

# Multiagent Model to Reduce the Bullwhip Effect

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**Keywords:** Bullwhip, Supply Chain, Multiagent System, Time Series Forecasting.

**Abstract:** There are several circumstances which, in recent decades, have granted the supply chain management a strategic role in the search for competitive advantage. One of the goals is, undoubtedly, the reduction of Bullwhip Effect, which is generated by the amplification of the variability of orders along the chain, from the customer to the factory. This paper applies multiagent methodology for reducing Bullwhip Effect. To do this, it considers the supply chain as a global multiagent system, formed in turn by four multiagent subsystems. Each one of them represents one of the four levels of the traditional supply chain (Shop Retailer, Retailer, Wholesaler and Factory), and it coordinates various intelligent agents with different objectives. Thus, each level has its own capacity of decision and it seeks to optimize the supply chain management. The problem is analyzed both from a non collaborative approach, where each level seeks the optimal forecasting methodology independently of the rest, and from a collaborative approach, where each level negotiates with the rest looking for the best solution for the whole supply chain.

## 1 INTRODUCTION

A supply chain encompasses all participants and processes involved in satisfying customer demands around some products. Analyzing it, Forrester (1961) noted that small changes in customer demand are amplified along the supply chain, leading to larger variations in demand supported by the different levels, as they are further away from customer. This is called the Bullwhip Effect (or Forrester Effect), which, according to the subsequent research by Lee et al. (1997), is due to four main causes: demand forecastings, order batching, price fluctuations, and shortage gaming.

There have been several changes in the last two decades in the macro environment of the companies that have set up a new business perspective. From this, the production function is considered to have a strategic role as a source of competitive advantage, so that the practices related to managing the supply chain now represent one of the main concerns of business. In these circumstances, it is especially emphasized the importance of proper management of the supply chain regarding different objectives. One of them is undoubtedly reducing the Bullwhip Effect. In fact, Disney et al. (2003) demonstrated that the Bullwhip effect leads the supply chain to unnecessary costs that can represent, in some cases,

more than 30% of the total costs thereof.

In this context, this paper proposes the application of Artificial Intelligence techniques to the problematic associated with the Bullwhip Effect, in order to create a tool aimed at reducing variations in the demands transmitted along the supply chain. More specifically, Distributed Intelligence is applied to the problem through a multiagent system. It determines the optimal order policy based on the best demand forecasting method for each one of the different levels that make up the supply chain, understanding the forecasting errors as the main causes in the creation of the Bullwhip Effect.

The presented document is divided into four sections besides this introduction. Section 2 shows a review of the most relevant and recent literature in terms of reducing the Bullwhip Effect, with special emphasis on models based on Distributed Intelligence. Section 3 describes the model created with the different agents that compose it, the structure which includes them and the relationships among them, which is the way in which intelligence has been introduced to the system. Section 4 presents the results, mainly related to reducing the Bullwhip Effect, for which we have used time series data from the literature. Finally, section 5 presents the conclusions according to the planned objectives.

## 2 BACKGROUND: REDUCING THE BULLWHIP EFFECT

### 2.1 Traditional Solutions

Each supply chain has its own characteristics, mainly conditioned by the type of product which is offered to the final consumer and by the market conditions in which it moves, and that unquestionably complicates the analysis of valid methodologies for reducing the Bullwhip Effect. However, it is possible to find some common problems to all of them, and several authors have proposed general strategies to be adapted to each particular supply chain. These traditional solutions to Bullwhip Effect are mainly based on collaboration among the various members of the supply chain, often sharing some information.

Thus, some practices that are carried out in some companies and which have been successful in reducing the Bullwhip Effect are:

- Use of Information Technology systems such as electronic data interchange (Machuca and Barajas, 2004).
- Postponement, which is based on a redesign of products with the aim that the differentiation takes place in nodes near the customer. (Chen and Lee, 2009).
- Efficient Consumer Response (ECR). These are associations of companies to synchronize the supply chain. (Disney et al., 2002).
- Vendor Managed Inventory (VMI). The supplier controls the inventory of the consumer, deciding on delivery times and quantities. (Holmström, 1997).
- Collaborative Planning, Forecasting and Replenishment (CPFR). It means that members of the supply chain can develop, in a collaborative way, business plans and processes (Ji and Yang, 2005).

