\gamma}_{\boldsymbol{j}+\boldsymbol{k}} \tag{2}$$

MSE^{DDI} in Eq. (2) is a function of lead-time L, SMA forecast's order N and auto-covariance function γ_j at time periods $j =$

Table 1
Recent works contributing on information sharing value.

Work	*Typology of demand*	*Forecasting method*	*Adopted inventory policy*	*Contributions*	*Limitations*
Ali et al. (2017)	$AR(1)$	Simple Moving Average	Order up to inventory policy	DDI provides MSE reductions and cost savings on real sales data	Restriction of the analysis to only one demand process
Ali and Boylan (2012)	$ARMA(p, q)$	Simple Moving Average and Single Exponential Smoothing	Order up to inventory policy	DDI is not possible with optimal forecasting methods or Single Exponential Smoothing but only with Simple Moving Average method	Not incorporating MSE or inventory metrics expressions for ARMA demand processes
Ali et al. (2012)	$AR(1)$, $MA(1)$ and $ARMA(1, 1)$	Minimum mean squared error	Order up to inventory policy	Analytical relationships between forecast accuracy and inventory holdings	Restriction of the analysis to only three demand processes
Ali and Boylan (2011)	$ARMA(p, q)$	Minimum mean squared error	Order up to inventory policy	DDI is valuable if demand process and parameters are known for the producer	Not incorporating MSE or inventory metrics expressions for ARMA demand processes
Hosoda, Naim, Disney, and Potter (2008)	$AR(1)$	Minimum mean squared error	Order up to inventory policy	Information sharing is benefic in terms of standard deviation of predicted errors	Restriction of the analysis to only three demand processes
Hosoda and Disney (2006)	$AR(1)$	Minimum mean squared error	Order up to inventory policy	The retailer's order history at the producer already contains information about the demand at the retail	Restriction of the analysis to only one demand process
Cheng and Wu (2005)	$AR(1)$	ARIMA methodology	Order up to inventory policy	FIS is valuable for two-level multi-retailer supply chain	Restriction of the analysis to only one demand process
Gaur, Giloni, and Seshadri (2005)	$ARMA(p, q)$	ARIMA methodology and Simple Moving Average	Myopic order up to inventory policy	The value of sharing demand information depends on the time series structure of the demand process	Not investigating Bullwhip effect for ARMA demand processes
Gilbert (2005)	$ARIMA(p, d, q)$	Minimum mean squared error	Order up to inventory policy	Different Bullwhip assumptions lead to different insights	Restriction of the analysis to NIS strategy
Zhang (2004)	$ARMA(p, q)$	Minimum mean squared error	Order up to inventory policy	The retailer's order history at the producer already contains information about the demand at the retail	Not incorporating MSE or inventory metrics expressions for ARMA demand processes
Alwan, Liu, and Yao (2003)	$AR(1)$	Simple Moving Average, Single Exponential Smoothing and minimum mean squared error	Order up to inventory policy	Improved forecasting cannot eliminate the Bullwhip effect	Restriction of the analysis to only one demand process
Raghunathan (2003)	$AR(1)$	ARIMA methodology	Order up to inventory policy	FIS is valuable for two-level multi-retailer supply chain	Restriction of the analysis to only one demand process
Raghunathan (2001)	$AR(1)$	Minimum mean squared error	Order up to inventory policy	DDI is possible for $AR(1)$ demand model	Restriction of the analysis to only one demand process
Chen et al. (2000)	$AR(1)$	Simple Moving Average	Order up to inventory policy	Bullwhip effect is commonly caused by demand forecasting and order lead times	Restriction of the analysis to only one demand process
Lee et al. (2000)	$AR(1)$	ARIMA methodology	Order up to inventory policy	Demand information sharing provides savings in inventory costs	Restriction of the analysis to only one demand process
Graves (1999)	$ARIMA(0, 1, 1)$	Exponential-weighted moving average	Adaptive base-stock control policy	The retailer's order history at the producer already contains information about the demand at the retail	Restriction of the analysis to only one demand process

$0, \ldots\ldots, L+N$. As γ_j is a decreasing function on j, and by looking at the four components of (2), it becomes clear that the third component overweight the fourth one, with respect to N. Indeed, as the third component is inversely proportional to N and N^2, we conclude that MSE^{DDI} reduces as the SMA order N increases. In the same way, the third component, which is proportional to L^2, in addition to the first component, overweight the fourth one with respect to lead-time L. Furthermore, by looking at third and fourth component, it is expected that MSE^{DDI} will be more sensitive to N, for higher values of L. Reciprocally, MSE^{DDI} is expected to be less sensitive to L, for higher values of N.

$$\boldsymbol{MSE^{FIS}} = \sigma_\xi^2 \left[\sum_{i=0}^{L} \left(\sum_{j=0}^{i} \psi_j \right)^2 \right] \tag{3}$$

MSE^{FIS} in Eq. (3) is a function of lead-time L, IMAR coefficients ψ_j, $j = 0, \ldots\ldots, L$ and is a linear function on σ_ξ^2. We can so expect that MSE^{FIS} improves as L increases, especially in a logarithmic manner when we know that ψ is a decreasing function. This finding is confirmed in Section 4.

$$\boldsymbol{MSE^{NIS}} = \sigma_\xi^2 \left[\sum_{i=0}^{L} \left(\sum_{j=0}^{i} \tilde{\psi}_j \right)^2 \right] = \beta^2 \sigma_\xi^2 \left[\sum_{i=0}^{L} \left(\sum_{j=0}^{i} \tilde{\psi}_j \right)^2 \right] \tag{4}$$

MSE^{NIS} in Eq. (4) is a function of lead-time L, IMAR coefficients $\tilde{\psi}_j$, $j = 0, \ldots\ldots, L$ and is a linear function on σ_ξ^2. The expression on β at the right side of (4) is only provided to show the relation with the variance of demand error. We make the same reasoning as before, and expect that MSE^{NIS} improves as L increases, especially in a logarithmic manner when we know that $\tilde{\psi}$ is a decreasing function. This finding is also confirmed in Section 4.

Second, we focus on studying the orders amplification (Bullwhip effect), for an $ARMA(p, q)$ demand process at the retailer. This metric is computable accordingly to the forecasting method adopted by the retailer and the resulting orders process placed at the producer. In this part, as the employed method affects the nature of orders process, we denote $\tilde{\psi}_j$ and $\tilde{\tilde{\psi}}_j$ the IMAR coefficients of orders process, respectively, in the cases where MMSE and SMA methods are adopted by the retailer.

On one hand, when the MMSE forecasting method is adopted by the retailer, the AIAO property (Zhang, 2004) provides a convenient means for quantifying the Bullwhip effect. As the $ARMA(p,q)$ process at the retailer transforms into an $ARMA(p, Max(p, q-L))$ process at the producer, and considering the IMAR coefficients of demand and orders processes, respectively, ψ_j and $\tilde{\psi}_j$, the ratio of the unconditional variance of the orders process to that of demand process, namely the Bullwhip effect is measured by the below equation.

$$\boldsymbol{BWeffect^{MMSE}} = \frac{\boldsymbol{Var(Y_t)}}{\boldsymbol{Var(D_t)}} = \left(\sum_{\boldsymbol{j=0}}^{\boldsymbol{L}} \boldsymbol{\psi_j}\right)^2 \left(\frac{\sum_{\boldsymbol{j=0}}^{+\infty} \tilde{\psi}_j^2}{\sum_{\boldsymbol{j=0}}^{+\infty} \boldsymbol{\psi_j}^2}\right) = \boldsymbol{\beta}^2 \left(\frac{\sum_{\boldsymbol{j=0}}^{+\infty} \tilde{\psi}_j^2}{\sum_{\boldsymbol{j=0}}^{+\infty} \boldsymbol{\psi_j}^2}\right) \quad (5)$$

