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ALTERNATIVE FORECASTING TECHNIQUES THAT REDUCE THE BULLWHIP EFFECT IN A SUPPLY CHAIN: A SIMULATION STUDY

ABSTRACT

The research of the Bullwhip effect has given rise to many papers, aimed at both analysing its causes and correcting it by means of various management strategies because it has been considered as one of the critical problems in a supply chain. This study is dealing with one of its principal causes, demand forecasting. Using different simulated demand patterns, alternative forecasting methods are proposed, that can reduce the Bullwhip effect in a supply chain in comparison to the traditional forecasting techniques (moving average, simple exponential smoothing, and ARMA processes). Our main findings show that kernel regression is a good alternative in order to improve important features in the supply chain, such as the Bullwhip, NSAmp, and FillRate.

KEY WORDS

Bullwhip effect, supply chain, kernel regression, system dynamics model

1. INTRODUCTION

An important feature in supply chain management is the Bullwhip effect which reflects the increase of demand variability as one moves up the supply chain, from the retailer to the manufacturer. Forrester [1] showed that this effect is a result of industrial dynamics, time varying behaviour or industrial companies, and proposed a methodology for the simulation of dynamic models: industrial dynamics, Towill [2]. The study of the Bullwhip effect has yielded many papers. Most of them focused on identifying its causes, such as: lead times, lack of information among the members of the supply chain, price fluctuations, and the demand forecasting method. Outstanding research studies in this area are: Metters [3], Lee et al. [4], McCulem and Towill [5], Chatfield et al. [6], Hosoda and Disney [7], Wright and Yuan [8], Campuzano et al. [9-12]. Another type of studies focused on how to reduce the Bullwhip effect, which put forward the smoothing of replenishment orders or new collaborative structures for information exchange among the supply chain members. The works of Deziel and Elion [13], Sterman [14], Lee et al. [15], Lee et al. [16], Disney et al. [17], Dejonckheere et al. [18], Ouyang [19], Mula et al. [20], Kastsianand and Mönnigmann [21] and Campuzano and Mula [11] are worth a mention.

This paper is dealing with one of the main causes of the Bullwhip effect, the demand forecasting method. There are some previous contributions in this area. For example, Chen et al. [22] and [23] studied the magnitude of the Bullwhip effect for a simple supply chain using two traditional forecasting methods (moving average, MA, and simple exponential smoothing, SES), and two particular demand patterns (correlated demands by means of a first-order autoregressive process, and demands with a linear trend). Also, Alwan et al. [24] and Zhang [25] quantified the Bullwhip effect when the minimal mean square error forecasting method (MMSE) is employed, just for the case of a first-order autoregressive process describing the customer demand. The latter obtained analytical expressions of the bullwhip measure for the MA, SES and MMSE forecasting methods. Hosoda and Disney [7] developed a similar study but for a three echelon supply chain.

It must be noted that Sun and Ren [26] provided a complete review of the impact of forecasting methods on the Bullwhip effect, where the most relevant results of the previous papers were included. As done in this paper, they considered a simple, two-stage supply chain that consisted of just a retailer and a manufacturer. According to their conclusions, we agree that one should use the MMSE method for a negative correlated process describing the demand because it can eliminate the Bullwhip effect. However, the MMSE method yields worse results than SES and MA for high positive correlated processes (correlation Pearson near to one). Finally, they stated that "it is interesting to explore the impact of more sophisticated methods on the bullwhip effect", because only simple forecasting techniques had been considered until then.

In this sense, Stamatopoulus et al. [27] proposed the exponential smoothing technique with 'best' smoothing parameter as a good alternative. This is in comparison to the SES method with fixed parameter and the MA technique, which is mainly for positive high correlated demand patterns. And recently, Chaharsooghi et al. [28] compared the Box-Jenkins (ARMA) forecasting method to the MA and SES using four different demand patterns. They stated that "having more accurate forecasting method is not equivalent to creating less bullwhip effect."