### 2.2 Multiagent Systems in the Supply Chain Management

The supply chain management, including all that related to the Bullwhip Effect, is a highly complex problem, conditioned by multiple agents, each of which has to serve a large number of variables. In the last two decades, authors have looked for different ways to optimize the management by using new techniques based on Artificial Intelligence. Among these methods, there are several authors who have approached the supply chain as a network of

intelligent agents. These are called multiagent systems.

Fox et al. (1993) were pioneers in the proposal of the organization of the supply chain as a network of cooperating intelligent agents. In their work, each agent executes one or more functions of the supply chain, coordinating their actions with other agents. Later, Shen et al. (1998) developed the tool MetaMorph II, which, through an agent-based architecture, integrates partners, suppliers and customers with a lead company through their respective mediators within a supply chain network via the Internet.

Kimbrough et al. (2002) studied whether a structure based on agents could be valid for the supply chain management, and they reached the conclusion that the agents were able to effectively play the well known Beer Game (Sterman, 1989), reducing the Bullwhip Effect. Moyaux et al. (2004) used a multiagent system for modeling the behavior of each company in the supply chain. The paper proposes a variant of the Beer Game, which they called "Quebec Wood Supply Game".

Liang and Huang (2006) developed, based on a multiagent architecture, a model which allowed predicting the order quantity in a supply chain with several nodes, where each one of them could use a different system of inventory. De la Fuente and Lozano (2007) presented an application of Distributed Intelligence to reduce the Bullwhip Effect in a supply chain, based on a genetic algorithm. Zarandi et al. (2008) introduced Fuzzy Logic in the analysis.

Wu et al. (2011) applied the multiagent methodology to establish a supply chain model and to analyze in detail the Bullwhip Effect created along the chain, considering the non existence of information exchange among different members. One of the last studies in that regard is the one by Saberi et al. (2012), It develops a multiagent system, and which links the various agents that form it, emphasizing the collaborative aspect.

We can conclude that supply chain has become a complex system that requires modern methodologies for its analysis, seeking to optimize their management.

## 3 CONSTRUCTION OF THE MODEL

### 3.1 Global Multiagent System

To prepare the base model, we have considered a

traditional supply chain with linear structure, which consists of five main levels: Consumer, Shop Retailer, Retailer, Wholesaler and Factory. Figure 1 shows the graphical representation of the levels, indicating the materials flow, which occurs from the top of the chain (Factory) to the lower levels (Consumer). Therefore, it is called downstream flow. The information flow is considered to be in the opposite way, which is called downstream flow.



Figure 1: Supply Chain Model.

The methodology used for the modeling and analysis in this research is based on multiagent systems. A multiagent system is a system composed of multiple intelligent agents, which interact among them. An agent can be defined as a computer system, which is able to perform autonomous and flexible actions that affect their environment according to certain design goals.

Thus, the behavior of each one of the main levels of the supply chain (Shop Retailer, Retailer, Wholesaler and Factory) will be simulated using a multiagent subsystem (which we will call MASS). The four multiagent subsystems form a global multiagent system (which we will call MAGS) which represents the whole supply chain. In turn, each subsystem will consist of several intelligent agents which interact among them, seeking to satisfy predefined objectives.

In our case, we consider static agents as they do not travel through the network, which have an internal symbolic reasoning model committed to the planning and negotiation for coordination with other agents. Thus, each agent has an incomplete knowledge of the problem, with decentralized data, so there is no overall control in the system.

All this means that each subsystem can represent a member of the supply chain, so that the global multiagent system has similar characteristics to the overall supply chain as:

- **Autonomy:** each level decides and executes without external intervention.

- **Social skills:** each level communicates with the other ones.
- **Reactivity:** each level modifies its behavior depending on the environment.

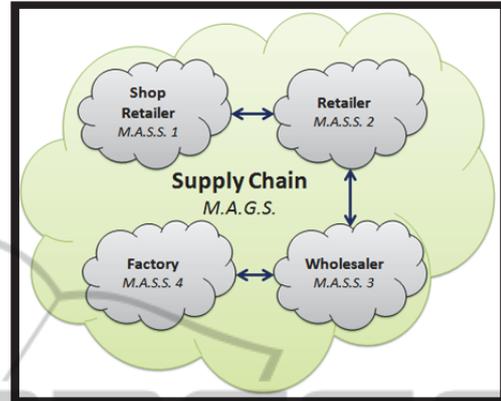


Figure 2: General model of the global multiagent system.

