Exploring the Interaction of Inventory Policies across the Supply Chain: An Agent-based Approach

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Abstract

The Bullwhip Effect, which refers to the increasing variability of orders traveling upstream the supply chain, has shown to be a severe problem for many industries. The inventory policy of the various nodes is an important contributory factor to this phenomenon, and hence it significantly impacts on their financial performance. This fact has led to a large amount of research on replenishment and forecasting methods aimed at exploring their suitability depending on a range of environmental factors, e.g. the demand pattern and the lead time. This research work approaches this issue by seeing the whole picture of the supply chain. We study the interaction between four widely used inventory models in five different contexts depending on the customer demand variability and the safety stock. We show that the concurrence of distinct inventory models in the supply chain, which is a common situation in practice, may alleviate the generation of inefficiencies derived from the Bullwhip Effect. In this sense, we show that the performance of each policy depends not only upon the external environment but also upon the position within the system and upon the decisions of the other nodes. The experiments have been carried out via an agent-based system whose agents simulate the behavior of the different supply chain actors. This technique proves to offer a powerful and risk-free approach for business exploration and transformation.

Keywords

Supply Chain Management; Bullwhip Effect; order-up-to inventory policy; agent-based modeling.

Abbreviations

ABMS – Agent-Based Modeling and Simulation
KAOS – Knowledge Acquisition autOmated Specification
MMSE – Minimum Mean Square Error
OUT – Order-Up-To
POUT – Proportional Order-Up-To
SCM - Supply Chain Management

1. Introduction

A supply chain encompasses all participants, and their relationships, involved in meeting consumer demands around some related products. Therefore, Supply Chain Management (SCM) covers a wide range of processes placed between the raw material suppliers (upper nodes) and the end consumers (lower nodes), which can be divided into three groups: product shipping (downstream material flow), sourcing (upstream information flow), and internal activities (e.g. manufacturing, assembly, storage, and monitoring). Several changes in the macro environment of the firms over the last two decades have set up a global business scene where SCM has been granted a strategic role as a source of competitive advantages. Under this context, a major concern for businesses is the inherent tendency to the increase of the variability of orders as they move up the supply chain.

This phenomenon is the so-called Bullwhip Effect, which is known since Forrester (1961) first observed the amplification and initiated the analysis. Sterman (1989) studied the Beer Game—a role-playing exercise created by the MIT to illustrate the complexity of effectively managing a supply chain, as a convoluted dynamic system, that provides evidence of the Bullwhip Effect—and concluded that the inefficiencies are generated from the local optimum solutions adopted by the different supply chain members, who consider their strategies individually instead of globally. The relevance of the Bullwhip Effect grew dramatically in the 90s, when large firms suffered from excessively variable order swings, such as increased inventory investments, low customer service level, inefficient use of transport, and the need for high production capacities (Lee et al., 1997). Metters (1997) estimated that the financial impact of this phenomenon can be as much as 30% of factory gate profits.

From its discovery, several studies have explored the underlying reasons of the Bullwhip Effect generation; see Lee et al. (1997) for the baseline four-cause analysis and Bhattacharya and Bandyopadhyay (2011) for an updated literature review on this subject. All of them concur in the key role of the replenishment rule used by the various supply chain partners (Dejonckheere et al., 2004). This fact, which translates into a great impact on the financial performance of the supply chain, justifies the large amount of research on inventory policies.

The order-up-to (OUT) algorithms are a class of replenishment strategies based on reviewing the inventory position every period and issuing an order to bring the net stock up to a defined level. Given the usual practice in retailing to replenish inventory very frequently and the tendency of manufacturers to produce to demand, the OUT methods are widespread in the real world (Dejonckheere et al., 2003). For example, Chen and Disney (2007) claimed that at least 60% of the sales value of two of the four largest UK grocery retailers was controlled by OUT policies.

The classic OUT algorithm, which aims to fully recover the gap between the target and the actual inventory, is optimal in the sense that it minimizes the expected sum of holding and shortage costs (Karlin, 1960). However, it undesirably contributes to the generation of Bullwhip Effect across the supply chain (Lee et al., 1997; Chen et al., 2000a; Dejonckheere et al., 2003), which has a negative impact on other sources of costs, such as production, ordering, and transportation costs (Disney and Lambrecht, 2008). For this reason, several variations have been proposed in order to deal with this issue and hence to improve the performance of the supply chain. In this sense, the proportional OUT (POUT) policy (Chen and Disney, 2007) should be mentioned. This algorithm incorporates a proportional controller into the inventory feedback loop—which regulates the amount of the inventory gap to recover—in order to directly control the Bullwhip Effect, on occasion at the expense of decreasing the inventory performance (Disney et al., 2004).

Forecasting also takes an important role in supply chain dynamics. Several works have studied how improving the forecast accuracy leads to taming the Bullwhip Effect when the supply echelons order according to an OUT model. Chen et al. (2000a, 2000b) considered and quantified the Bullwhip Effect when moving averages and exponential smoothing are used to forecast. Dejonckheere et al. (2003) demonstrated that the classic OUT algorithm will always amplify the variance of orders for both forecasting methods regardless of the demand pattern and the lead time. Other forecasting techniques explored as mechanisms to cope with the Bullwhip phenomenon are the ARIMA models (Gilbert, 2005), the Holt's and Brown's methods (Wright and Yan, 2008), the damped trend (Li et al., 2014), and artificial neural networks (Jaipuria and Mahapatra, 2014).

The literature has thoroughly investigated the consequences provoked independently by the various OUT algorithms and forecasting methods on the Bullwhip Effect. From this starting point, this article analyzes the interaction of different replenishment policies and forecasting techniques throughout the supply chain, as this can be understood as a common situation in real production and distribution systems. That is, by seeing the whole picture, we aim to explore whether the concurrence of different ordering policies and forecasting methods accentuates or mitigates the generation of inefficiencies in the supply chain. This leads us to study if the efficiency and suitability of each policy depend upon the position within the supply chain and upon the behaviors of the other nodes.

To tackle these research questions, we have used the classic OUT policy with naïve forecasting as the baseline. From that point, three smoothing rules common in the literature have been introduced: (1) moving average forecasting; (2) exponential smoothing forecasting; and (3) addition of a proportional controller. This problem has been analyzed in a traditional (non-collaborative) serially linked supply chain under five different scenarios characterized by the variability in customer demand (an uncontrollable factor, representing the external uncertainty) and the safety stock (a controllable factor, representing the target service level).

We have employed simulation techniques to approach to this problem, as it would be unfeasible the experimentation with real systems and intractable by means of analytical tools—the system-in-focus is the overall supply chain and the model incorporates several nonlinearities. Within this field, we have resorted to agent-based modeling and simulation (ABMS) techniques as they enable researchers to accurately analyze the complex behavior of supply chains (Gilbert, 2008). In this sense, we intend to highlight the development of the agent-based supply chain, based on Knowledge Acquisition autOmated Specification (KAOS) meta-modeling (Dardenne et al., 1993), as a valuable contribution of this paper. In addition, we also aim to show the potential of ABMS systems as powerful decisions support systems for managers since they ease business comprehension as several recent works have shown (Chatfield and Pritchard, 2013; Dominguez et al., 2014; Costas et al., 2015).

Our research line, which is spread across six sections, has been the following:

(1) *Problem statement* (section 1). We highlight the strategic role of the Bullwhip Effect in terms of supply chain performance, as well as the common interaction of distinct ordering algorithms and forecasting techniques across the system.
(2) *Problem world* (section 2). It involves a literature review around the impact of both replenishment and forecasting methods on the Bullwhip Effect and the applications of agent-based techniques in SCM.

(3) *Problem clarification* (section 3). It includes the conceptual design of the supply chain model. A p-diagram is used to define the scope of our research (parametric space, noise sources, and key metrics), after setting up the initial assumptions.

(4) *ABMS development of the model* (section 4). First, the meta-model is devised by means of KAOS methodology. Next, the simulation system is implemented within a C# environment. Last, it is verified and validated.

(5) *Experimentation of different scenarios* (section 5). It refers to the design of the experiments and the collection of the results in the defined scenarios, as well as to the discussion after revisiting the objectives of this research.

(6) *Findings, recommendations and next steps* (section 6). We derive implications of this research work and propose future research lines.

2. Problem World: Background

2.1 Order-Up-To (OUT) Policies and Bullwhip Effect: Literature Review

The traditional OUT replenishment method is conceptually simple. It is a periodic review system for issuing orders to bring the net stock position up to a target level. Orders are thus placed depending on the incoming demand and the (on-hand and on-order) inventory. Karlin (1960) showed its foundation and demonstrated that this algorithm is optimal to minimize inventory costs when holding and shortage costs are proportional to the volume. However, this policy tends to generate the Bullwhip Effect across the supply chain (Lee et al., 1997) and this unevenness translates into a large increase of production and/or ordering costs that may overweigh the improvement in inventory-related costs (Wang and Disney, 2016). Later, the POUT policy was proposed (Towill, 1982) in order to cope with these issues. It can be understood as a generalization of the OUT algorithm in which the amount of gap (between the target and the actual inventory) to be replaced is regulated by proportional controllers.

The literature contains a wide variety of POUT models; see Lalwani et al. (2006) for a review. The generic version considers two proportional controllers (John et al., 1994): $k_i=1/T_i$ regulates the gap in inventory on-hand (net stock) and $k_w=1/T_w$ regulates the gap in inventory on-order (work-in-progress). A particular setting is the one proposed by Deziel and Eilon (1967), which modulates equally both controllers $k=k_i=k_w$. (Note that if $k=k_i=k_w=1$ this model turns into the traditional OUT policy).