This paper compares, through a simulation study, the impact of six forecasting methods (three of them not considered before) on the Bullwhip effect and also other interesting features in a supply chain such as NSAmp (Net Stock Amplification) and Fillrate. Six different demand patterns have been used in this research. The paper is organized as follows. In Section 2, the six simulated demand patterns are introduced, whereas in Section 3 the supply chain conditions are included. In Section 4 the six forecasting methods are described. Section 5 deals with the simulation results and analysis of computing the Bullwhip, NSAmp and Fillrate among all possible demand pattern and forecasting methods. Finally, in Section 6 some conclusions of the study are showed.

2. SIMULATED DEMAND PATTERNS

The simulation study was developed for six different demand patterns, all of them with the same mean (μ = 21) and the same standard deviation (σ = 7). Five samples for each of the six patterns were generated. The length of each simulated demand series was 720, which corresponds to a three-year daily demand (weekends not included).

The demand patterns considered can be classified in two types: three of them were independent and identically distributed (i.i.d.) and the other three were first-order autoregressive processes (AR(1)).

The three i.i.d. simulated demand patterns correspond to the Gaussian, Beta, and Extrem distributions

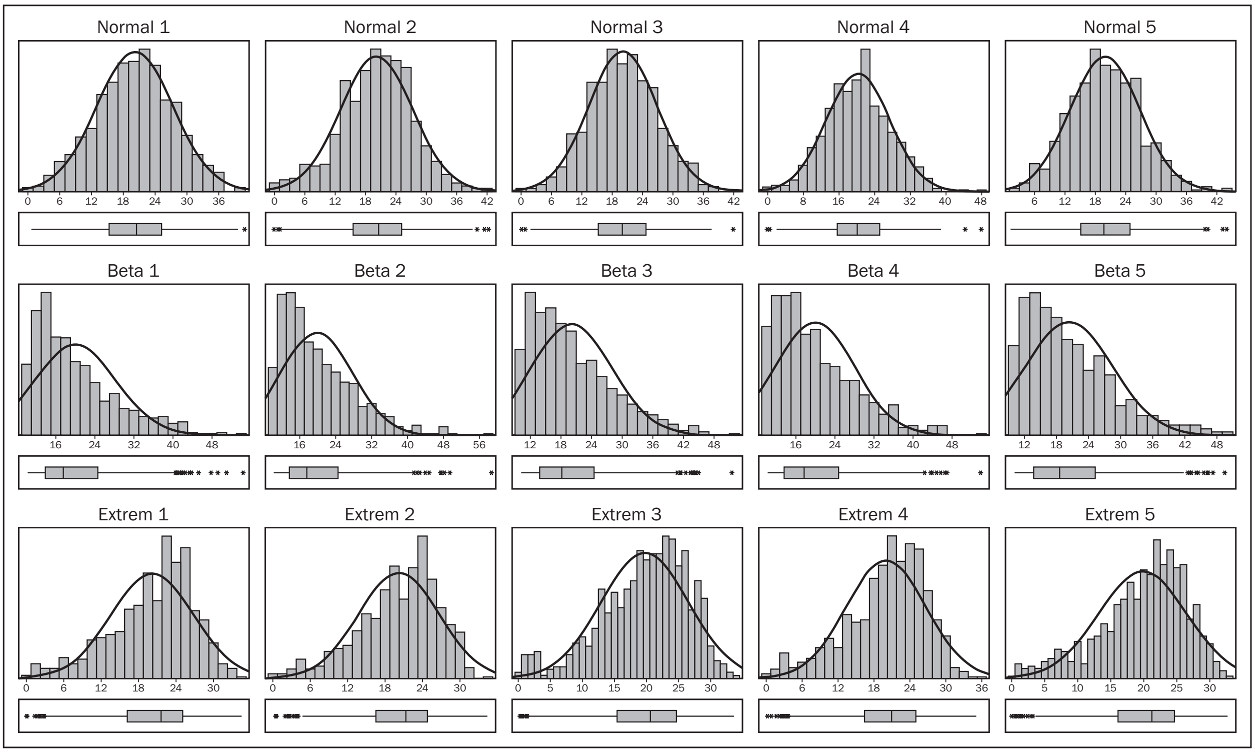

Figure 1 - The i.i.d. simulated demand patterns

respectively. The Gaussian distribution was used to simulate symmetric demand series, where most of the demands are placed around the mean (μ = 21) and very few of them are low or high demands (note that the 2-sigma interval is (7.35)). The Beta distribution was used to simulate asymmetric right-tailed demand series, with prevalence of low demands and very exceptional high demands. Finally, the asymmetric left-tailed demand series were simulated through the Extrem distribution, with prevalence of high demands and very exceptional low demands. Observe that these two distribution models (Beta and Extrem) had not been used