Figure 2, by way of synthesis, shows a scheme of the global multiagent system (MAGS) which simulates the supply chain, formed in turn by four local multiagent subsystems.

Thus, the supply chain management through a multiagent system allows the creation of an agile network which reacts in real-time to customer demands, compared to traditional systems, where everything is decided before the client makes the request.

### 3.2 Multiagent Subsystems

Each multiagent subsystem replicates the behavior of one of the levels of the supply chain. In turn, this subsystem will consist of several interconnected intelligent agents. Each multiagent subsystem will have some set goals that it will try to meet as best as possible, given certain conditions in its environment.

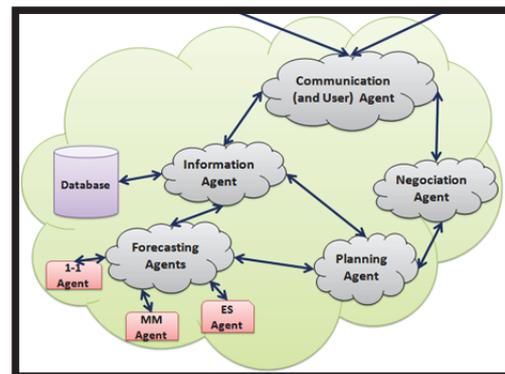


Figure 3: Detail of the multiagent subsystem on each level of the supply chain.

Figure 3 shows the detail of the internal structure of a multiagent subsystem. There, it is possible to identify five types of agents: Communication Agent, Information Agent, Planning Agent, Forecasting Agents –which, in turn, include three agents according to the used method of demand forecasting– and Negotiation Agent. It also highlights the existence of a database to store the most relevant information for each subsystem.

### 3.2.1 Information Agent

The database associated with each multiagent subsystem store a temporary data series for the level of the supply chain partner. These mainly include:

- Information on the demands received.
- Information on demand forecasting to be considered.
- Information on the situation of inventory at the beginning and at the end of periods to be considered.
- Information on deliveries to the lower level of the supply chain.
- Information about orders to the top level of the supply chain.

Thus, the Information Agent's main objective is the mediation between the database and the other agents. So, they do not see a database, but another agent, and thus we achieve uniformity in the system. The Information Agent will only respond to requests for information from other agents and it will store the data given to him.

### 3.2.2 Communication (and User) Agent

Communication (and User) Agent will be responsible for carrying out the interactions of the multiagent subsystem with the adequate agents. It works, thus, as a spokesman. Communications among the various levels of the supply chain will be only through Communication Agents. Each one works in two ways:

- It transmits purchase orders received by the agents of its own level to the top level of the supply chain.
- It collects the purchase orders received from the lower level and it provides them to the other agents at its level.

Furthermore, the Communication (and User) Agent acts as an intermediary between the multiagent subsystem and the user, so that the other agents do not relates directly to the user. This agent communicates with the user through a graphical

interface, with two objectives:

- To allow the user to enter information that may condition the environment of the agents.
- To show the user the most relevant information on the supply chain management.

### 3.2.3 Forecasting Agents

Forecasting Agents are the real core of the system. Each one will carry out the calculations of demand forecasting for future periods based on a predetermined method. All forecasting methods will make their decisions based on historical data, received from the Information Agent.

Initially, the system consists of three agents, but it is an open group, so that in future we can add new forecasting methods, increasing its capabilities.

1-1 Agent forecasts using one-one method, which is based on estimating the demand at any period as the one in the previous period. It can be expressed as follows:

$$\hat{D}_t = D_{t-1} \quad (1)$$

Where  $\hat{D}_t$  is the forecast of demand in period  $t$ , and  $D_{t-1}$  is the demand received in period  $t$ .

MM Agent forecasts using the moving average method of order  $n$ , which estimates the demand in any period as the average of the latest  $n$  demands. It can be expressed as:

$$\hat{D}_t = \frac{1}{n} [D_{t-1} + D_{t-2} + \dots + D_{t-n}] \quad (2)$$

Where  $\hat{D}_t$  is the forecast of demand in period  $t$ ,  $n$  is the number of periods to be considered for the moving average and  $D_{t-i}$  ( $i \in [1, n]$ ) is the demand received in period  $t-i$ .