For the Deziel and Eilon (1967) case, figure 1 displays graphically the relationship of the controller with the Bullwhip ratio (ratio of the variance of outgoing orders to the variance of incoming orders; see *equation 14*) and the net stock amplification (ratio of the variance of the net stock to the variance of incoming orders; see Cannella and Ciancimino, 2010) when assuming (Disney et al., 2016): (1) the APIOBPCS supply chain model (John et al., 1994); (2) an independent and identically distributed random demand; (3) minimum mean squared error (MMSE) forecasting; and (4) that the product is received in the immediate period after the order is placed. Under this context, the inventory cost is an increasing function of the Bullwhip ratio (Kahn, 1987) while the production and/or ordering cost is an increasing function of the net stock amplification ratio (Disney et al., 2012). This graph therefore illustrates the potential of the proportional controller in mitigating the Bullwhip Effect but, at the same time, it highlights that the regulator might negatively impact the inventory performance.

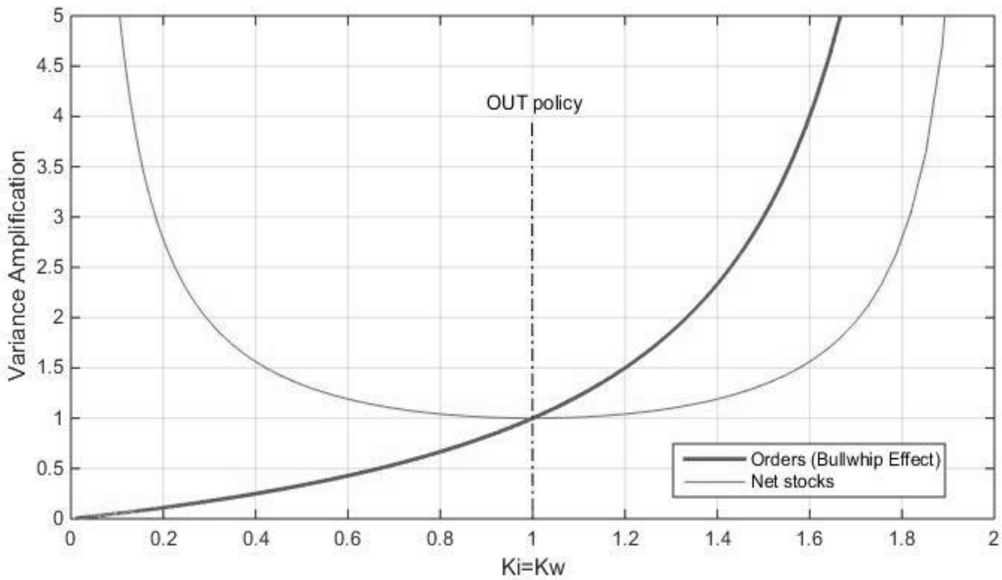

Fig. 1 Orders and net stock amplification in function of the proportional controller

While figure 1 displays the mathematical function for the aforementioned assumptions, several studies have demonstrated that the baseline rationale behind it remain valid when such assumptions do not apply (Dejonckheere et al. 2004; Disney and Lambrecht, 2008; Wright and Yuan, 2008; Cannella and Ciancimino, 2010; Disney et al., 2016). That is, the POUT policy limits the over and under-reactions to changes in orders—it is thus a smoothing replenishment rule. Hence, it effectively deals with the Bullwhip Effect. However, this mitigation may have damaging consequences on the service level and/or on the inventory costs.

Under these circumstances, the tuning of the controller has become a fruitful area of study, mainly from a control engineering perspective, to find a right balance between the desired effect (on orders) and the counter-effect (on inventories) of the proportional controller. For example, Naim and Towill (1995) proposed $k=k_i=k_w=1/4$ after studied the Sterman's (1989) optimum setting for the Beer Game; Disney and Towill (2003) recommended $k_i= 1/7$ and $k_w=1/28$ to minimize the Bullwhip Effect and the inventory investment while maximizing service levels; and Disney et al. (2006) showed that tuning the controller with the inverse of the golden ratio ($k=k_i=k_w=1/1.618...$) is the optimal solution to minimize the sum of inventory and ordering costs when both are equally relevant.

It should be highlighted that the performance of the inventory policy highly depends on the accuracy of the forecasting method (Wright and Yuan, 2008). For this reason, several studies have focused on this subject. Chen et al. (2000a) quantified the Bullwhip Effect across a two-step supply chain facing a correlated customer demand when an OUT algorithm is used to order and a moving average is employed to forecast. They showed that in every case (depending on the demand correlation, the level of information sharing in the system, and the lead time) the larger the time horizon of the forecast, the bigger the reduction in the Bullwhip Effect. These authors (Chen et al., 2000b) carried out a similar analysis when the supply chain echelons forecast according to an exponential smoothing method. It was inferred that the Bullwhip Effect was an increasing function of the smoothing parameter (that refers to the weight placed on the most recent observation of demand).

Moving averages and exponential smoothings are the most widely used techniques in the Bullwhip Effect literature (Dejonckheere et al. 2003; Disney and Lambrecht, 2008; Cannella and Ciancimino, 2010; Spiegler et al., 2012; Costas et al., 2015); nonetheless, other mechanisms have also been explored. Gilbert (2005) showed how this phenomenon can be mitigated by using an ARIMA time-series model to forecast. Wright and Yuan (2008) explored the Holt's and Brown's double-smoothing methods in an OUT replenishment model. They concluded that the Bullwhip Effect could not be removed, but it was substantially alleviated. Li et al. (2014) applied the Damped Trend forecasting method within an OUT model and demonstrated that this mechanism sometimes generates Bullwhip Effect and sometimes can eliminate it, which is a remarkable difference. Jaipuria and Mahapatra (2014) introduced artificial intelligence in the analysis by means of neural networks and showed how these techniques enable the Bullwhip mitigation.

The underlying idea of these works is the key role of forecasting in terms of Bullwhip reduction: they show that a better forecasting model generally results in the Bullwhip reduction. In this sense, MMSE forecasts (given by its conditional expectation for non-correlated random demands; i.e. an infinite-horizon moving average or an exponential smoothing whose parameter is null) has shown to minimize the Bullwhip Effect (Disney et al., 2016).

2.2 Applications of Agent-based Systems in Supply Chain Management (SCM)

The analytical approach is very useful for gaining insight into supply chain dynamics. For example, control theory has been widely and fruitfully employed in this field; see Dejonckheere et al. (2003) for a discussion on its relevance. It assumes system linearity, but real supply chains often operate in nonlinear contexts (Gruen et al., 2002; Spiegler et al., 2012). Adding complexity to the supply chain model makes mathematical expressions become unmanageable under an analytical approach (Hosoda and Disney, 2006). In this context, simulation can be of utmost importance: it enables firms to understand complex interdependences and to achieve their optimal state (Holweg and Bicheno, 2002; Kelepouris et al., 2008).

Among these techniques, ABMS is an emerging technological field. It involves building a model consisting of 'agents', who are able to interact with each other and programmed to be proactive and autonomous as well as to perceive its environment (Gilbert, 2008). This approach can capture both the network of relationships among the agents and the heterogeneity in their attributes (Rahmandad and Sterman, 2008). Hence, several authors have stood up for ABMS in the SCM analysis based on its own nature: supply chains tend to be decentralized systems with nodes acting independently according to their own interests, which fits perfectly with the ABMS paradigm (Dominguez et al., 2015). In a similar vein, Chatfield et al. (2006) highlighted that SCM represents a complex problem influenced by the interaction of many variables and ABMS offers suitable models to analyze its complex dynamic behavior.

For these reasons, since Fox et al. (1993) first represent the supply chain as a network of intelligent agents, several works have followed this line. Strader et al. (1998) used ABMS to study the impact of information sharing on the service level. Kimbrough et al. (2002) explored the agent's capability of managing a supply chain, showing that they clearly outperform humans when playing the Beer Game. Liang and Huang (2006) used this approach to develop a demand forecasting system. Lau et al. (2008) designed a multi-agent system for real-time control of supply chains aimed at maintaining global consistency and optimality.

Chatfield et al. (2006) made an outstanding contribution to this field by developing SISCO, an agent-based decision support system built in Java for easily performing simulation analysis of supply chains. The work by Dominguez et al. (2015) should also be highlighted. They used a Java-based architecture to design SCOPE, which employs a two-layer framework to differentiate between the connections among companies and the link between the organizational functions. SCOPE allows the user to create supply chains of any structure, defining customers and suppliers for each member. Chatfield et al. (2013) later developed SISCO2, a version built in the NetLogo environment (Wilensky, 1999) that incorporates a discrete-event engine to replicate the activities that occur within the nodes. Costas et al. (2015) used a similar architecture, also in NetLogo, to build an agent-based supply chain. They employed additional breeds of agents to perform other functions within the system and designed the supply chain actors (the main breed) with different engines—although only one active in each moment—to represent their replenishment methods.