On the second hand, when the SMA forecasting method is adopted by the retailer, the $ARMA(p,q)$ process at the retailer transforms into an $ARMA(p, q+N)$ process at the producer where $\tilde{\xi}_t = (\frac{L}{N}+1)\xi_t$ is the error term of orders process (Ali & Boylan, 2012). We show in the proof below, that the $ARMA(p, q+N)$ process at the producer can be rewritten in a second manner, as an $ARMA(p,q)$ process where $\tilde{\tilde{\xi}}_t = (\frac{L}{N}+1)\xi_t - \frac{L}{N}\xi_{t-N}$ is the error term of orders process. Considering the lead-time L, the parameter N and the IMAR coefficients of demand and orders processes, respectively, ψ_j and $\tilde{\tilde{\psi}}_j$, the Bullwhip effect is measured by the below equation.

$$\boldsymbol{BWeffect^{SMA}} = \frac{\boldsymbol{Var(Y_t)}}{\boldsymbol{Var(D_t)}} = \frac{2\boldsymbol{L}^2 + \boldsymbol{N}^2 + 2\boldsymbol{NL}}{\boldsymbol{N}^2} \left(\frac{\sum_{\boldsymbol{j=0}}^{+\infty} \tilde{\tilde{\boldsymbol{\psi}}}_{\boldsymbol{j}}^2}{\sum_{\boldsymbol{j=0}}^{+\infty} \boldsymbol{\psi_j^2}}\right) \quad (6)$$

Proof:

Let Y_t be the orders process arriving at the producer. Under SMA method, Y_t is expressed by (see Ali & Boylan, 2012):

$$Y_t = c + \sum_{j=1}^{p} \phi_j Y_{t-j} + \sum_{j=0}^{q} \theta_j \tilde{\xi}_{t-j} - \left(\frac{L}{L+N}\right) \sum_{j=0}^{q} \theta_j \tilde{\xi}_{t-N-j}$$

With

$$\tilde{\xi}_t = \left(\frac{L}{N}+1\right)\xi_t$$

where ξ_t is the error term of demand process at period t.

Let

$$\tilde{\tilde{\xi}}_{t-j} = \tilde{\xi}_{t-j} - \frac{L}{L+N}\tilde{\xi}_{t-N-j} \ \forall \ j = 1, \ldots, q$$

Y_t can be written in a second manner as follows:

$$Y_t = c + \sum_{j=1}^{p} \phi_j Y_{t-j} + \sum_{j=0}^{q} \theta_j \tilde{\tilde{\xi}}_{t-j}$$

where $\tilde{\tilde{\xi}}_t = \tilde{\xi}_t - \frac{L}{L+N}\tilde{\xi}_{t-N} = (\frac{L}{N}+1)\xi_t - \frac{L}{N}\xi_{t-N}$ is the error term of orders process at period t and $\tilde{\tilde{\xi}}_t \sim N(0, \frac{2L^2+N^2+2NL}{N^2}\sigma_\xi^2)$

Hence, we show that the $ARMA(p,q)$ process at the retailer transforms into an $ARMA(p,q)$ process at the producer with different error terms. Let $\tilde{\tilde{\psi}}_j$ be the IMAR coefficients of the orders process Y_t.

As $\sigma_{\tilde{\tilde{\xi}}}^2 = Var(\tilde{\tilde{\xi}}_t) = Var((\frac{L}{N}+1)\xi_t - \frac{L}{N}\xi_{t-N}) = \frac{2L^2+N^2+NL}{N^2}\sigma_\xi^2$, we finally obtain:

$$BWeffect^{SMA} = \frac{Var(Y_t)}{Var(D_t)} = \frac{Var\left(\sum_{j=0}^{+\infty} \tilde{\tilde{\psi}}_j \tilde{\tilde{\xi}}_{t-j}\right)}{Var\left(\sum_{j=0}^{+\infty} \psi_j \xi_{t-j}\right)} = \frac{\left(\sum_{j=0}^{+\infty} \tilde{\tilde{\psi}}_j^2\right)\sigma_{\tilde{\tilde{\xi}}}^2}{\left(\sum_{j=0}^{+\infty} \psi_j^2\right)\sigma_\xi^2}$$

$$\Leftrightarrow \ BWeffect^{SMA} = \frac{2L^2+N^2+2NL}{N^2}\left(\frac{\sum_{j=0}^{+\infty} \tilde{\tilde{\psi}}_j^2}{\sum_{j=0}^{+\infty} \psi_j^2}\right)$$

Considering the obtained expressions of Bullwhip effect with MMSE and SMA methods, we can simply consider the ratio of $BWeffect^{SMA}$ to $BWeffect^{MMSE}$ which may be a convenient indicator of Bullwhip effect improvement between the two methods. We denote this indicator by BWP which is expressed by the below equation.

$$\boldsymbol{BWP} = \frac{\boldsymbol{BWeffect^{SMA}}}{\boldsymbol{BWeffect^{MMSE}}} = \frac{2\boldsymbol{L}^2 + \boldsymbol{N}^2 + 2\boldsymbol{NL}}{(\boldsymbol{N\beta})^2} \left(\frac{\sum_{\boldsymbol{j=0}}^{+\infty} \tilde{\tilde{\boldsymbol{\psi}}}_{\boldsymbol{j}}^2}{\sum_{\boldsymbol{j=0}}^{+\infty} \tilde{\boldsymbol{\psi}}_{\boldsymbol{j}}^2}\right) \quad (7)$$

BWP is a linear function of the ratio of the squared IMAR coefficients resulted from the orders process when SMA method is employed, to the squared IMAR coefficients resulted from the orders process when MMSE method is employed.

We go on to establish the producer Average Inventory levels $\tilde{I}_t$ expressions under DDI, NIS and FIS.

3.2. Average Inventory level generalization under $ARMA(p,q)$ demand model

In this section, we establish Average Inventory levels $\tilde{I}_t$ expressions associated with DDI, FIS and NIS strategies. The Average Inventory level under Order-Up-To policy is given by the below equation (see Ali, Boylan, & Syntetos, 2012):

$$\tilde{I}_t = T_t - E\left(\sum_{i=1}^{L+1} Y_{t+i}\right) + \frac{E(Y_t)}{2} \quad (8)$$

Where T_t is the producer optimal Order-Up-To inventory level. In this case, T_t is given by the below equation (see Lee et al., 2000):

$$T_t = M_t + K\sigma_{\xi}\sqrt{V} \quad (9)$$

And where M_t and V are respectively, the conditional expectation and conditional variance of the total demand over the lead-time, and $K = F_{N(0,1)}^{-1}(\frac{s}{s+h})$ for the standard normal distribution $F_{N(0,1)}$. Eq. (8) allows us to write:

$$\tilde{I}_t^{DDI} = T_t^{DDI} - E\left(\sum_{i=1}^{L+1} Y_{t+i}\right) + \frac{E(Y_t)}{2} \quad (8a)$$

$$\tilde{I}_t^{FIS} = T_t^{FIS} - E\left(\sum_{i=1}^{L+1} Y_{t+i}\right) + \frac{E(Y_t)}{2} \quad (8b)$$

$$\tilde{I}_t^{NIS} = T_t^{NIS} - E\left(\sum_{i=1}^{L+1} Y_{t+i}\right) + \frac{E(Y_t)}{2} \quad (8c)$$

First, we express the terms in common, $E(Y_t)$ and $E(\sum_{i=1}^{L+1} Y_{t+i})$. On one hand, we have:

$$E(Y_t) = \mu_y = \frac{c}{\phi_0 - \sum_{j=1}^{p} \phi_j} = c\left(1 - \sum_{j=1}^{p} \phi_j\right)^{-1}$$

On the other hand, we have:

$$E\left(\sum_{i=1}^{L+1} Y_{t+i}\right) = (L+1)\mu_y + E\left(\sum_{i=1}^{L+1} y_{t+i}\right)$$

$$\Leftrightarrow E\left(\sum_{i=1}^{L+1} Y_{t+i}\right) = (L+1)\mu_y + E\left(\sum_{i=1}^{L+1}\sum_{j=0}^{+\infty} \tilde{\psi}_j \xi_{t+i-j}\right) = (L+1)\mu_y$$

$$\Leftrightarrow E\left(\sum_{i=1}^{L+1} Y_{t+i}\right) = c\ (L+1)\ \left(1-\sum_{j=1}^{p}\phi_j\right)^{-1}$$

We notice here that expected orders at time period t and expected orders over time period equal to lead-time plus one time period, are stationary over time and simply functions of constants c, lead-time L and autoregressive coefficients $\phi_j, j = 0, \ldots\ldots, p$. Hence, we move on to develop the Average Inventory level $\tilde{I}_t$ under the three different strategies.