ES Agent, finally, determines forecasts according to the simple exponential smoothing method, which estimates the demand in any period as the weighted average of the last period demand and the forecast of demand in that period. It can be expressed as follows:

$$\hat{D}_t = \alpha \cdot D_{t-1} + (1 - \alpha) \cdot \hat{D}_{t-1} \quad (3)$$

Where  $\hat{D}_t$  is the forecast of demand in period  $t$ ,  $\hat{D}_{t-1}$  is the forecast of demand in period  $t-1$ ,  $D_{t-1}$  is the demand received in period  $t-1$ , and  $\alpha \in [0,1]$  is the exponential smoothing coefficient or weighing of the forecasting error.

MM Agent evaluates all the moving averages from  $n = 2$  to  $n = 15$  (for  $n = 1$ , it coincides with

one-one method), selecting, on the basis of available data, the optimal moving average. The ES Agent evaluates all the forecasts for coefficients from  $\alpha = 0.1$  to  $\alpha = 0.9$ , with jumps of 0.1, selecting the optimal coefficient. In both cases, we choose the optimal forecast according to the mean square error criterion, which must be minimized, expressing it as follows:

$$MSE = \frac{1}{m} \sum_{t=1}^m (\widehat{D}_t - D_t)^2 \quad (4)$$

Where  $\widehat{D}_t$  is the forecast of demand in period  $t$ ,  $D_t$  is the real demand in period  $t$  and  $m$  is the number of available data.

### 3.2.4 Planning Agent

Planning Agent collects the forecasts made by the Forecasting Agents, and it is the responsible of deciding which one is the best, based on the Bullwhip Effect generated in the supply chain. Many authors quantify the Bullwhip Effect in supply chain as follows:

$$BW = \frac{\sigma_{df}^2}{\sigma_{dc}^2} \quad (5)$$

Where  $\sigma_{dc}^2$  is the variance in consumer demand for the product, and  $\sigma_{df}^2$  represents the variance in the rate of the factory production.

Likewise, the Bullwhip Effect generated at each step can be defined as the ratio of the variance in orders sent to the upper node of the supply chain, and the variance in orders received from the bottom node of the supply chain.

$$BW_i = \frac{\sigma_{out}^2}{\sigma_{in}^2} \quad (6)$$

Where  $BW_i$  represents the Bullwhip Effect generated in the level  $i$ ,  $\sigma_{out}^2$  is the variance in orders sent to the upper node of the supply chain,  $y$   $\sigma_{in}^2$  represents the variance in the orders received from the lower node of the supply chain. This allows expressing the Bullwhip Effect along the chain as the product of the ratios that define the Bullwhip Effect at each level.

In these circumstances, the Planning Agent will select as the optimal forecasting method that which minimizes the effect generated in that level, seeking to reduce the effect generated in the chain, unless it

is activated Negotiation Agent, in which case the selection of the optimal method is detailed later.

From there, the Planning Agent will be responsible for providing the Information Agent the necessary information on the node to complete the database. This information, for each period, includes:

- The forecast of demand ( $\widehat{D}_t$ ) according to the optimal method.
- The initial inventory situation ( $S_{I_t}$ ), which is the sum of the final situation of the inventory in the previous period ( $S_{F_{t-1}}$ ) and orders received at the beginning of the period, which, considering a unitary lead time, are assumed to have been made during the previous period ( $O_{t-1}$ ).

$$S_{I_t} = S_{F_{t-1}} + O_{t-1} \quad (7)$$

- The final situation of the inventory ( $S_{F_t}$ ), which is the difference between the initial situation of the inventory ( $S_{I_t}$ ) and the demand received in the current period ( $D_t$ ), so that negative values show stock-out.

$$S_{F_t} = S_{I_t} - D_t \quad (8)$$

- The deliveries to the lower level of the supply chain ( $Y_t$ ), which coincides with the demand ( $D_t$ ), unless it is impossible to satisfy it completely.

$$Y_t = \min\{D_t, S_{I_t}\} \quad (9)$$

- The orders to be made to the upper level of the supply chain ( $O_{t-1}$ ), which can be expressed as the difference between the forecast of the demand ( $\widehat{D}_t$ ) and the final situation of the inventory ( $S_{F_t}$ ), or zero, if the above difference is negative.

$$O_t = \max\{\widehat{D}_{t+1} - S_{F_t}, 0\} \quad (10)$$

### 3.2.5 Negotiation Agent

Negotiation Agent will be activated by the user, when it is considered appropriate by the latter, from the interface of the developed tool. When it is active, it will allow the management of forecasting demand in the supply chain in a coordinated way through collaboration between Shop Retailer and Retailer, on the one hand, and Wholesaler and Factory, on the other.