These platforms have significantly contributed to the understanding of complex dynamic responses throughout supply chains, as they allow experimenters to study problems that would be intractable through other approaches. For example, Chatfield et al. (2004) based on SISCO to explore the impact of the information quality on the Bullwhip Effect; Dominguez et al. (2014) used SCOPE to analyze the difference in the generation of this phenomenon between serial and divergent supply chains; and Ponte et al. (2016) demonstrated how developing a global strategy through the Theory of Constraints leads the supply chain to breakthrough improvements in its financial performance. It should be underscored that SISCO2 enables the detailed analysis of the modeling assumptions, which represents a new stream on the SCM literature; see Chatfield (2013) and Chatfield and Pritchard (2013).

3. Problem Clarification and Mathematical Model

3.1 Assumptions and Scope

In line with relevant and recent studies (e.g. Chatfield and Pritchard, 2013; Cannella et al., 2014; Costas et al., 2015), we have analyzed the supply chain under the Beer Game scenario since it provides researchers with a rich enough framework to explore its dynamic behavior (Macdonald et al., 2013). That is, we have considered a traditional serially linked supply chain composed of five nodes. Four of them (i.e. the supply chain echelons: factory, wholesaler, retailer, and shop retailer) are responsible for managing the supply chain in order to meet the other's (customer) single-product needs. In this context, each echelon only communicates with the immediately lower and upper ones in a double way: to place and observe the orders (information flow) and to send and receive the product (material flow). Thereby, the unknown customer demand is only observed by the shop retailer.

The operation in the four echelons strictly follows the order of events in the Beer Game (Sterman, 1989), which can be summarized into four sequential states:

(1) *Reception state.* The product, from the upstream node, and the order, from the downstream node, are received. The product is added to the available inventory.
(2) *Serving state*. The incoming order and past backorders (if they exist) are satisfied from net stock. The product is sent to the downstream node.
(3) *Updating state.* The inventory on-hand (net stock) and work-in-progress (inventory on-order) are updated. If necessary, a new backorder is generated.
(4) *Sourcing state*. The needs of product are forecast, the target inventory (OUT) level is determined, and the order is issued to the upstream node.

Note that backlog is allowed; that is, the product that cannot be immediately fulfilled from inventory will be delivered as soon as the net stock becomes available. Besides, each echelon receives the product a fixed lead time (in the material flow) after sent by its immediately upstream node. Meanwhile, we consider that the lead time in the information flow is null, so orders are instantly received after being placed. Other assumptions adopted to model the supply chain are the following: (1) Unlimited production, storage and shipping capacities; (2) Unconstrained raw material supply, i.e. the factory will be always able to fully produce the orders placed; (3) Non-negative orders, i.e. product cannot be returned to the supplier.

Figure 2 points out the parameter diagram that shows our research scope. The center shows the operational system function: transforming raw materials into finished products. This is threatened by the uncontrollable (noise) factors displayed in the top part. The inefficiencies generated in the system come both from its outside, the demand variability, and from within it, the lead time and the nodes' self-centered behavior. The bottom part shows the controllable factors (parametric space). These will be modified in the designed experiments: inventory policy, forecasting method, and safety stock. Lastly, the performance metrics indicate how we measure the inefficiencies within the supply chain; namely, through the Bullwhip ratio.

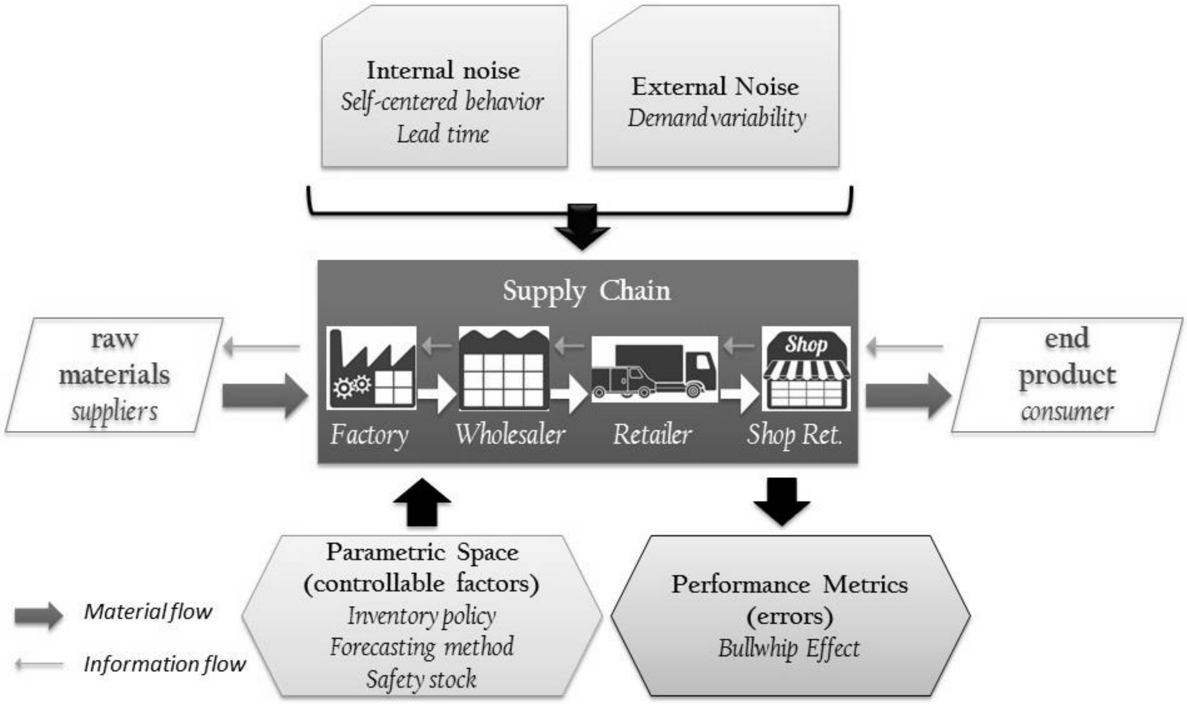

Fig. 2 Scope of the analysis through a parameter diagram

3.2 Supply Chain Mathematical Model

Table 1 reports the model notation. First, it includes the indices. It must be noted that the total number of echelons is $N=4$ (factory: $n=1$; wholesaler: $n=2$; retailer: $n=3$; shop retailer: $n=4$). Next, the abbreviation of the variables and parameters of the supply chain model, including the replenishment and forecasting methodologies, can be seen. Last, we show the performance metrics and the associated statistics. Next, the mathematical formulation of the supply chain nonlinear model is detailed.

Table 1 Model notation

Indices			
n	Echelon in the supply chain	N	Total number of echelons
t	Time period	T	Time horizon of the test
Supply chain model variables and parameters			
D_n	Demand (purchase order received)	I_n	On-hand inventory (net stock)
R_n	Receipts (units of product received)	S_n	Shipment (units of product delivered)
O_n	Purchase order issued	B_n	Backlog
W_n	Work-in-progress (on-order inventory)	l	Lead time
Inventory model variables and parameters			
F_n	Demand forecast	Y_n	Order-up-to point
SS_n	Safety stock	m	Moving average periods
k	Proportional controller	f	Smoothing factor
Statistics and performance metrics			
Var	Variance	Avg	Average
BE_n	Bullwhip Effect		

The (on-hand) inventory balance equation expresses the net stock at the end of each period as the accumulated difference between the units received from the upper node and the units delivered to the lower node (*equation 1*). This amount of shipped product is the minimum value between the demand received, considering past backlog, and the inventory position after the units of product arrive (*equation 2*). The final backlog is hence the difference between the demand, plus the previous backlog, and the shipment (*equation 3*). Finally, the work-in-progress—i.e. the product that has been ordered but not yet received—is modeled as the accumulated sum of the difference between the previous order and the current receipts.

$$I_n(t) = I_n(t-1) + R_n(t) - S_n(t) \tag{1}$$

$$S_n(t) = \min\{D_n(t) + B_n(t-1), I_n(t-1) + R_n(t)\} \tag{2}$$

$$B_n(t) = D_n(t) + B_n(t-1) - S_n(t) \tag{3}$$

$$W_n(t) = W_n(t-1) + O_n(t-1) - R_n(t) \tag{4}$$

Note that both the on-hand inventory and the backlog will always be positive or zero. If the demand is entirely satisfied (i.e. if $D_n(t) + B_n(t-1) \leq I_n(t-1) + R_n(t)$), the net stock is positive and the backlog is null; while if the available product is not enough (i.e. if $D_n(t) + B_n(t-1) > I_n(t-1) + R_n(t)$), the backlog is positive and the inventory is null.

Communication between two consecutive supply chain members occurs through the two aforementioned flows: (1) each node's receipt is the units shipped by the immediately upstream one *l* periods before (*equation 5*); and (2) each node's demand is the order issued by the immediately downstream node this period (*equation 6*).

$$R_n(t) = S_{n-1}(t-l) \tag{5}$$

$$D_n(t) = O_{n+1}(t) \tag{6}$$

In this regard, two considerations must be done: (1) $D_4=O_5$ represents the customer demand, which is assumed to be an independent and identically distributed random variable following a continuous uniform distribution between *a* and *b* (i.e. $D_4(t) \to U(a,b)$); and (2) $R_1=S_0$ represents the production in the factory, which, according to the previous assumptions, equals the manufacturing orders placed *l* periods before ($S_0(t) = O_1(t-l)$).

3.3 Order-Up-To (OUT) Replenishment Policies

In the classic OUT policy (e.g. Chen et al., 2000b), the order is issued to entirely recover the difference between the OUT point and the actual (on-hand and on-order) inventory position (*equation 7*). Note that the backlog must also be considered and, since we assume forbidden returns, the orders issued cannot be negative.