3.2.1. Derivation of the Average Inventory level under DDI strategy

Under DDI strategy, the producer optimal Order-Up-To inventory level T_t^{DDI} is expressed by the below equation.

$$T_t^{DDI} = M_t^{DDI} + K\sigma_{\tilde{\xi}}\sqrt{V^{DDI}} \tag{9a}$$

Where

$$M_t^{DDI} = E\left(\sum_{i=1}^{L+1} f_{t+i}\right) = E[(L+1)f_{t+1}]$$

$$\Leftrightarrow M_t^{DDI} = E\left((L+1)\left(\mu_d + \frac{1}{N}\sum_{k=0}^{N-1} d_{t-k}\right)\right)$$

$$\Leftrightarrow M_t^{DDI} = (L+1)\mu_d + \frac{1}{N}E\left(\sum_{k=0}^{N-1} d_{t-k}\right)$$

$$\Leftrightarrow M_t^{DDI} = (L+1)\mu_d$$

$$\Leftrightarrow M_t^{DDI} = c(L+1)\ \left(1-\sum_{j=1}^{p}\phi_j\right)^{-1}$$

And

$$V^{DDI} = MSE^{DDI}$$

So, by substituting M_t^{DDI} and V^{DDI} expressions in (9a) and then by substituting (9a) expression in (8a), finally obtain $\tilde{I}_t^{DDI}$ expressed by the below equation.

$$\boldsymbol{\tilde{I}_t^{DDI}} = \frac{\boldsymbol{c}}{2\left(1-\sum_{j=1}^{p}\phi_j\right)} + \boldsymbol{K\sigma_{\tilde{\xi}}}\left[(\boldsymbol{L}+1)\boldsymbol{\gamma}_0 + 2\sum_{i=1}^{L}\boldsymbol{i}\ \boldsymbol{\gamma}_{L+1-j} + (\boldsymbol{L}+1)^2\left(\frac{\boldsymbol{\gamma}_0}{\boldsymbol{N}} + \frac{2}{\boldsymbol{N}^2}\sum_{j=1}^{N-1}\boldsymbol{j}\ \boldsymbol{\gamma}_{N-j}\right) - \frac{2(\boldsymbol{L}+1)}{\boldsymbol{N}}\sum_{i=1}^{L+1}\sum_{k=0}^{N-1}\boldsymbol{\gamma}_{i+k}\right]^{\frac{1}{2}} \tag{10a}$$

$\tilde{I}_t^{DDI}$ in (10a) is a function of constants c and K, autoregressive coefficients ϕ_j, standard error of orders process $\sigma_{\tilde{\xi}}$, lead-time L, SMA forecast's order N and auto-covariance function γ_j at time periods $j = 0, \ldots\ldots, L+N$. As the component in brackets in (10a) is the MSE^{DDI}, we expect that $\tilde{I}_t^{DDI}$ behave approximatively in the same way as MSE^{DDI}. It implies that $\tilde{I}_t^{DDI}$ reduces as the SMA order N increases and improves when the lead-time L increases. The same sensitivity analysis as the one done for MSE^{DDI} is expected. We move on to develop the approximate expressions for the producer's average inventory, under FIS strategy.

3.2.2. Derivation of the Average Inventory level under FIS strategy

Under FIS strategy, the producer optimal Order-Up-To inventory level T_t^{FIS} is expressed by the below equation.

$$T_t^{FIS} = M_t^{FIS} + K\sigma_{\tilde{\xi}}\sqrt{V^{FIS}} \tag{9b}$$

Where

$$M_t^{FIS} = E\left(\sum_{i=1}^{L+1} D_{t+i}/\tau_t\right) \approx c\ (L+1)\ \left(1-\sum_{j=1}^{p}\phi_j\right)^{-1} + \sum_{i=0}^{T}\left(\sum_{j=1+i}^{L+1+i}\psi_j\right)\xi_{t-i}$$

And

$$V^{FIS} = MSE^{FIS}$$

So, by substituting M_t^{FIS} and V^{FIS} expressions in (9b) and then by substituting (9b) expression in (8b), finally we obtain $\tilde{I}_t^{FIS}$ expressed by the below equation.

$$\boldsymbol{\tilde{I}_t^{FIS}} = \frac{\boldsymbol{c}}{2\left(1-\sum_{j=1}^{p}\phi_j\right)} + \sum_{i=0}^{T}\left(\sum_{j=1+i}^{L+1+i}\boldsymbol{\psi_j}\right)\boldsymbol{\xi_{t-i}} + \boldsymbol{K\sigma_{\tilde{\xi}}\sigma_{\xi}}\left[\sum_{i=0}^{L}\left(\sum_{j=0}^{i}\boldsymbol{\psi_j}\right)^2\right]^{\frac{1}{2}} \tag{10b}$$

$\tilde{I}_t^{FIS}$ in (10b) is a function of constants c and K, autoregressive coefficients ϕ_j, IMAR coefficients ψ_j, $j = 0, \ldots\ldots, T+L+1$, standard error of orders process $\sigma_{\tilde{\xi}}$, standard error of demand process σ_{ξ}, lead-time L, and error terms at time periods $j = t, \ldots\ldots, t-T$. It is clear that $\tilde{I}_t^{FIS}$ improve when lead-time L increase. We expect that $\tilde{I}_t^{FIS}$ would also improve when autoregressive order p increase and especially when $\sum_{j=1}^{p}\phi_j$ approach one. We move on to develop the approximate expression for the producer's average inventory, under NIS strategy.

3.2.3. Derivation of the Average Inventory level under NIS strategy

Under NIS strategy, the producer optimal Order-Up-To inventory level T_t^{NIS} is expressed by the below equation.

$$T_t^{NIS} = M_t^{NIS} + K\sigma_{\tilde{\xi}}\sqrt{V^{NIS}} \tag{9c}$$

Where

$$M_t^{NIS} = E\left(\sum_{i=1}^{L+1} Y_{t+i}/\rho_t\right) \approx c\ (L+1)\ \left(1-\sum_{j=1}^{p}\phi_j\right)^{-1} + \sum_{i=0}^{T}\left(\sum_{j=1+i}^{L+1+i}\tilde{\psi}_j\right)\tilde{\xi}_{t-i}$$

And

$$V^{NIS} = MSE^{NIS}$$

So, by substituting M_t^{NIS} and V^{NIS} expressions in (9c) and then by substituting (9c) expression in (8c), finally we obtain $\tilde{I}_t^{NIS}$ expressed by the below equation.

$$\tilde{I}_t^{NIS} = \frac{c}{2\left(1-\sum_{j=1}^{p}\phi_j\right)} + \sum_{i=0}^{T}\left(\sum_{j=1+i}^{L+1+i}\tilde{\psi}_j\right)\tilde{\xi}_{t-i} + K\sigma_{\xi}^2\left(\left[\sum_{i=0}^{L}\left(\sum_{j=0}^{i}\tilde{\psi}_j\right)^2\right]\right)^{\frac{1}{2}} \tag{10c}$$

$\tilde{I}_t^{NIS}$ in (10c) is a function of constants c and K, autoregressive coefficients ϕ_j, IMAR coefficients $\tilde{\psi}_j$, $j = 0, \ldots\ldots, T+L+1$, standard error of orders process σ_{ξ}, lead-time L, and error terms at time periods $j = t, \ldots\ldots, t-T$. It is clear that $\tilde{I}_t^{NIS}$ improve when lead-time L increase. We expect that $\tilde{I}_t^{FIS}$ would also improve when autoregressive order p increase and especially when $\sum_{j=1}^{p}\phi_j$ approach one. Before moving on to Section 4, we precise that our expected findings in this section will be confirmed by simulation. Thus, we continue in Section 4, with simulation in order to generalize conclusions and managerial implications under a general $ARMA(p,q)$ demand model.