Every Negotiation Agent will initiate a process

of discussion with the Negotiation Agent to which it relates, through the Communication Agent. The collaborative framework is mainly based on the sharing of information between the agents with the goal of finding a balance between a forecast considered acceptable in local terms, and a forecast which is profitable to the whole system, since both terms can sometimes come into opposition.

Thus, the Negotiation Agent for each level interacts with the Planning Agent, seeking the optimal policy, which not only tries to minimize the Bullwhip Effect generated in the node, but it also seeks to minimize the global Bullwhip Effect generated in the supply chain.

### 3.3 Implementation of the Model

To implement the model, we have used NetLogo 5.0.1. Figure 4, by way of example, shows a screenshot of the interface of the implemented model in a particular instant of a simulation.

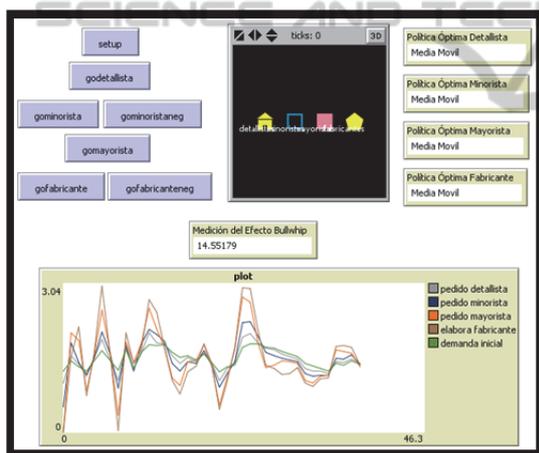


Figure 4: Screenshot of the interface.

NetLogo is a programming environment created by Uri Wilensky (1999) and continuously developed by the Center for Connected Learning and Computer-Based Model, which allows the development of multiagent models for simulation and analysis of phenomena of a different type.

## 4 NUMERICAL APPLICATION

### 4.1 Tests with Random Demands

First, we describe numerically some tests carried out on the developed multiagent model, considering random demands, which follow certain statistical

distributions. We have used samples with 30 temporary data.

Table 1 presents the results of the fifteen tests, where the columns contain the following values: the number of the test; the statistical distribution which follows the demand, which can be normal  $N(\mu, \sigma)$  (where  $\mu$  refers to the mean demand and  $\sigma$  refers to its standard deviation) or Poisson  $P(\mu)$  (where  $\mu$  is the mean of demand); the Bullwhip Effect generated in the case that all levels use the one-one model (BW1); the Bullwhip Effect generated by using the developed tool without activating the Agent Negotiation (BW2); and the Bullwhip Effect generated by using the developed tool when activating the Agent Negotiation (BW3).

In all cases, it is considered that the initial inventory at all levels of the supply chain coincides with the average of the corresponding statistical distribution.

Table 1: Results of tests with random demands.

Test	Demand	BW1	BW2	BW3
1	$N(100,10)$	266.42	12.64	2.37
2	$N(100,10)$	234.88	10.17	2.79
3	$N(100,10)$	256.26	26.16	3.33
4	$N(100,5)$	692.59	12.70	2.41
5	$N(100,5)$	699.37	30.54	3.33
6	$N(100,5)$	649.15	30.29	3.49
7	$N(100,1)$	1399.00	25.43	3.11
8	$N(100,1)$	2717.60	13.87	2.16
9	$N(100,1)$	2010.94	7.51	1.97
10	$P(100)$	323.64	16.68	2.18
11	$P(100)$	259.36	2.19	1.48
12	$P(100)$	396.19	19.96	3.09

The results presented in Table 1 show, broadly speaking, the huge efficiency of the multiagent model developed in this paper versus one-one model. In all cases, the achieved results, in terms of Bullwhip Effect, improve the performance of the one-one model in several orders of magnitude.

In these circumstances, the shown results demonstrate the poor performance of the model 1-1 when the demand for a particular product can be estimated through a Poisson or normal distribution. In the case of normal distribution, the Bullwhip Effect generated along the supply chain considerably increases when the standard deviation of consumer demand decreases. In this case, the variance in orders along the supply chain will also decrease, but the variation will be smaller in relative terms.

So, with such a degree of randomness, the approximation of the demand in a certain period according to the demand in the previous period is a

bad alternative. In fact, the model tends to select moving averages of a large number of periods. In the same vein, the model determines that the best solutions with exponential smoothing are offered by very low parameters, in order to minimize the effect of the latest demands in the forecast.