The OUT point, which represents the target inventory level, considers the forecast, the safety stock, and the desired work-in-progress (*equation 8*). A common approach in the literature (John et al., 1994; Dejonckheere et al., 2003; Cannella et al., 2014) considers a constant safety stock—a decision variable related to the target service level—, and a variable desired work-in-progress, aimed at a covering the expected demand over the lead time.

Thereby, a key process is demand forecasting. The simplest method to estimate the demand is to use the latest demand (Li et al., 2014), which is called naïve forecasting (*equation 9*). We consider it as the baseline of this research work: *model 0 (equations 7, 8, and 9*).

$$O_n(t) = \max\{Y_n(t) - [I_n(t) - B_n(t) + W_n(t)],0\} \tag{7}$$

$$Y_n(t) = F_n(t) + SS_n + (l-1) \cdot F_n(t) = l \cdot F_n(t) + SS_n \tag{8}$$

$$F_n(t) = D_n(t) \tag{9}$$

From this basis, three simple improvements common have been introduced. The first one is the use of a moving average to perform the forecast as the mean of the last *m* demands (*equation 10*). It is a common method in practice that easily allows managers to reduce the harmful Bullwhip Effect (Chen et al., 2000a). We name it *model 1* (*equations 7, 8, and 10).*

$$F_n(t) = \frac{1}{m}\sum_{i=0}^{i=m-1} D_n(t-i) \tag{10}$$

The demand signal smoothing (Dejonckheere et al., 2003) is a variation of the classic OUT policy that periodically updates the OUT level by considering the difference of the last two demands multiplied by a smoothing factor (*equation 11*). This factor, which is a constant between 0 and 1 and enables the mitigation of the Bullwhip phenomenon, can be understood as a consequence of the exponential smoothing forecasting. We refer to it as *model 2 (equations 7 and 11)*.

$$Y_n(t) = Y_n(t-1) + f \cdot [D_n(t) - D_n(t-1)] \tag{11}$$

Lastly, we consider the addition of a proportional controller into the inventory loop as a mechanism to decrease the variation in the orders. This translates the OUT into the POUT policy (Chen and Disney, 2003), where the difference between the actual and the target inventory level is not fully but partially recovered (*equations 12 and 13*). We use the Deziel and Eilon (1967) model, in which the same regulator modulates the gap in net stock and the gap in work-in-progress. In this case, we employ naïve forecasting to analyze separately the consequences of the controller over the baseline model. We consider this to be *model 3 (equations 12, 13, and 10)*.

$$O_n(t) = \max\{Y(t) - k \cdot [I_n(t) - B_n(t) + W_n(t)], 0\} \tag{12}$$

$$Y_n(t) = F_n(t) + k \cdot [SS_n + (l-1) \cdot F_n(t)] \tag{13}$$

3.4 Performance Metric

We use the Bullwhip Effect as the dependent variable of our study, since it is a common approach to measure the performance of the supply chain (Disney et al., 2006). The Bullwhip Effect in the echelon *n* is usually quantified as the ratio of the variance of the orders issued to the variance of the orders received (i.e. its demand), adjusted both the numerator and the denominator by the mean value (Cannella et al., 2013). Nonetheless, when backlog is allowed, both means are the same for stationary random signals over longs periods of time (Disney and Lambrecht, 2008), which simplifies the previous expression (*equation 14*).

As the orders issued by each supply chain member are the orders received by its immediately upstream node, the total Bullwhip Effect in the production and distribution system can be expressed as the product of the four local Bullwhip ratios (*equation 15*). When this overall ratio is higher than 1, there is Bullwhip Effect across the supply chain. In this sense, the reduction of the Bullwhip ratio is assumed to reflect the improved cost efficiency of the operations made by the various supply chain partners.

$$[BE_n]_{t=1}^{t=T} = \left[\frac{Var(O_n)/Avg(O_n)}{Var(D_n)/Avg(D_n)}\right]_{t=1}^{t=T} \cong \left[\frac{Var(O_n)}{Var(D_n)}\right]_{t=1}^{t=T} \tag{14}$$

$$[BE_{SC}]_{t=1}^{t=T} = \left[\frac{Var(O_K)/Avg(O_K)}{Var(D_1)/Avg(D_1)}\right]_{t=1}^{t=T} \cong \left[\frac{Var(O_K)}{Var(D_1)}\right]_{t=1}^{t=T} = \prod_{n=1}^{n=K} [BE_n]_{t=1}^{t=T} \tag{15}$$

4. ABMS Development of the Model

4.1 KAOS Goal Diagram

KAOS methodology (Dardenne et al., 1993) has been used for the conceptual design of the agent-based supply chain. In the development of a software application, this technique links the overall objective that should be met and the specific requirements that should be considered. It roughly consists of: (1) identifying and progressively refining the goals at different levels as well as the main obstacles to their achievement; (2) translating these goals into requirements and expectations of the various agents that make up the system; and (3) describing the operations that these agents perform to achieve these goals. This relies on the construction of a requirements model, whose graphical part is represented by the KAOS Goal Diagram. The KAOS Goal Diagram developed for this research work is displayed in figure 3. It shows how ABMS can guide the supply chain towards a meaningful improvement.

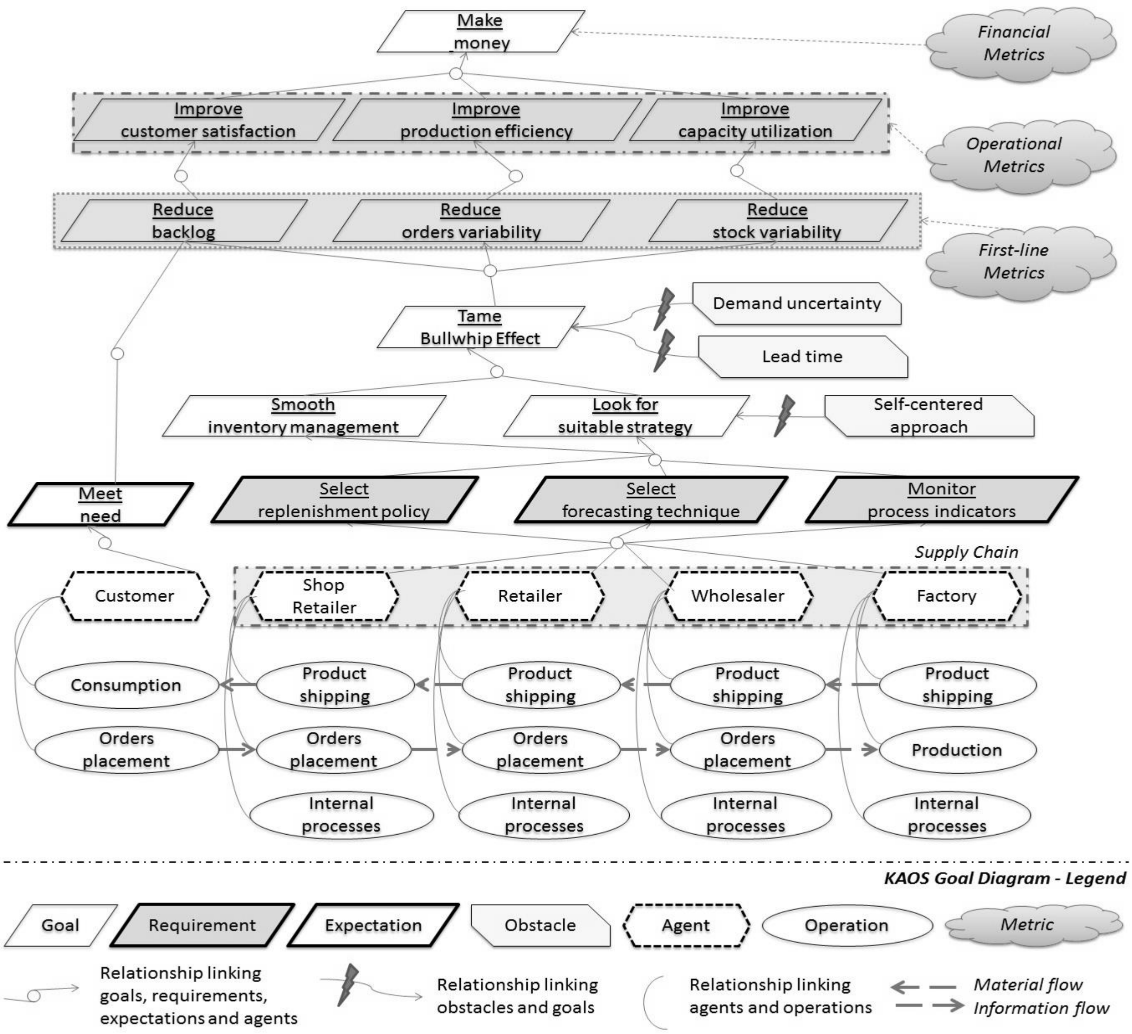

Fig. 3 Conceptual design of the system through a KAOS Goal Diagram

The supply chain is simulated via an ABMS system, which is made up of five main agents called actors. Four actors represent the supply chain echelons, while the other actor replicates the customer behavior. These five actors carry out three main operations: (1) product shipping (consumption at the lower node), related to the material flow; (2) order placement (production in the upper node) related to the information flow; and (3) internal processes.