4. Simulation

We develop simulation of different $ARMA(p,q)$ demand and orders processes and we generate the performance metrics values and figures under Matlab 2013b software on windows system. In this section, we study DDI strategy sensibilities with autoregressive and moving average parameters at first, and with regard to lead-time and SMA parameters at second. Then, we make a comparative study with NIS and FIS strategies. Finally, we study the improvement in terms of Bullwhip effect, resulting from using SMA method rather than MMSE method. We note also that all simulations and computations of equations in Section 3 were carried on a Matlab manuscript. Since it is impossible to compute infinitely the ψ-weights, we compute the first 1000 IMAR coefficients of each process and hence, all obtained results are estimations.

4.1. DDI sensitivity with regard to autoregressive and moving average orders and coefficients

We first simulate $ARMA(p,q)$ demand models with different orders values $(p, q \in \{0,1,2,4,8\}^2)$ while maintaining causality and invertibility criteria's (ϕ_j and θ_j do not add up to one) and taking into account the uniqueness of demand processes (Zhang, 2004). In this first part of simulation, we compute both MSE^{DDI} and $\tilde{I}_t^{DDI}$, for the following fixed parameters: $c = 10;\ \sigma_{\xi}^2 = 1; L = 5; N = 12;\ h = 1;\ s = 2$. These parameters were randomly chosen but still similar to literature parameters to ensure comparability for future works.

Table 2 resumes results for simulating $ARMA(p,q)$ demand processes and calculating the producer's MSE^{DDI} and $\tilde{I}_t^{DDI}$, and this for $\phi_j \in [-1,1]\ \forall j = 1, \ldots.., p$ and $\theta_j \in [-1,1]\ \forall j = 1, \ldots.., q$. From the first three models of the table, when the demand parameters are fixed at $p = 1$ and $q = 0$, we can see that MSE^{DDI} and $\tilde{I}_t^{DDI}$ deteriorate on ϕ_1. This result coincides with the literature findings for an $AR(1)$ demand process. The same finding is made for the next three models of Table 2; MSE^{DDI} and $\tilde{I}_t^{DDI}$ deteriorate on θ_1 for a $MA(1)$ demand model. The percentage increase of the two indexes clearly differs on $AR(p)$ and $MA(q)$ models. Indeed, in our simulation, when ϕ_1 increased from 0.5 to 0.6, MSE^{DDI} deteriorated by about 38% and $\tilde{I}_t^{DDI}$ by about 28%. Facing it, when θ_1 increased from 0.5 to 0.6, MSE^{DDI} deteriorated by about 11% and $\tilde{I}_t^{DDI}$ by about 5%. The AR and MA structures clearly influence MSE^{DDI} and $\tilde{I}_t^{DDI}$ results and so decision makers must take into account the structure of the demand as an important factor for improving their forecast.

Important comparison cases take place when we compare results for fixed p and variable q or vice versa. Intuitively, we expected that, MSE^{DDI} and $\tilde{I}_t^{DDI}$ would increase on p for fixed q or on q for fixed p. Simulation proved that is not the case. Indeed, for example, the MSE^{DDI} and $\tilde{I}_t^{DDI}$ results, for the simulated $ARMA(8,1)$ in Table 2, are lower than $ARMA(1,1)$'s results. We have the same findings when comparing $ARMA(8,2)$ and $ARMA(1,2)$'s results. It concludes that MSE^{DDI} and $\tilde{I}_t^{DDI}$ would depend on ϕ_j's values $\forall j = 1, \ldots.., p$ and θ_j's values $\forall j = 1, \ldots.., q$ rather than autoregressive order p and moving average order q.

Then, for all the rest of simulated $ARMA(p,q)$ demand processes (from model 7 to model 19), we find the same results as for $AR(1)$ and $MA(1)$ processes; i.e. for fixed orders p and q, MSE^{DDI} and $\tilde{I}_t^{DDI}$ deteriorates in a first way, as ϕ_i increase while maintaining $\{\phi_{j=1,\ldots..,p;\ j\neq i}\}$ and $\{\theta_{j=1,\ldots\ldots,q}\}$ having fixed values; or in a second way, deteriorates when θ_i increase while $\{\phi_{j=1,\ldots\ldots,q}\}$ and $\{\theta_{j=1,\ldots..,q;\ j\neq i}\}$ are fixed sets. This means that DDI performance depend on demand time-series structure, and especially would increase as demand is less correlated to delayed demands and error terms. It would be interesting to study and mathematically generalize how the two performance metrics evolve with regard of ϕ_j and θ_j increase. Since this is not a straightforward task, we plan to focus on this line for future work.

4.2. DDI sensitivity with regard to lead-time and SMA parameters

We move on to study the stability of the two performance metrics behaviors with regard to N and L. Table 3 presents the considered $ARMA(p,q)$ autoregressive and moving average coefficients for all the figures set. Here also, we simulated $ARMA(p,q)$ processes by considering ϕ_i and θ_j that do not add up to one and consider the following fixed parameters: $c = 10;\ \sigma_{\xi}^2 = 1; h = 1;\ s = 2$

The figures below (Figs. 1–4) show the 3D-behavior of MSE^{DDI} and $\tilde{I}_t^{DDI}$ for different $ARMA(p,q)$ demand processes and for variable parameters L and $(L = 1, \ldots.., 20\ \&\ N = 1, \ldots.., 20)$. Then, for each figure, we present (see Appendix B) the projection on the first plan and the projection on the second plan. This is done for a better understanding and analysis of MSE^{DDI} and $\tilde{I}_t^{DDI}$ behaviors.

The figures set show the robustness of the typical behavior of MSE^{DDI} and $\tilde{I}_t^{DDI}$ performance metrics. The results are shown in different colors. The SMA parameter N increases as we move from the blue to the red color. For each color (each fixed N), MSE^{DDI} and $\tilde{I}_t^{DDI}$ deteriorate on lead-time L. We note that the improvements of MSE^{DDI} and $\tilde{I}_t^{DDI}$ on N is logarithmic, but the two performance metrics descent slopes are different. It means that, as it was noticed in the literature, the percentage of amelioration in MSE^{DDI} and $\tilde{I}_t^{DDI}$ is different. Note also that these ameliorations differ for low and high values of N. For example, when we look at the projections on the first plan ($MSE \sim N$), the point $N = 12$ can be considered as a threshold above which the MSE^{DDI} and $\tilde{I}_t^{DDI}$ ameliorations are not anymore important, in comparison with low values of N where improvements are considerable. Mathematically, this findings are understandable due to the non-linear form that links MSE^{DDI} to $\tilde{I}_t^{DDI}$.