In the referred cases with high randomness, it is necessary to use other methods of forecasting, and a system based on intelligent agents is, in view of the data, a good way to coordinate them. The collected results show that using simple forecasting methods, such as moving averages or exponential smoothing, allows reaching great results in reducing the Bullwhip Effect.

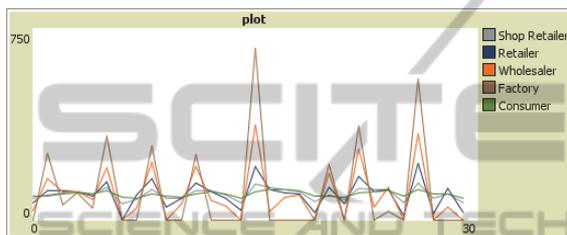


Figure 5: Variation of orders along the supply chain in the test 1 with One-One model.

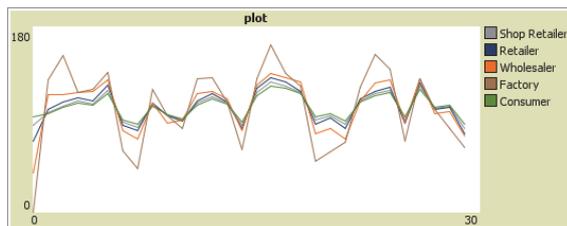


Figure 6: Variation of orders along the supply chain in the test 1 with the developed multiagent model.

By way of example, Figures 5 and 6 show variations of purchase orders made by the four levels of the supply chain in test 1, as well as consumer demand, obtained from a normal distribution with mean 100 and standard deviation 10. It is clearly seen how the consumer demand, which is the same in both cases, is much more amplified in the case of one-one model than in the case of multiagent system. Table 2 shows, in each case, the optimal policy for each level of the supply chain.

The results obtained also show that close negotiation and collaboration in the supply chain between Factory and Wholesaler, on the one hand, and Shop Retailer and Retailer, on the other, is a very appropriate strategy for the reduction of the Bullwhip Effect. Collaboration significantly improves the performance of multiagent model, achieving amazing results.

Table 2: Optimal Policy for each level of the supply chain in test 1.

Level	Optimal Forecasting Method
Shop Retailer	Exponential Smoothing with $\alpha = 0.2$
Retailer	Exponential Smoothing with $\alpha = 0.2$
Wholesaler	Moving Average with $N = 12$
Factory	Moving Average with $N = 14$

## 4.2 Tests with Real Demands

For further analysis, some tests with real data on developed multiagent model will be shown. We have chosen eight time series obtained from databases. Table 3 shows, for each one of the eight series, the series name; the database which contains the information; the content of the information; and the number of data which comprise the series.

Table 3: Data on the time series used to test the multiagent model.

Series	Database	Content	Number of data
AL03	Abraham (1983)	Electricity Consumption	106
AL04		Car sales	108
AL09		Mortgage – Loan Differences	159
AL11		Gas Consumption	106
BJ02	Box – Jenkins (1976)	Price of IBM shares	369
BJ06		Wolfer sunspots	100
BJ08		Airline company passengers	144
BJ15		Warehouse sales	150

Table 4 presents the results of applying the genetic algorithm on the eight series, where the columns contain the following values: the number of the test; the used series; the Bullwhip Effect generated if all levels of the supply use the one-one model (BW1); the Bullwhip Effect generated by using the developed tool without activating the Agent Negotiation (BW2); and the Bullwhip Effect generated by using the developed tool by activating the Agent Negotiation (BW3).

As in the case of random demands, it is considered that the initial inventory, in all cases, coincides with the demand of the first period.

The obtained results again demonstrate the effectiveness of multiagent model in reducing Bullwhip Effect generated along the supply chain. In all cases, the results generated by the one-one model are improved, although the difference is more relevant in some cases than in other ones.

Table 4: Results of tests with real demands.

Test	Series	BW1	BW2	BW3
1	AL03	65.90	1.54	1.22
2	AL04	48.70	1.32	1.11
3	AL09	29.93	3.29	2.61
4	AL11	13.74	6.00	2.88
5	BJ02	4.20	1.12	1.05
6	BJ06	15.41	4.18	3.35
7	BJ08	12.28	1.25	1.18
8	BJ15	2.75	1.13	1.03

This situation evidences again that the use of simple forecasting methods, coordinated through a multiagent system allows a great improvement, in terms of Bullwhip Effect, comparing to the results of the one-one model. There is not clear proportionality between the result provided by the multiagent system and the result provided when all agents use the one-one model, which indicates again that the fitness of each forecasting method depends on the characteristics of the time series.