We follow Goldratt's view: the only purpose of the supply chain is to make money—now and in the future—and all operations within the supply chain must be oriented to this goal. This is assessed through the control of key financial metrics, both in absolute terms (e.g. net profit) and in relative terms (e.g. return-on-investment). The next question to explore is how the supply chain can achieve this goal. A second level of objectives emerges: customer satisfaction, production efficiency, and capacity utilization must be improved. These are the main fields of action and enhancement to be dealt with in this work and can be evaluated through operational indicators, such as the throughput and the operating expense.

The third level consists of three goals directly related to the above ones. Customer satisfaction increases if the backlog decreases, production efficiency grows if the orders variability is reduced, and capacity utilization improves if the net stock variability diminishes. These can be easily measured through first-line metrics. How can these goals be attained? The Bullwhip Effect is now the answer, as it leads the system to the reduction of its variability, and hence to the decrease of stock-outs. This harmful phenomenon faces two main obstacles: the demand uncertainty and the lead time. Note that if the demand was completely predictable or the lead time was null, the Bullwhip Effect would not appear in this supply chain.

Hence, the decrease of the Bullwhip ratio is linked to the main system goal through two intermediate levels. In line with prior works (e.g. Disney and Lambrecht, 2008), alleviating the Bullwhip Effect increases the profitability of the supply chain.

In this work, four inventory models—including both replenishment and forecasting methods—have been implemented. In this sense, the Bullwhip ratio can be reduced if the most suitable model is chosen at each node. However, in this traditional scenario, supply chain echelons make decisions aimed at optimizing their local indicators, which is a hurdle for the increase of the overall efficiency. Thereby, each node must decide its inventory model, while monitoring process indicators to control its efficiency—these are its requirements. Meanwhile, the customer expectation is to satisfy its need immediately.

4.2 Agent-Based Approach and Implementation

Figure 4 presents an overview of the multi-agent system that has been implemented in a C# environment. Four actors (Factory Agent, Wholesaler Agent, Retailer Agent, and Shop Retailer Agent) represent the behavior of the various echelons that influence and are influenced by the management of the supply chain. Each one of them works according to the agent engine (related to the four inventory models previously defined) that is active. Besides, they administer an attached database, which stores the most relevant information of each node, and monitor the Bullwhip Effect. Moreover, a Customer Agent simulates the action of the consumers. The five nodes are communicated in pairs and with the interface. This interface controls the engines that are active in the different members, the Bullwhip Effect, the conditions that define the supply chain scenario, and the setup parameters of the simulation.

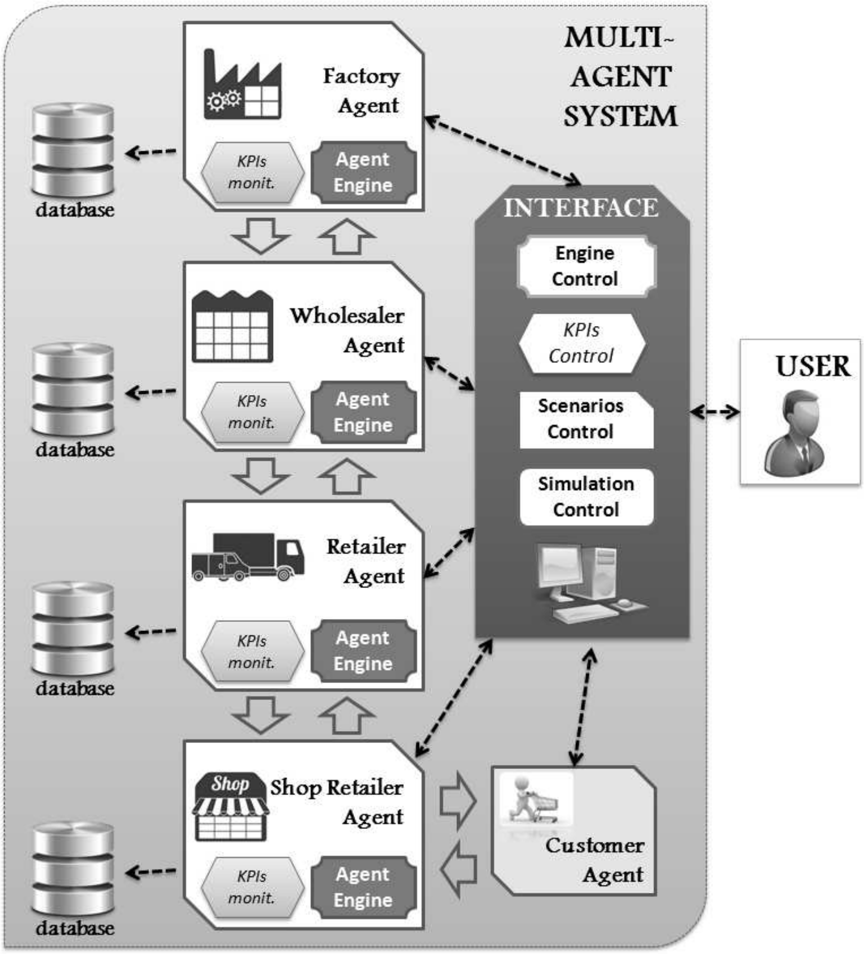

Fig. 4 Overview of the multi-agent system

The business logic of each node, which is similar for the four actors (it slightly varies in the Factory Agent, who does not issue a purchase but a production order), is shown in figure 5. They work using a finite state machine schema: (1) idle state; (2) reception state; (3) serving state; (4) updating state; (5) sourcing state; and (6) reporting state. These are detailed next; note that the four intermediate states cover the sequence of events previously described.

Firstly, the agent is idle until the action is triggered. At that moment, a purchase order is received from the immediately lower echelon, while the product is accepted and stored. Then, the net stock is checked in order to prepare the shipping. If the order (and previous backlog) can be fulfilled, the required quantity is sent; otherwise, a new backorder is generated and all the available product goes downstream. This process is delayed according to the lead time. Next, the net stock and the work-in-progress are updated, while the sourcing step depends on the active agent. Before calculating the purchase quantity, the forecast and the OUT level are obtained. The order is then sent upstream. Finally, the Bullwhip ratio is reported.

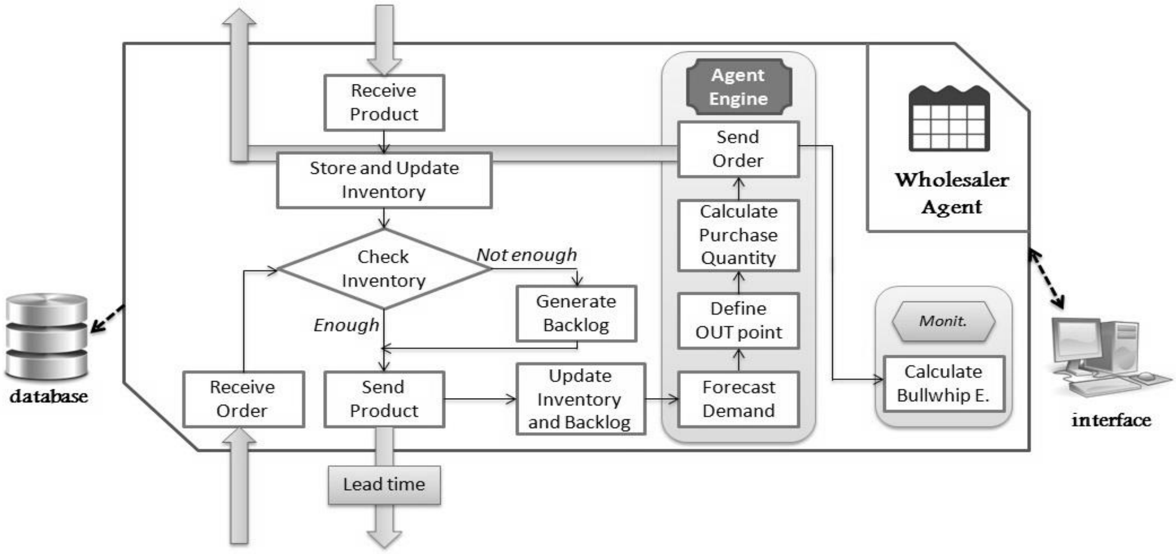

Fig. 5 Outline of the state flow of each agent (example for the Wholesaler Agent)

4.3 Verification and Validation

Model verification is a fundamental step in any simulation process in order to check its cohesion and consistency. The development must match the logic of the conceptual design. The model was created following strict rules of clean code in order to prevent failures. This has been complemented with some mechanisms for early detection of any malfunction.

The validation phase is another essential step. The model should match reasonably well the reality, so that it is useful to analyze the problem. To validate it, we have used factory acceptance testing. This allow us to confirm that the model exhibits a well-known behavior when exposed to controlled conditions. As an example, one of these tests is shown in table 2. We have studied in detail the results to check that the system responds as can be expected.

Table 2 Factory acceptance test #1 (example)

Test conditions	(I)	Constant customer demand: 80 units / period.
	(II)	Constant purchase order (in each node): 100 units / period.
Expected behavior & acceptance criteria (in steady state)	(I)	Shop retailer stock grows steadily: 20 units / period.
	(II)	Backlog is not generated (at any node).
	(III)	Bullwhip Effect is null.