From the projections on the second plans ($MSE \sim L$), we can see that the deterioration of MSE^{DDI} when the lead-time L increases, has an exponential shape. This exponential deteriorate is such important as N decreases. For $\tilde{I}_t^{DDI}$ level metric, the shape is logarithmic for high values of N and becomes linear for low values of N. These numerical findings confirm our theoretical analysis as MSE^{DDI} and $\tilde{I}_t^{DDI}$ are less sensible to L for higher values of N.

We conclude from this analysis that, for any causal invertible $ARMA(p,q)$ demand at the retailer, the producer's forecast will be more valuable in terms of MSE^{DDI} and $\tilde{I}_t^{DDI}$ when he uses higher values of SMA parameter N, and relatively lower values of

Table 2
$\boldsymbol{MSE^{DDI}}$ and $\boldsymbol{\tilde{I}_t^{DDI}}$ results for simulated $\boldsymbol{ARMA(p, q)}$ demands.

Model	Autoregressive order p	Moving average order q	Autoregressive coefficients ϕ_j	Moving average coefficients θ_j	MSE^{DDI}	$\tilde{I}_t^{DDI}$
1	1	0	$\phi_1 = 0.400$		20.3867	11.5614
2	1	0	$\phi_1 = 0.500$		26.7926	14.3894
3	1	0	$\phi_1 = 0.600$		36.5808	18.7090
4	0	1		$\theta_1 = 0.400$	16.2400	07.4301
5	0	1		$\theta_1 = 0.500$	18.5000	07.7789
6	0	1		$\theta_1 = 0.600$	20.9400	08,1536
7	1	1	$\phi_1 = 0.400$	$\theta_1 = 0.051$	22.3074	11.8812
8	1	1	$\phi_1 = 0.400$	$\theta_1 = 0.100$	24.2527	12.2041
9	1	1	$\phi_1 = 0.400$	$\theta_1 = 0.300$	33.2078	13.6816
10	1	2	$\phi_1 = 0.400$	$\theta_1 = 0.300$ $\theta_2 = 0.100$	37.4282	14.4392
11	1	2	$\phi_1 = 0.400$	$\theta_1 = 0.300$ $\theta_2 = 0.150$	39.6913	14.8415
12	1	2	$\phi_1 = 0.400$	$\theta_1 = 0.300$ $\theta_2 = 0.200$	42.0563	15.2594
13	1	4	$\phi_1 = 0.400$	$\theta_1 = 0.300$ $\theta_2 = 0.180$ $\theta_3 = 0.060$ $\theta_4 = 0.050$	44.6284	15.8453
14	2	1	$\phi_1 = 0.200$ $\phi_2 = 0.150$	$\theta_1 = 0.100$	19.6140	10.8756
15	4	1	$\phi_1 = 0.200$ $\phi_2 = 0.150$ $\phi_3 = 0.120$ $\phi_4 = 0.100$	$\theta_1 = 0.100$	24.1279	15.9735
16	4	2	$\phi_1 = 0.200$ $\phi_2 = 0.150$ $\phi_3 = 0.120$ $\phi_4 = 0.100$	$\theta_1 = 0.100$ $\theta_2 = 0.065$	26.5067	16.4101
17	4	4	$\phi_1 = 0.200$ $\phi_2 = 0.150$ $\phi_3 = 0.120$ $\phi_4 = 0.100$	$\theta_1 = 0.100$ $\theta_2 = 0.065$ $\theta_3 = 0.060$ $\theta_4 = 0.051$	29.7530	17.0342
18	8	1	$\phi_1 = 0.200$ $\phi_2 = -0.150$ $\phi_3 = 0.120$ $\phi_4 = -0.100$ $\phi_5 = 0.080$ $\phi_6 = 0.070$ $\phi_7 = 0.060$ $\phi_8 = -0.051$	$\theta_1 = 0.100$	12.8447	8.4158
19	8	2	$\phi_1 = 0.200$ $\phi_2 = -0.150$ $\phi_3 = 0.120$ $\phi_4 = -0.100$ $\phi_5 = 0.080$ $\phi_6 = 0.070$ $\phi_7 = 0.060$ $\phi_8 = -0.051$	$\theta_1 = 0.100$ $\theta_2 = 0.060$	13.8480	8.6012

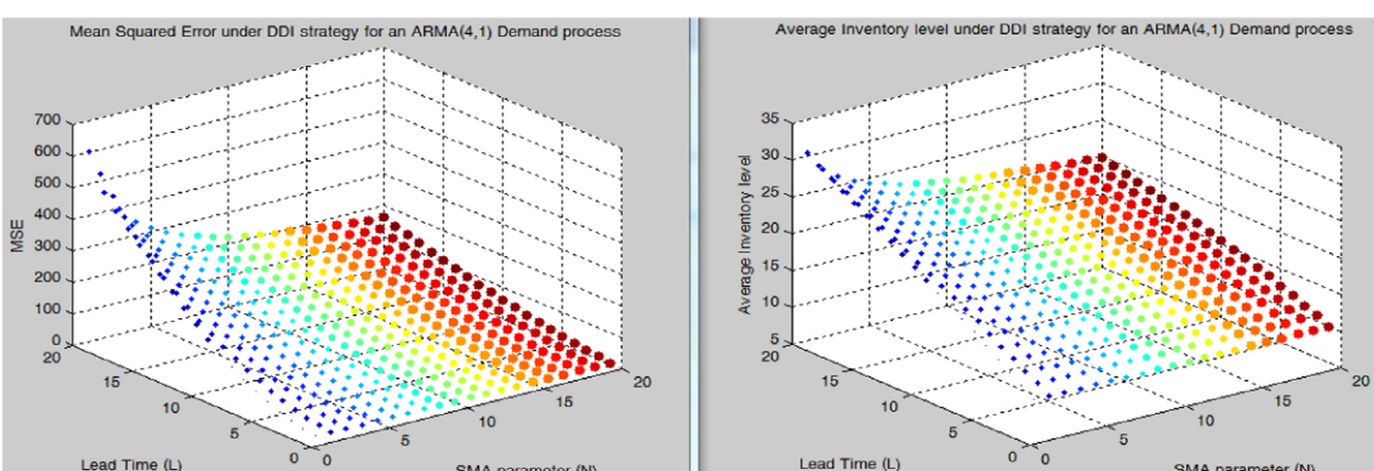

Fig. 1. 3D plots of MSE^{DDI} and $\tilde{I}_t^{DDI}$ behaviors under $ARMA(4, 1)$ demand model.

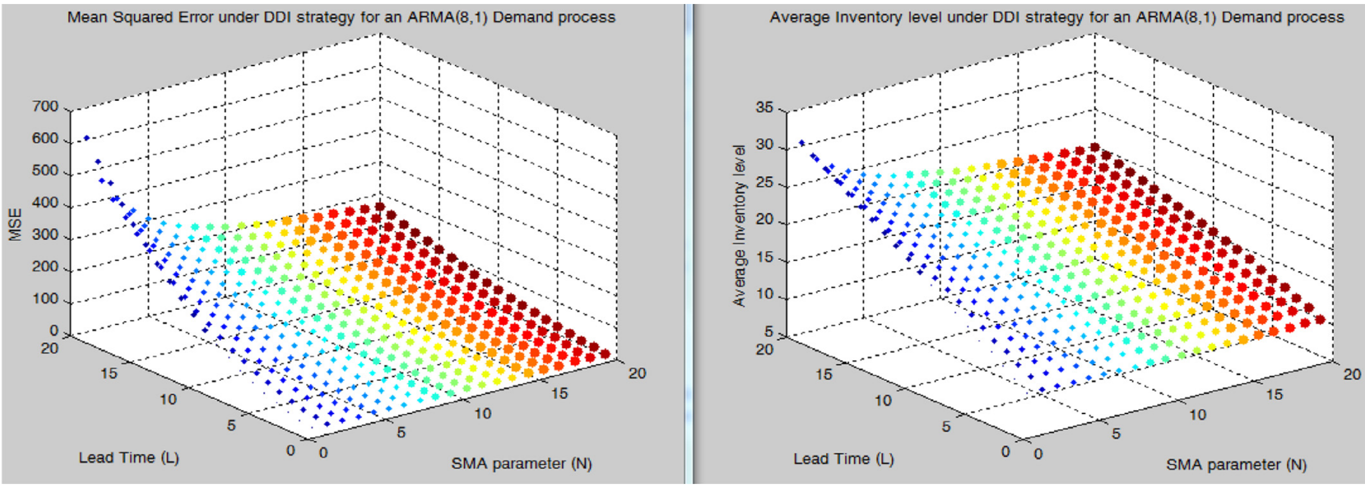

Fig. 2. 3D plots of MSE^{DDI} and $\tilde{I}_t^{DDI}$ behaviors under $ARMA(8,1)$ demand model.