When analyzing the results, it is more appropriate to do it from a relative point of view that from an absolute one. When considering a larger number of data, and since the series in some cases have definite trends, the values of the Bullwhip Effect are significantly lower than in the cases analyzed with random demands.

AL09 time series is a clear example where the results of the multiagent system significantly improve the results of the one-one model. Without introducing Negotiation Agent, the Bullwhip Effect is divided by 9 when using the model. Figures 7 and 8 show variations of purchase orders made by the four levels of the supply chain. Comparing the vertical scale of both graphs, it is possible to see the huge difference. Table 5 shows, in each case, the optimal policy for each level of the supply chain.

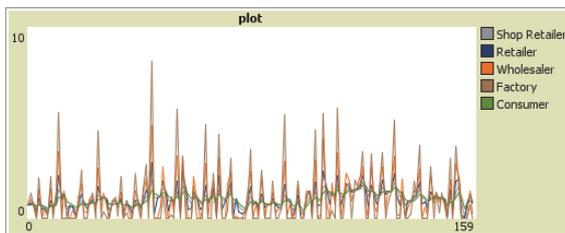


Figure 7: Variations in orders along the supply chain for the AL09 series with the one-one model.

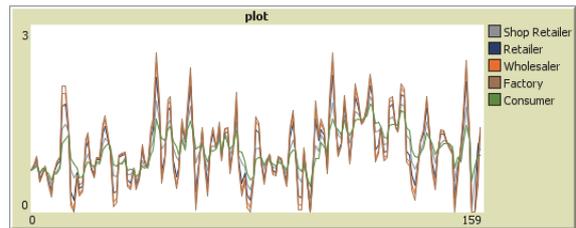


Figure 8: Variations in orders along the supply chain for the AL09 series with the multiagent model.

Table 5: Optimal Policy for each level of the supply chain for the AL09 series.

Level	Optimal Forecasting Method
Shop Retailer	Moving Average with $N = 2$
Retailer	Moving Average with $N = 2$
Wholesaler	Moving Average with $N = 14$
Factory	Moving Average with $N = 14$

A reverse situation is the one for the time series AL11. Figures 9 and 10 show the variations of purchase orders made by the four levels of the supply chain. With these data, the multiagent system is not able to produce such a high improvement over the one-one method, given the strongly stationary character in the series.

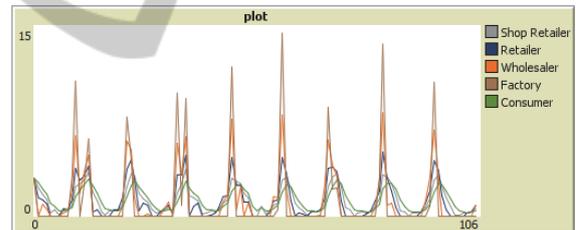


Figure 9: Variations in orders along the supply chain for the AL11 series with the one-one model.

The results obtained in the analysis also suggest that collaboration in the supply chain is an appropriate solution for reducing the Bullwhip Effect.

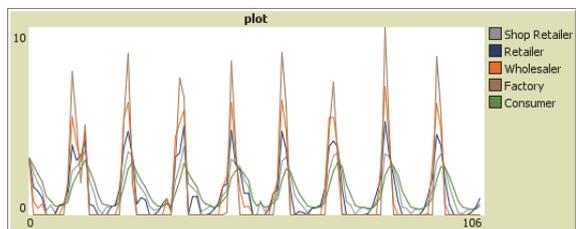


Figure 10: Variations in orders along the supply chain for the AL11 series with the multiagent model.

### 4.3 Application of Advanced Forecasting Methods

Finally, after having demonstrated the effectiveness of the multiagent model, we consider the introduction of advanced forecasting methods, such as the autoregressive integrated moving average (ARIMA models). The objective is to assess the extent whether these techniques can help for reducing the Bullwhip Effect. Then, we use the same series as in section 4.2, but considering that the first stage of the supply chain (Retailer) performs the demand forecasting using ARIMA techniques.