5. Experimentation: Results and Discussion

5.1 Design of Experiments

This research aims to analyze the impact of the interaction of different replenishment methods and forecasting techniques throughout production and distribution systems. Since the effect of the lead time is not in the scope of this work, we have selected $l=1$ for the experimentation. As previously mentioned, we have included four inventory models in the agent-based supply chain. To set the factors associated to them, we have sought for values that has been successful in the literature in terms of Bullwhip Effect mitigation. These are the following:

- According to Chen et al. (2000a), we have chosen $m=5$ periods as the time horizon of the moving average (*model 1*), since this value significantly buffered in all the scenarios analyzed the Bullwhip Effect generated in the supply chain.
- We have used a factor $f=0.2$ within the demand signal smoothing method (*model 2*). This has been obtained from Dejonckheere et al. (2003), who studied the impact of different values of this factor and achieved a great Bullwhip mitigation for it.
- We have modulated the proportional controller by $k=0.4850$ (time constant: 2.0618) in the POUT method (*model 3*) as this value provoked a great reduction of avoidable costs associated to the Bullwhip phenomenon in Chen and Disney (2003).

The experiments have been carried out on scenarios based on the combinations of two factors. Firstly, an exogenous variable (external noise factor): the demand variability (*DV*). Secondly, an endogenous variable (controllable factor): the safety stock (*SS*). In each one of these factors, we have defined three different levels (low, moderate, and high).

Customer demand has been simulated through a uniform statistical distribution with a mean of 80, while the values of the minimum and maximum values were varied. For the low variability context, we have used 70 and 90 as the endpoints (demand coefficient of variation:

7.22%). To represent the moderate variability, we have employed 60 and 100 (demand coefficient of variation: 14.43%). For the high variability context, we have chosen 40 and 120 (demand coefficient of variation: 28.87%). Meanwhile, the values selected for the safety stock have been: 5 units (low; 6.25% of the mean demand), 10 units (moderate; 12.5% of the mean demand), and 20 units (high, 25% of the mean demand).

The design of experiments comprises five supply chain scenarios. In scenarios I, II, and III, demand variability varies while safety stock is moderate. In scenarios III (the intermediate case), IV, and V, the safety stock changes, while the variability in demand is moderate. This can be understood as double single-factor design. We have run three tests for each scenario (15 in total). Table 3 summarizes the scenarios defined and the tests performed.

Table 3 Design of Experiments: Scenarios

Factor	Level	Feature
Demand Variability (DV)	Low	U(70,90)
	Moderate	U(60,100)
	High	U(40,120)
Safety Stock (SS)	Low	5 units
	Moderate	10 units
	High	20 units

Scenario (Tests)	Demand Var. (DV)	Safety Stock (SS)
I (1-3)	Low	Moderate
II (4-6)	High	Moderate
III (7-9)	Moderate	Moderate
IV (10-12)	Moderate	Low
V (13-15)	Moderate	High

In this sense, we will explore all the different combinations of interactions among the different inventory models in each test. To do so, we create a variable: inventory policies interaction (*IPI*), which ranges from 0 to 255 representing the decimal number associated to the combination formed by the inventory models of the four nodes in the base-4 system. For instance, if the shop retailer uses the model 1, the retailer employs the model 2, the wholesaler orders according to the model 0, and the factory's inventory management is defined by the model 3, the overall combination would be (1,2,0,3) and $IPI=1\cdot 4^3+2\cdot 4^2+0\cdot 4^1+3\cdot 4^0=99$. Each test thus involves 256 simulation runs (treatments), whose time horizon has been set to $T=300$ periods, with the same randomly generated customer demand. This time horizon is enough to check the stability and repetitiveness of the results according to the common practices; see the narrowness of the confidence intervals in tables 4 to 8.

Under these circumstances, the supply chain performance—measured through the Bullwhip Effect (*BE*)—can be expressed as a function of these three variables. Hence, the experimentation approach can be written as $[BE] = f(DV,SS,IPI) + \xi$, where the residuals ($\xi$) refer to the unexplained part of the response.

5.2 Numerical Results

Tables 4, 5, 6, 7, and 8, one for each scenario, report the numerical results of the experiments. For the sake of simplicity and according to our research goal, they focus on the top five treatments as well as on those in which the same inventory model is used in the four echelons (baseline treatments). The first row is the table identifier (scenario, tests, levels of demand variability and safety stock). The columns contain the following information: the value of the *IPI* variable (highlighting the best solutions); the inventory model of the various supply chain members; and both the locals and overall Bullwhip Effect—we show the 95% confidence interval for the mean of each value; i.e. the mean of the three tests ± the standard error times the critical value of the standard normal distribution.

It should be reminded that the reference numbers of the models refer to:

(0) Classic OUT policy with naïve forecasting;
(1) Classic OUT policy with moving average forecasting;
(2) Classic OUT policy with demand exponential smoothing;
(3) POUT policy with naïve forecasting.

Table 4 Results of tests 1, 2, and 3 (scenario I)

Scenario **I**	Test **1,2,3**	Demand Variability **Low**		Safety Stock **Moderate**		
Inv. Policies Interaction	**OUT Policies** *SR-Re-Wh-Fa*	**Bullwhip Effect** *Shop Ret.*	*Retailer*	*Wholesaler*	*Factory*	*Sup. Chain*
0	0-0-0-0	6.51 ±0.12	4.06 ±0.10	1.93 ±0.02	1.42 ±0.02	72.49 ±0.02
85	1-1-1-1	1.47 ±0.01	1.56 ±0.02	1.63 ±0.01	1.70 ±0.01	6.36 ±0.09
170	2-2-2-2	1.50 ±0.03	1.58 ±0.03	1.64 ±0.03	1.70 ±0.02	6.61 ±0.45
255	3-3-3-3	2.17 ±0.08	2.18 ±0.04	2.05 ±0.01	1.88 ±0.03	18.33 ±1.42
105 (1st)	*1-2-2-1*	1.47 ±0.01	1.50 ±0.04	1.57 ±0.04	1.55 ±0.01	5.34 ±0.31
90 (2nd)	*1-1-2-2*	1.47 ±0.01	1.56 ±0.02	1.49 ±0.03	1.57 ±0.04	5.35 ±0.032
102 (3rd)	*1-2-1-2*	1.47 ±0.01	1.50 ±0.04	1.55 ±0.01	1.57 ±0.04	5.35 ±0.29
150 (4th)	*2-1-1-2*	1.50 ±0.03	1.47 ±0.02	1.56 ±0.02	1.57 ±0.04	5.38 ±0.34
153 (5th)	*2-1-2-1*	1.50 ±0.03	1.47 ±0.02	1.57 ±0.04	1.56 ±0.01	5.39 ±0.29

Table 5 Results of tests 4, 5, and 6 (scenario II)

Scenario **II**	Test **4, 5, 6**	Demand Variability **High**		Safety Stock **Moderate**		
Inv. Policies Interaction	**OUT Policies** *SR-Re-Wh-Fa*	**Bullwhip Effect** *Shop Ret.*	*Retailer*	*Wholesaler*	*Factory*	*Sup. Chain*
0	0-0-0-0	2.26 ±0.05	1.78 ±0.08	1.39 ±0.00	1.27 ±0.03	7.09 ±0.08
85	1-1-1-1	1.46 ±0.01	1.54 ±0.01	1.62 ±0.02	1.68 ±0.02	6.14 ±0.18
170	2-2-2-2	1.46 ±0.02	1.54 ±0.01	1.61 ±0.01	1.67 ±0.01	6.01 ±0.14
255	3-3-3-3	1.50 ±0.01	1.53 ±0.02	1.38 ±0.02	1.27 ±0.01	4.01 ±0.11
159 (1st)	*2-1-3-3*	1.46 ±0.02	1.46 ±0.01	1.36 ±0.01	1.33 ±0.01	3.87 ±0.04
111 (2nd)	*1-2-3-3*	1.46 ±0.01	1.46 ±0.02	1.36 ±0.01	1.33 ±0.01	3.88 ±0.04
191 (3rd)	*2-3-3-3*	1.46 ±0.02	1.43 ±0.02	1.41 ±0.02	1.32 ±0.02	3.89 ±0.08
239 (4th)	*3-2-3-3*	1.49 ±0.00	1.44 ±0.02	1.39 ±0.02	1.31 ±0.02	3.90 ±0.11
127 (5th)	*1-3-3-3*	1.46 ±0.01	1.46 ±0.02	1.41 ±0.02	1.30 ±0.02	3.91 ±0.11

Table 6 Results of tests 7, 8, and 9 (scenario III)

Scenario **III**	Test **7, 8, 9**	Demand Variability **Moderate**		Safety Stock **Moderate**		
Inv. Policies Interaction	**OUT Policies** *SR-Re-Wh-Fa*	**Bullwhip Effect** *Shop Ret.*	*Retailer*	*Wholesaler*	*Factory*	*Sup. Chain*
0	0-0-0-0	3.51 ±0.26	2.69 ±0.14	1.62 ±0.08	1.39 ±0.02	21.14 ±0.86
85	1-1-1-1	1.50 ±0.02	1.56 ±0.01	1.63 ±0.00	1.69 ±0.01	6.46 ±0.16
170	2-2-2-2	1.46 ±0.01	1.54 ±0.01	1.61 ±0.01	1.66 ±0.01	5.99 ±0.16
255	3-3-3-3	1.86 ±0.06	1.88 ±0.03	1.79 ±0.00	1.53 ±0.05	9.53 ±0.57
165 (1st)	*2-2-1-1*	1.46 ±0.01	1.54 ±0.01	1.48 ±0.01	1.56 ±0.01	5.18 ±0.05
153 (2nd)	*2-1-2-1*	1.46 ±0.01	1.49 ±0.02	1.54 ±0.01	1.56 ±0.01	5.21 ±0.06
150 (3rd)	*2-1-1-2*	1.46 ±0.01	1.49 ±0.02	1.57 ±0.01	1.53 ±0.01	5.22 ±0.04
90 (4th)	*1-1-2-2*	1.50 ±0.02	1.56 ±0.01	1.46 ±0.01	1.54 ±0.01	5.24 ±0.07
105 (5th)	*1-2-2-1*	1.50 ±0.02	1.46 ±0.01	1.54 ±0.01	1.56 ±0.01	5.25 ±0.06