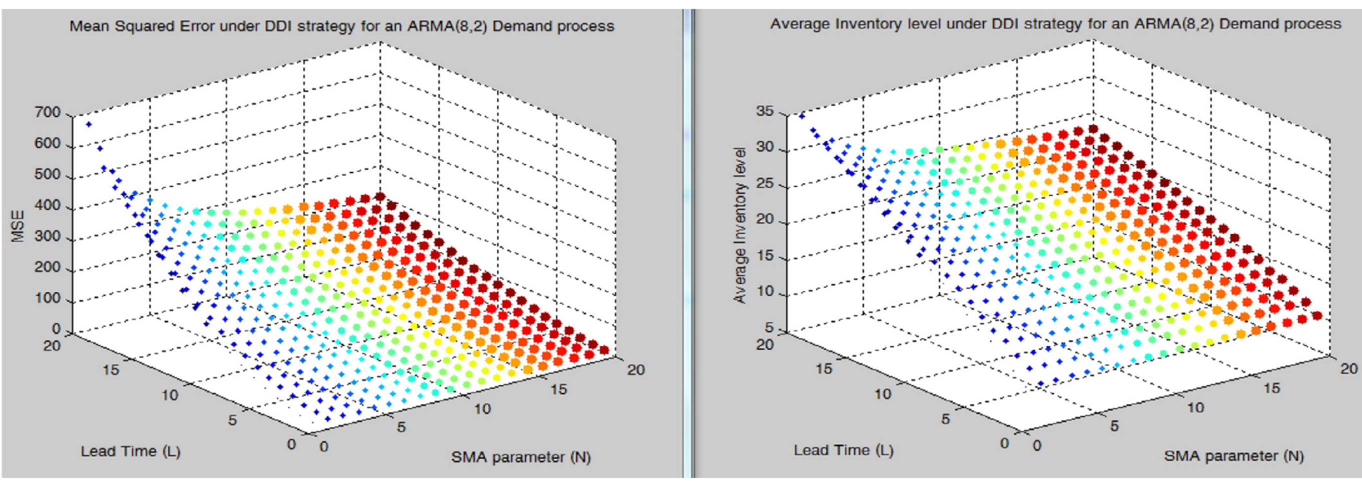

Fig. 3. 3D plots of MSE^{DDI} and $\tilde{I}_t^{DDI}$ behaviors under $ARMA(8,2)$ demand model.

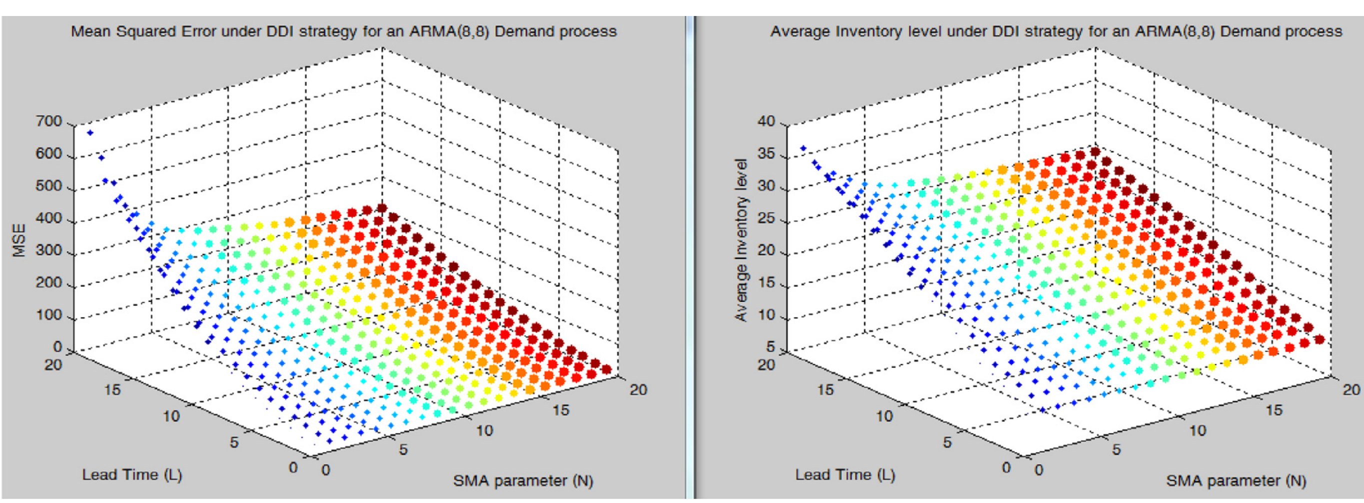

Fig. 4. 3D plots of MSE^{DDI} and $\tilde{I}_t^{DDI}$ behaviors under $ARMA(8,8)$ demand model.

Table 3
Considered $ARMA(p, q)$ autoregressive and moving average coefficients.

Model	p	q	ϕ_i	θ_j
20	4	1	$\phi_1 = 0.25$ $\phi_2 = 0.2$ $\phi_3 = 0.12$ $\phi_4 = 0.09$	$\theta_1 = 0.2$
21	8	1	$\phi_1 = 0.25$ $\phi_2 = 0.2$ $\phi_3 = -0.12$ $\phi_4 = 0.09$ $\phi_5 = -0.08$ $\phi_6 = 0.07$ $\phi_7 = 0.06$ $\phi_8 = -0.051$	$\theta_1 = 0.2$
22	8	2	$\phi_1 = 0.25$ $\phi_2 = 0.2$ $\phi_3 = -0.12$ $\phi_4 = 0.09$ $\phi_5 = -0.08$ $\phi_6 = 0.07$ $\phi_7 = 0.06$ $\phi_8 = -0.051$	$\theta_1 = 0.2$ $\theta_2 = 0.15$
23	8	8	$\phi_1 = 0.25$ $\phi_2 = 0.2$ $\phi_3 = -0.12$ $\phi_4 = 0.09$ $\phi_5 = -0.08$ $\phi_6 = 0.07$ $\phi_7 = 0.06$ $\phi_8 = -0.051$	$\theta_1 = 0.2$ $\theta_2 = 0.15$ $\theta_3 = -0.1$ $\theta_4 = -0.09$ $\theta_5 = 0.08$ $\theta_6 = 0.075$ $\theta_7 = 0.065$ $\theta_8 = 0.05$

Table 4
MSE and $\tilde{I}_t$ results under the three considered strategies.