The ARIMA model, introducing the seasonality, can be defined by:

$$(p, d, q)(P, D, Q)_n$$

Where p (P) is the order of the autoregression, d (D) is the order of differentiation and q (Q) is the order of the moving average. Lowercase parameters are nonseasonal, while uppercase parameters are seasonal, where n is the order of seasonality.

To carry out the analysis, we use IBM SPSS Statistics 19. Table 6 contains the proposed model for each one of the eight time series.

Table 6: ARIMA models of the time series.

Series	Database	ARIMA Model
AL03	Abraham (1983)	$(0,0,1)(0,1,1)_{12}$
AL04		$(2,0,0)(0,1,0)_{12}$
AL09		$(1,0,0)$
AL11		$(1,0,0)(0,1,1)_{12}$
BJ02	Box – Jenkins (1976)	$(0,1,0)$
BJ06		$(0,0,2)(1,0,0)_{11}$
BJ08		$(0,1,1)(0,1,1)_{12}$
BJ15		$(1,1,1)$

Table 7 is an extension of table 3 but adding a column with the results when considering the ARIMA models to forecast demand in the first level of the supply chain (BW4). Furthermore, we show the reduction achieved in each case.

The results presented show that the use of advanced forecasting methods leads to the reduction of Bullwhip Effect. Thus, the inclusion of ARIMA models at the lowest level of the supply chain provides very interesting results, and it can significantly reduce, in many cases, the Bullwhip Effect. In these circumstances, we consider to incorporate them to the multiagent model, through a new agent within the Forecasting Agents.

Table 7: Results of the tests using ARIMA models.

Test	Series	BW2	BW4	Reduction
1	AL03	1.54	1.52	1.30%
2	AL04	1.32	1.28	3.03%
3	AL09	3.29	2.54	22.80%
4	AL11	6.00	3.89	35.17%
5	BJ02	1.12	1.13	0.89%
6	BJ06	4.18	3.45	17.46%
7	BJ08	1.25	1.23	1.60%
8	BJ15	1.13	1.12	0.88%

Figures 11 and 12 depict, by way of example, the results obtained for the two cases to compare, in the series BJ06. It is possible to see how the use of ARIMA models significantly reduces, above 15%, the variability of orders along the supply chain.

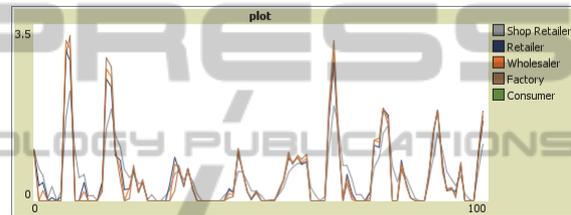


Figure 11: Variation of orders along the supply chain for the BJ06 series with multiagent model.

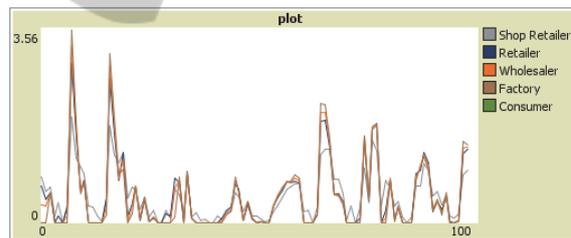


Figure 12: Variation of orders along the supply chain for the BJ06 series with multi-agent model, using ARIMA forecasts in the lower level of the supply chain.

## 5 CONCLUSIONS

The paper describes an application of multiagent methodology aimed at reducing the Bullwhip Effect in a supply chain. This is represented as a global multiagent system, itself composed of four subsystems multiagent. Each of them refers to one of the levels of the supply chain (Shop Retailer, Retailer, Wholesaler and Factory).

Tests performed on the raw data show that the one-one method greatly amplifies demand variability of end consumer throughout the supply chain, especially when the demands have a high degree of

randomness. In this context, the application of multiagent model, with other forecasting methods, markedly reduces the Bullwhip Effect generated.

To develop the tool, we have considered only simple forecasting methods, such as moving averages and exponential smoothing, so that each level of the chain uses the best one that suits the demand it should deal with. With them, it is possible to achieve great results in reducing Bullwhip Effect. Even so, we have also shown that the inclusion of more advanced forecasting methods (ARIMA models) allows an even better system performance.

Lastly, we have analyzed the effect of negotiation and collaboration among different levels of the supply chain, verifying that it is an adequate solution in reducing the Bullwhip Effect.

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