Table 7 Results of tests 10, 11, and 12 (scenario IV)

Scenario **IV**	Test **10, 11, 12**	Demand Variability **Moderate**		Safety Stock **Low**		
Inv. Policies Interaction	**OUT Policies** *SR-Re-Wh-Fa*	**Bullwhip Effect** *Shop Ret.*	*Retailer*	*Wholesaler*	*Factory*	*Sup. Chain*
0	0-0-0-0	2.35 ±0.12	2.33 ±0.04	1.61 ±0.06	1.30 ±0.03	11.53 ±0.67
85	1-1-1-1	1.48 ±0.05	1.55 ±0.04	1.62 ±0.03	1.69 ±0.02	6.30 ±0.58
170	2-2-2-2	1.47 ±0.04	1.55 ±0.04	1.61 ±0.04	1.67 ±0.04	6.14 ±0.63
255	3-3-3-3	1.40 ±0.03	1.48 ±0.04	1.53 ±0.01	1.45 ±0.03	4.59 ±0.15
191 (1st)	*2-3-3-3*	1.47 ±0.04	1.32 ±0.02	1.38 ±0.02	1.41 ±0.02	3.77 ±0.19
111 (2nd)	*1-2-3-3*	1.48 ±0.05	1.47 ±0.04	1.29 ±0.01	1.34 ±0.00	3.78 ±0.19
159 (3rd)	*2-1-3-3*	1.47 ±0.04	1.48 ±0.05	1.29 ±0.01	1.34 ±0.00	3.78 ±0.17
123 (4th)	*1-3-2-3*	1.48 ±0.05	1.34 ±0.01	1.45 ±0.04	1.33 ±0.01	3.83 ±0.20
175 (5th)	*2-2-3-3*	1.47 ±0.05	1.55 ±0.04	1.26 ±0.02	1.34 ±0.01	3.86 ±0.20

Table 8 Results of tests 13, 14, and 15 (scenario V)

Scenario **V**	Test **13, 14, 15**	Demand Variability **Moderate**		Safety Stock **High**		
Inv. Policies Interaction	**OUT Policies** *SR-Re-Wh-Fa*	**Bullwhip Effect** *Shop Ret.*	*Retailer*	*Wholesaler*	*Factory*	*Sup. Chain*
0	0-0-0-0	5.27 ±0.10	3.00 ±0.16	1.77 ±0.02	1.38 ±0.02	38.63 ±1.95
85	1-1-1-1	1.50 ±0.04	1.59 ±0.04	1.66 ±0.03	1.71 ±0.03	6.79 ±0.57
170	2-2-2-2	1.46 ±0.04	1.54 ±0.04	1.61 ±0.03	1.67 ±0.03	6.03 ±0.55
255	3-3-3-3	2.25 ±0.07	2.19 ±0.04	1.97 ±0.06	1.60 ±0.04	15.52 ±0.62
153 (1st)	*2-1-2-1*	1.46 ±0.04	1.50 ±0.04	1.53 ±0.04	1.57 ±0.04	5.28 ±0.55
165 (2nd)	*2-2-1-1*	1.46 ±0.04	1.54 ±0.04	1.50 ±0.04	1.57 ±0.04	5.28 ±0.54
150 (3rd)	*2-1-1-2*	1.46 ±0.04	1.50 ±0.04	1.57 ±0.04	1.53 ±0.05	5.29 ±0.57
102 (4th)	*1-2-1-2*	1.50 ±0.04	1.46 ±0.05	1.58 ±0.04	1.53 ±0.04	5.32 ±0.58
105 (5th)	*1-2-2-1*	1.50 ±0.04	1.46 ±0.05	1.54 ±0.04	1.57 ±0.03	5.32 ±0.56

5.3 Discussion

5.3.1 Basic insights: Individual analysis of the inventory models.

These results provide formal evidence of the well-known fact that OUT policies tend to significantly amplify the orders variance, which acts a damaging source of unevenness throughout the supply chain. That is, the generation of Bullwhip Effect seems inevitable under this local optimization approach, but it can be observed that this phenomenon can be greatly mitigated if each node looks for the appropriate combination of controllable factors (replenishment policy, forecasting method, and safety stock).

We first focus exclusively on the four baseline treatments where the same model is used in the four supply chain participants (see *IPI={0,85,170,255}* in tables 4, 5, 6, 7, and 8). These are summarized in table 9. As expected, the classic OUT policy with naïve forecasting *(model 0)* is greatly outperformed by the other policies. The introduction of a smoothing mechanism is thus a fruitful solution for coping with the Bullwhip Effect and hence for improving the supply chain operation. In this work, we have explored three of them: moving average forecasting (*model 1*), demand exponential smoothing (*model 2*), and adding a proportional controller (*model 3*).

Table 9 95% confidence interval for the mean when the same inventory model is used in the four echelons.

Inv. Policies Interaction	OUT Policies *SR-Re-Wh-Fa*	Bullwhip Effect *Shop Ret.*	*Retailer*	*Wholesaler*	*Factory*	*Sup. Chain*
0	0-0-0-0	3.98 ±1.63	2.77 ±0.75	1.66 ±0.17	1.35 ±0.06	30.18 ±23.29
85	1-1-1-1	1.48 ±0.02	1.56 ±0.01	1.63 ±0.01	1.69 ±0.01	6.41 ±0.21
170	2-2-2-2	1.47 ±0.01	1.55 ±0.02	1.61 ±0.01	1.67 ±0.01	6.16 ±0.23
255	3-3-3-3	1.83 ±0.34	1.85 ±0.30	1.74 ±0.25	1.55 ±0.20	10.40 ±5.62

By comparing them, we observe that both the moving average and the exponential smoothing not only reduce dramatically the Bullwhip Effect but they also offer a much more robust performance against the environmental factors; note the confidence intervals are much narrower. The Bullwhip Effect generated is fairly similar in the five scenarios: the mean Bullwhip ratio ranges between 6.15 and 6.79 for the moving average (see *IPI=85* in tables 5 and 8) and between 5.99 and 6.61 (see *IPI=170* in tables 4 and 6). Differences are neither significant between the difference supply chain echelons.

On the contrary, the performance offered by the addition of the controller strongly depends on the supply chain scenario. In this regard, the proportional regulator is especially efficient in terms of Bullwhip reduction when the demand variability is high in comparison with the safety stock; see tables 5 and 7. Indeed, its positive impact is stronger than the two forecasting techniques in this scenarios. It can also be underlined that, while the amplification presents a slightly growing trend for *models 1 and 2*, the Bullwhip ratio is decreasing in the position of the supply chain in *model 3*.

5.3.2 The impact of the interaction.

We now consider the entire range of combinations among the inventory models of the four echelons. In this sense, figure 6 compares the previous baseline treatments (we do not represent *model 0* for the sake of clarity) with the optimal solution for the supply chain in one test within each scenario (tests 1, 5, 8, 12, and 14). To analyze the Bullwhip Effect, this graph represents the standard deviation of the orders issued throughout the system.

This figure provides the reader with a clear message: the best solution for the supply chain is not derived from applying the same—optimal—policy in all the nodes. In other words, the interaction of different replenishment methods and forecasting techniques across traditional (non-collaborative) supply chains may have a positive impact on performance.

This idea can be observed in the five scenarios. For example, we focus on scenario III. Figure 6 shows that the most appropriate inventory model in this case is the demand exponential smoothing (*model 2*; see *IPI=170* in table 6). However, the use of moving averages to forecast in the upper nodes of the supply chain (see *IPI=165*) leads the supply chain to an operational improvement—the Bullwhip Effect is reduced from 5.99 to 5.18.

We can therefore conclude that the harmful effects of different replenishment and forecasting methods can be buffered when working with other models throughout the system. It means that the suitability of each alternative depends not only on the external environment, but also on the decisions taken in the other members and even on the position of the node.

To analyze these results in more detail, we roughly divide them into two groups: (1) when the safety stock is relatively low or moderate in comparison with the demand variability; i.e. scenarios I, III, and V; and (2) when the safety stock is relatively high in comparison with the demand variability; i.e. scenarios II and IV.