Model	MSE^{NIS}	MSE^{DDI}	MSE^{FIS}	$\tilde{I}_t^{NIS}$	$\tilde{I}_t^{DDI}$	$\tilde{I}_t^{FIS}$
1	67.3756	20.3867	13.5072	19.6936	11.5614	9.4501
2	138.3996	26.7926	17.4580	33.0452	14.3894	11.1082
3	300.1029	36.5808	23.1328	62.3794	18.7090	13.6147
4	11.7600	16.2400	10.8000	7.8951	07.4301	6.2638
5	13.5000	18.5000	12.2500	8.5608	07.7789	6.3640
6	15.3600	20.9400	13.8000	9.3215	08,1536	6.4833
7	74.3786	22.3074	14.7117	21.3331	11.8812	9.5112
8	81.4330	24.2527	15.9216	23.0569	12.2041	9.5812
9	113.5408	33.2078	21.3956	31.7447	13.6816	9.9825
10	131.3007	37.4282	23.8242	37.0936	14.4392	10.0655
11	140.6645	39.6913	25.0987	40.1215	14.8415	10.1215
12	150.3507	42.0563	26.4134	43.2234	15.2594	10.1873
13	166.6726	44.6284	27.6609	48.7798	15.8453	9.9736
14	49.8496	19.6140	13.0142	17.7593	10.8756	8.5646
15	82.8049	24.1279	15.8459	34.5483	15.9735	11.6831
16	90.6387	26.5067	17.1084	37.3469	16.4101	11.6717
17	99.4028	29.7530	18.4831	41.1695	17.0342	11.4517
18	14.6534	12.8447	8.8315	10.3757	8.4158	6.9187
19	15.5426	13.8480	9.5114	10.5792	8.6012	6.9232

lead-time L. This characterization is independent of demand's autoregressive and moving average orders (p, q) and coefficients ϕ_i and θ_j.

4.3. DDI strategy with regard to NIS and FIS strategies

For our comparative study, we considered the same models simulated in Table 2 and the same fixed parameters: $c = 10$; $\sigma_\xi^2 = 1$; $L = 5$; $N = 12$; $h = 1$; $s = 2$. Then, we compute each performance metric for the three strategies. The results of our simulations are shown in Table 4.

From the first look at Table 4, FIS outperforms both NIS and DDI in terms of MSE and $\tilde{I}_t$ and so, for any considered $ARMA(p, q)$ of demand process at the retailer. We obtain the same evidence as previous researches. On one hand, FIS outperforms NIS due to beneficial effects of information sharing. On the other hand, FIS outperforms DDI due to MMSE method's accuracy, which is more accurate than SMA method.

We then focus on comparing DDI to NIS. We first analyze the reported results in Table 4 by considering the three first models. For $AR(1)$ demand models, our findings are similar to the literature results. DDI strategy outperforms NIS for ϕ_1 large enough ($\phi_1 \in \{0.4, 0.5, 0.6\}$). Ali et al. (2017) illustrated the break-point from which DDI outperforms NIS, and which was evaluated at 0.24 for $L = 1$ and $N = 6$.

For $MA(1)$ demand models 4–6, we find that MSE^{DDI} exceedsMSE^{NIS}, despite $\tilde{I}_t^{NIS}$ exceeds $\tilde{I}_t^{DDI}$. This finding is an expected result because, when the autoregressive order p is equal to 0, the demand is only depending on error terms, and the optimal MMSE method outperforms the SMA method as the method effect overweight the Bullwhip effect. Hence, NIS is more valuable than DDI in terms of MSE. We verify this result, which stay valid for any $MA(q)$, $q > 0$ demand models.

From model 7 to model 19 in Table 4, we vary the autoregressive and moving average parameters p and q and for different $ARMA(p, q)$ models, MSE and $\tilde{I}_t$ kept the same behavior through the three strategies, but we notice that percentage ameliorations are different between the two performance metrics. This can be explained by the non-linear function, which relies $\tilde{I}_t$ to MSE in Eq. (8).

Before we go on to next subsection, we briefly recall the obtained results. DDI performance depends on demand time-series structure, and especially would increase as demand is less correlated to delayed demands and error terms. When adopting DDI strategy, supply chain managers should exponentially increase the SMA parameter N in their forecast when lead-time L increases. FIS always outperforms DDI and NIS due to information sharing benefits. In terms of MSE, DDI outperforms NIS beyond a certain break-point depending on demand time-series structure. In terms of $\tilde{I}_t$, DDI outperforms NIS for all simulated demand processes. We go on to study the Bullwhip effect performance, which separates SMA to MMSE.

4.4. Simulation on Bullwhip effect

To numerically illustrate the behavior of the so-called Bullwhip effect, we consider as an example, an $ARMA(2, 2)$ demand process with $c = 10$ and $\sigma_\xi^2 = 1$ and then we consider different values of coefficients ϕ_j and θ_j, SMA parameter N and lead-time L. We mainly compute the BWP in order to have an idea on the Bullwhip effect accordingly to the employed forecast method.

Table 5 provides some conclusions on the behavior of Bullwhip effect when MMSE and SMA methods are used in the forecasts of the retailer. The BWP indicator decreases as the autoregressive coefficients

$\phi_1$and ϕ_2 increase. This means that the performance of SMA method, compared to the MMSE method, improves as the demand's auto-regression is more important. In the same way, the BWP indicator decreases as the moving average coefficients θ_1 and θ_2 increase, which means that the performance of SMA method, compared to the MMSE method, improve as the demand becomes more correlated with delayed errors. Accordingly to the lead-time L, the BWP indicator increases as L increases. That means that the performance of SMA, compared to the MMSE method, deteriorates on L. Reversely, accordingly to the SMA parameter N, the BWP indicator decreases as N increases. That means that the performance of SMA, compared to the MMSE method, improves on N.

Through the totality of models in Table 5, the SMA method outperforms the MMSE method in terms of Bullwhip effect ($BWP < 1$). This is a strong point for the SMA method, compared to the MMSE method, as SMA method provides a lower variability of orders processes.

Table 5
Bullwhip effect performance between SMA and MMSE methods.

Model	*Autoregressive coefficients ϕ_j*	*Moving average coefficients θ_j*	***L***	***N***	***BWP***
24	$\phi_1 = 0.4$	$\theta_1 = 0.15$	5	12	0.1960
	$\phi_2 = 0.2$	$\theta_2 = 0.10$			
25	$\phi_1 = 0.45$	$\theta_1 = 0.15$	5	12	0.1528
	$\phi_2 = 0.2$	$\theta_2 = 0.10$			
26	$\phi_1 = 0.5$	$\theta_1 = 0.15$	5	12	0.1178
	$\phi_2 = 0.2$	$\theta_2 = 0.10$			
27	$\phi_1 = 0.4$	$\theta_1 = 0.15$	5	12	0.1309
	$\phi_2 = 0.3$	$\theta_2 = 0.10$			
28	$\phi_1 = 0.4$	$\theta_1 = 0.20$	5	12	0.1926
	$\phi_2 = 0.2$	$\theta_2 = 0.10$			
29	$\phi_1 = 0.4$	$\theta_1 = 0.20$	5	12	0.1883
	$\phi_2 = 0.2$	$\theta_2 = 0.15$			
30	$\phi_1 = 0.4$	$\theta_1 = 0.15$	8	12	0.2469
	$\phi_2 = 0.2$	$\theta_2 = 0.10$			
31	$\phi_1 = 0.4$	$\theta_1 = 0.15$	5	15	0.1703
	$\phi_2 = 0.2$	$\theta_2 = 0.10$			

Table 6
NIS and DDI results for $ARMA(2, 1)$ demand process.

Adopted strategy	NIS	DDI	% of reduction when adopting DDI rather than NIS
MSE	49.8496	19.6140	60.6536
$\tilde{\boldsymbol{I}}_t$	17.7593	10.8756	**63.2948**

Despite the accuracy of MMSE method, SMA method remains a convenient mean to reduce the Bullwhip effect as it employs the less variable demand due to inference. As accuracy implication (Inventory costs) remains the end measure that must be taken into account, rather than accuracy itself (BWP), we propose in the next section, a concrete managerial insight, where DDI with SMA method, is much more valuable than NIS with MMSE method.

5. A revenue sharing contract as a practical recommendation

In this section, we provide a convenient way to show that practical limitations of DDI strategy can be canceled in the cases where both supply chain actors are favorable for negotiation. Let first consider an example where the demand follows an $ARMA(2, 1)$. We have already shown the results reported in Table 6.

This example shows that adopting DDI strategy by both the retailer and the producer, results in a reduction of nearly 63% in the producer's Average Inventory level, in comparison with NIS strategy. Based on this reduction, the producer can deduce the percentage decrease on his average inventory cost, over a duration of T periods. The producer may propose a contract to the retailer based on principal agent, or the two actors can negotiate through proposal generation. As example, a revenue sharing contract can be proposed by the producer, over a certain period T.

If the retailer has already adopted the SMA forecast method, he only endures the basic costs of data transfer (SMA parameter, demand process and updated coefficients every time period t). We denote C^1 the total costs of the retailer, related to data transfer, over the period T.

In the case where the retailer was adopting another forecasting method, the retailer has additional costs related to the dismantling of the old method and the adoption of the SMA method (time, labor and technical requirements). We denote C^2 the total costs of the retailer related to SMA method adoption, over the period T.

Information systems of both supply chain actors can be compatible. Otherwise, the retailer will bear an additional cost C^3 if he is the only responsible of systems compatibility. Assuming $C^i > 0$ and $\sum_{i=1}^{3} C^i < CR$, where CR is the average cost reduction at the producer over the period T, resulting from adopting DDI strategy, the producer can propose a revenue sharing contract based on Table 7.

Our main recommendation is to adopt the DDI approach if it has value. Table 7 provides a mean to distinguish when DDI is valuable. Accordingly to the situation case, the shared revenue SR is expressed by the below equation.

$$SR = \alpha \left(CR - \sum_{i=1}^{3} C^i \right) \quad (11)$$

Where SR is the shared revenue at the end of period T and α is the fraction of revenue (subject of negotiation) proposed by the producer to the retailer. The α coefficient may be determined by considering the bargaining power of actors. Otherwise, 0.5 can be a fair value for both parties.

This reasoning can be extended to supply chains where there is more than two actors. Every upstream actor can propose such a contract to his formal downstream actor in order to adopt DDI strategy and the overall supply chain will considerably gain in terms of costs and trust for future cooperative approaches. If we suppose that all costs at the downstream actor, related to DDI adoption are lower than average cost reduction at the upstream actor; moreover, if we suppose that a whole supply chain adopts DDI strategy through such revenue sharing contracts, then every actor i within the supply chain, will gain the revenue R_i expressed by the below equation.

$$R_i = \alpha_{i-1}(CR_{i-1} - C_i) + (1 - \alpha_i)(CR_i - C_{i+1}) \quad (12)$$

Where α_{i-1} and α_i are the fractions of revenues proposed respectively, by the upstream actor $(i-1)$ to actor i, and by the actor i to his formal downstream actor $(i+1)$, CR_{i-1} and CR_i are the average inventory cost reductions respectively, at upstream actor $(i-1)$ and at actor i over the period T, and finally, C_i and C_{i+1} are the total costs related to DDI adoption, respectively, at actor i and at downstream actor $(i+1)$ over the period T. Therefore, if we consider a N-level supply chain, the total supply chain revenue $SC\_Revenue$ from adopting DDI strategy with a revenue sharing contract between every couple of actors, is expressed by the below equation.

Table 7
Different situations where DDI is valuable.

Retailer's forecast method	Costs borne by the retailer for adopting DDI strategy: *Information systems are compatible*	*Information systems are incompatible*
SMA is already adopted	• Costs of data transfer C^1 ➢ *DDI is valuable if* $C^1 < CR$	• Costs of data transfer C^1 • Costs of systems compatibility C^3 ➢ *DDI is valuable if* $C^1 + C^3 < CR$
SMA is not yet adopted	• Costs of data transfer C^1 • Costs of SMA method adoption C^2 ➢ *DDI is valuable if* $C^1 + C^2 < CR$	• Costs of data transfer C^1 • Costs of SMA method adoption C^2 • Costs of systems compatibility C^3 ➢ *DDI is valuable if* $C^1 + C^2 + C^3 < CR$

$$SC\_Revenue = \sum_{i=1}^{N-1} (CR_i - C_{i+1}) \tag{13}$$

We conclude this section by recalling our results. When the demand follows $ARMA(p, q)$ process, supply chains can considerably be enhanced by adopting DDI strategy where SMA method is used for demand forecast. By proposing contracts of revenue sharing, the actors within a decentralized supply chain may approach optimal solutions through inventory cost reduction. Other types of contracts may still be proposed.

6. Conclusion

For many years, studying decentralized information structures was one of the main research topics for both academic and practitioner views. The main question of enhancing the performance of an overall supply chain, where actors do not want or are unable to share information still persist through time. In a decentralized two-level supply chain constituted by a producer and retailer where demand information is not shared, we study the robustness of a relatively new phenomenon called Downstream Demand Inference (DDI) in a more general demand context. This strategy allows an upstream actor to infer the demand arriving at his formal downstream actor who uses Simple Moving Average (SMA) method in his forecast instead of using optimal Minimum Mean Squared Error (MMSE) method. DDI allows the upstream actor to improve its forecast Mean Squared Error (MSE) and Average Inventory level ($\tilde{I}_t$), which directly lower inventory costs.

This paper is a follow-up study to previous work with the purpose of generalizing existing results through theoretical analysis of a model based on some strong assumptions. This paper generalizes MSE and $\tilde{I}_t$ expressions for causal invertible $ARMA(p, q)$ demand processes under DDI strategy, No Information Sharing (NIS) and Forecast Information Sharing (FIS), computes the Bullwhip effect generated by employing SMA method and provides an indicator, which measures the performance separating SMA to MMSE method. In a simulation section, the paper analyses the behavior of the three performance metrics with respect to Simple Moving Average (SMA) parameter N, lead-time L, demand's autoregressive order p and coefficients ϕ_i, and moving average order q and coefficients θ_j.

The implications of our paper are relevant. Supply chain managers can introduce the use of SMA forecast method for a more generalized $ARMA(p, q)$ demand model. First, the paper concludes that DDI performance depends on demand time-series structure, and especially would increase as demand is less correlated to delayed demands and error terms. Second, the paper concludes that supply chain managers, in the case where DDI is adopted, should exponentially increase the SMA parameter N in their forecast when lead-time L increases. Third, the paper confirms that FIS always outperforms DDI and NIS due to information sharing benefits. The value of information sharing is incontestable and FIS remains the optimal strategy for supply chain actors. Fourth, in terms of MSE, DDI outperforms NIS beyond a certain break-point depending on demand time-series structure. In terms of $\tilde{I}_t$, DDI outperforms NIS for all simulated demand processes. Fifth, the paper concludes that despite the accuracy of MMSE method, SMA method remains a convenient mean to reduce the Bullwhip effect as it employs the less variable demand due to inference. Finally, the paper presents a revenue sharing contract as a practical recommendation in a managerial accessible manner in order to adopt DDI strategy within supply chains.

We conclude our paper with lines for future researches. First, DDI strategy can still be evaluated through other forecasting methods. Second, it would be interesting to establish a general mathematical relation, which allows determining the break-point of any $ARMA(p, q)$, $p > 0$ model, from which DDI is more valuable than NIS strategy, in terms of MSE. Finally, our study may still be generalized to an $ARIMA(p, d, q)$ model.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2018.09.034.

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