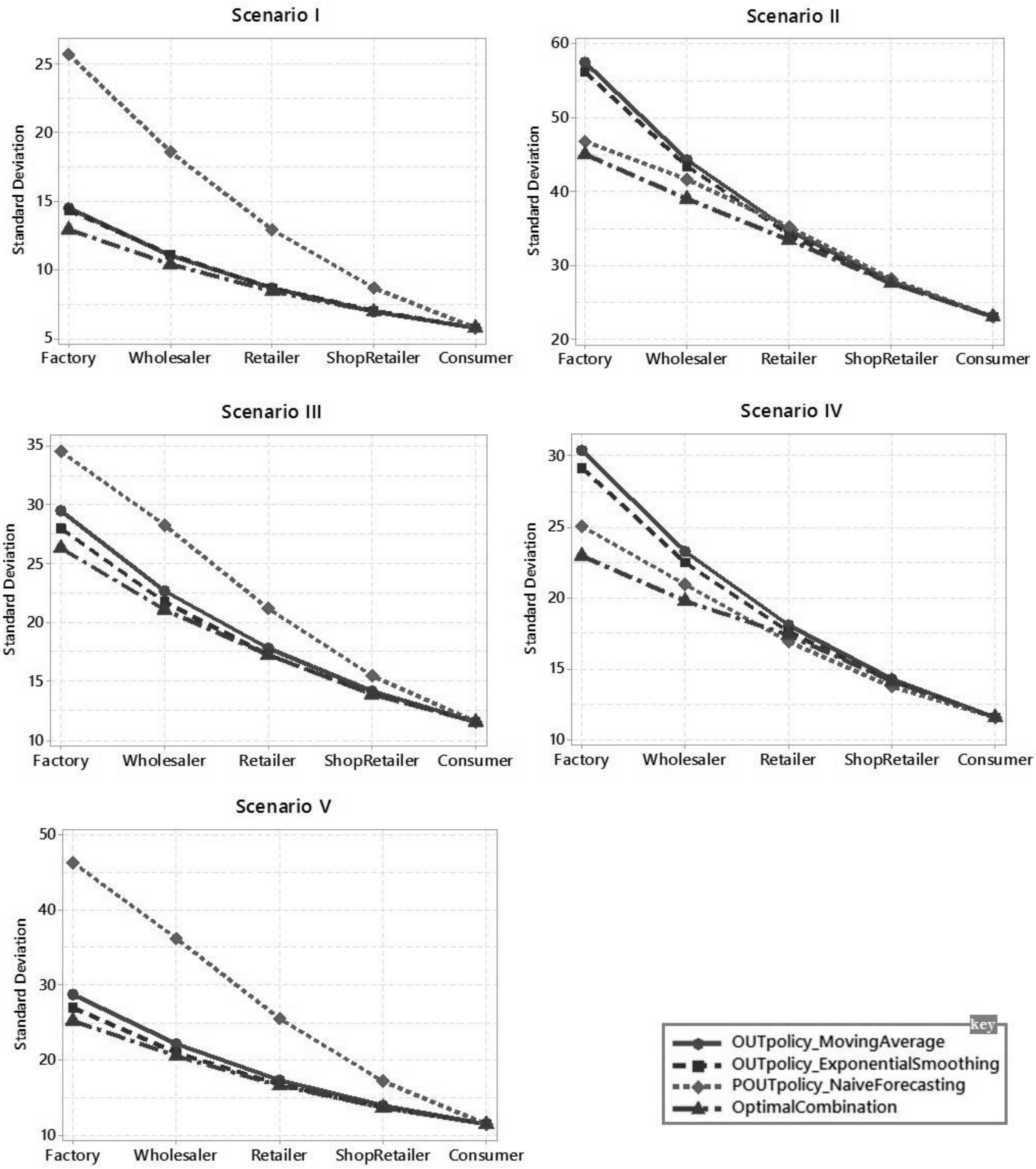

Fig. 6 Standard deviation of the orders issued in the supply chain in the four scenarios

In the first context (see tables 4, 6, and 8), the combination of moving average and exponential smoothing forecasts proves to be the best solution for the supply chain. For instance, the optimal interaction in scenario I arises when both the upper and lower echelons use a moving average to forecast and at the same time the intermediate echelons employ an exponential smoothing. The Bullwhip ratio is reduced from 6.36 and 6.61 to 5.34 (*IPI={85,170,105}*; see table 4) when they are combined. Hence, the use of different forecasting methods in the system mitigates the Bullwhip Effect generation.

However, the system behaves differently in the second context (tables 5 and 7). As seen in the individual study, the controller offers a great operational performance. In these scenarios with high customer demand variability—in which the Bullwhip Effect provokes that the swings become even bigger—, adding an inventory controller is a successful solution, especially in the upper nodes. Its combined effect with other smoothing solutions alleviates the Bullwhip phenomenon. For example, in test 12 the regulator together with moving average and exponential smoothing forecasts enables the mitigation of the increase in the variability of orders, reducing the Bullwhip ratio from 4.59 to 3.77 (*IPI={255,159}*; see table 7).

By way of illustration, figure 7 displays the variability of the orders transmitted in the supply chain over 30 consecutive periods in test 1 from scenario I. The first 15 periods represent the orders issued in the treatment *IPI=0* (where all echelons use naïve forecasting in a traditional OUT policy) while the last 15 periods are related to the treatment *IPI=105* (the best solution for the supply chain). The figures clearly show the great reduction in the Bullwhip Effect—indeed, it decreases from 74.49 to 5.02 over the entire simulation time.

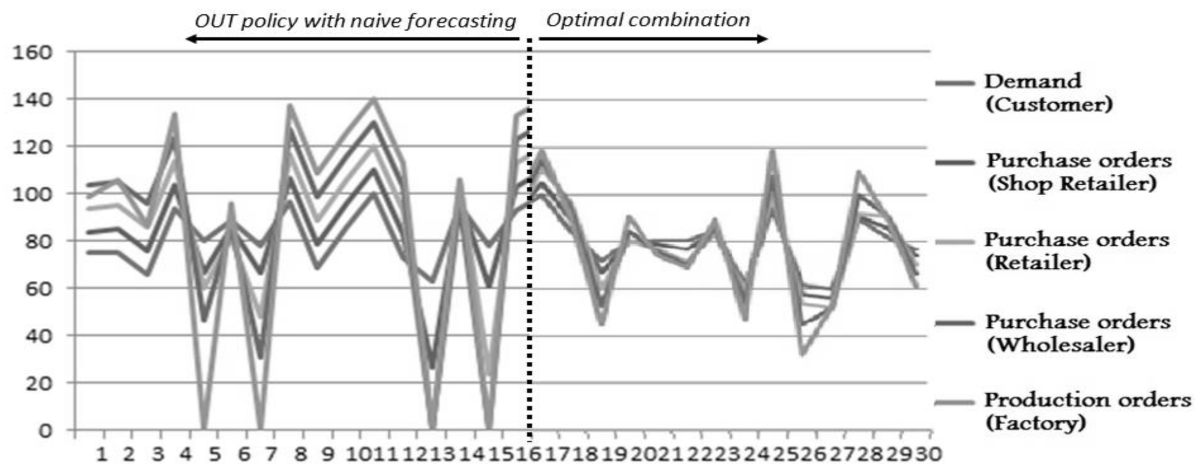

Fig. 7 Difference between the orders issued in the supply chain in test 1 in the treatments *IPI=0* and IPI=105.

6. Conclusions and Future Research Lines

After analyzing a sample of 14,933 buyer-supplier dyad observations in different US industries, Isaksson and Seifert (2016) reported an average increase in the variability (measured through the coefficient of variation) of the orders between echelons that equaled 90%. This magnitude illustrates the current prevalence of the Bullwhip Effect, which harmfully impacts the firms that experience it. They do not only incur in high operating expenses but also in excessive investment levels to cope with a greater uncertainty.

The simultaneous adoption of local optimum solutions by the various nodes is a major cause of this phenomenon. This study approaches to this organizational issue by focusing on the interaction of distinct replenishment methods and forecasting techniques throughout the supply chain. We therefore model the production and distribution system as a set of organizations, each one operating with a different inventory model and taking individual decisions.

An interesting finding of this article is that the combination of different smoothing mechanisms across the supply chain has a positive impact on the overall performance. Under this traditional scenario, the Bullwhip phenomenon proves to be unavoidable, but the inefficiencies generated individually by self-centered policies can be significantly buffered by their interaction throughout the system. In this regard, our results provide evidence of the fact that the efficiency of each inventory model depends not only on the external environment but also on the decisions of the other levels, and even on the position within the supply chain.

More specifically, we have implemented a baseline OUT algorithm and three smoothing rules—moving average forecasting, demand exponential smoothing, and the addition of an inventory controller—in five different scenarios depending on an exogenous variable (customer demand variability) and an endogenous variability (safety stock).

We have observed that the interaction of different forecasting techniques mitigates the generation of the Bullwhip Effect, especially in contexts in which the safety stock is relative high in comparison to the demand variability (i.e. when the target customer service level is high). When the demand variability is high in relative terms, the controller offers a great performance, mainly in the upper nodes of the supply chain, which can be understood as a managerial implication of this work. In this sense, forecasting has shown to be a more robust mechanism than the proportional controller to cope with the Bullwhip Effect.

There is a range of possibilities for future research that we plan to undertake as next steps in this field. The ABMS development allows us to easily increment the system functionality—and hence the research scope. For example, by add new prediction techniques, such as the MMSE forecasting or artificial intelligence-based methods. Another venue of future work would be to explore the design of a robust adaptive mechanism so that each node is able to readjust its inventory model (controller setting, safety stock, forecasting rules) depending on the changes in the environment. Modifying its dynamic response is essential in the current fast-moving global scene in order to ensure the long-term viability of the supply chain, and we strongly stand up for ABMS as a powerful tool in the decision-making process aimed at achieving a resilient and flexible system.

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