previously to quantify the impact of the forecasting methods on the Bullwhip effect as far as we know. However, the Gaussian distribution is the model most commonly used in literature to simulate a symmetric i.i.d. demand series. We refer to Bartezzaghi et al. [29] to study the importance of the shape of the demand pattern.

Figure 1 shows the histograms and box plots corresponding to each of the five samples of the three i.i.d. patterns described above.

The three correlated demand patterns corresponds to the first-order autoregressive processes with correlation coefficients 0.25, 0.50 and 0.75 respectively. Those are low, medium, and high auto correlated demand models. A first-order autoregressive demand process can be represented by:

$$D_t = a + \rho \cdot D_{t-1} + \varepsilon_t \qquad (1)$$

where D_t is the demand at time t, ρ is the correlation coefficient, $-1 < \rho < 1$, and ε_t is a random noise independent from the demands.

The first-order autoregressive process has been the most employed model in literature to quantify the influence of forecasting methods on the Bullwhip effect (see the references in the introduction).

Figure 2 shows the histograms and box plots corresponding to each of the five samples of the three autoregressive models described above.

3. SUPPLY CHAIN CONDITIONS

The dynamic model used herein to develop the proposed simulation study is based on system dynamics methodology (Forrester [1]) and includes the necessary variables to characterize the demand management process (inventory levels, replenishment orders, manufacturing, forecasts, etc.). This model considers the capacity constraints, management of backlogged orders, fill rate, measurement of the bullwhip effect and the inventory costs associated with each level. Moreover, different types of supply chain management strategies (different scenarios) can be recreated to measure the impact of these strategies in the demand management process (see [9] for more details).

This work studies the demand management process along a two-stage supply chain. The main characteristics of the system considered are summarized in the following points:

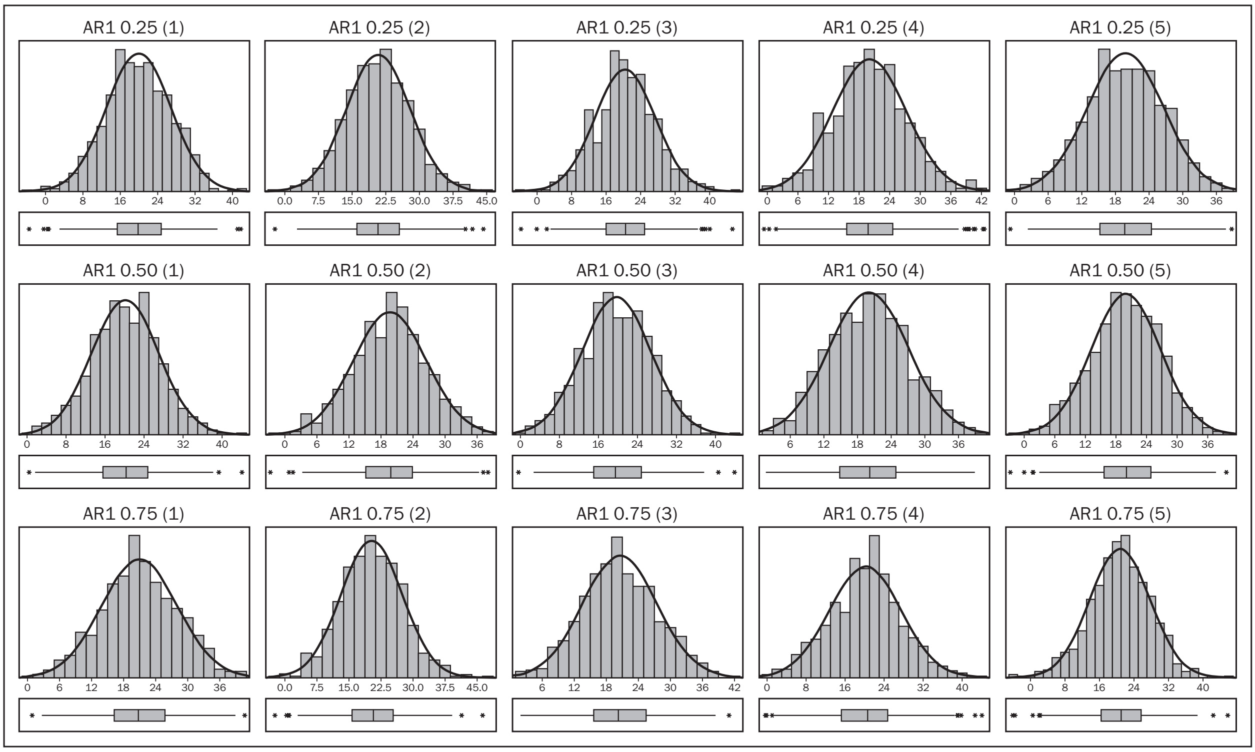

Figure 2 - The autoregressive simulated demand patterns

- A two-stage supply chain system consisting of a customer and a manufacturer, in which the customer orders products only at its upper stage (manufacturer).
- Manufacturer ships goods immediately upon receiving the order if there is a sufficient amount of on-hand inventory. A pull planning strategy was used.
- Orders may be partially fulfilled (each order to be delivered includes current demand and backlogged orders, if any), and unfulfilled orders are backlogged.
- Shipped goods arrive with a transit lead time, and they are also delayed because of the information lead time.
- Last stage (manufacturer) receives raw materials from an infinite source and manufactures finished goods under capacity constraints. In this work, capacity constraints do not influence the size of the manufacturing orders since the manufacturing capacity was set high enough to prevent those constraints from having an impact on the proposed analysis.

The variables employed to create the two-level supply chain causal diagram depicted in *Figure 3* have been selected by taking the APIOBPCS (Automatic Pipeline, Inventory and Order-Based Production Control System) order as a reference, see John et al. [30]. The APIOBPCS system can be expressed in words as "Let the production (or distribution) targets be equal to the sum of: averaged demand (exponentially smoothed over predefined time units), a fraction of the inventory difference in actual stock compared to target stock and the same fraction of the difference between target Work In Progress (WIP) and actual WIP". The APIOPBCS model uses three components to generate orders in the supply chain. The first type of information is a forecast. The second component of the order rate is a fraction of the discrepancy between target inventory and actual Inventory. The fraction is used because it is easily understood and known to be quite capable of "locking on" to target inventory levels if the production leadtime is known. The third component of the order rate is a fraction of the discrepancy between target and actual WIP (or error between the target inventory on order but not yet received and the actual inventory on order but not yet received in the language of the Beer Game (Sterman [14]). The fraction is used because it is easily understood and known to be quite capable of "locking on" to target WIP levels if the production lead-time is known. The APIOBPCS model is particularly powerful because it can represent, by setting particular controller values to specific values, a wide range of supply chain strategies such as Lean and Agile supply chains.

These variables employed in our model are set up below:

a) Final customer demand.
b) Firm orders. Firm orders will consist of the demand sent by the level immediately downstream of the

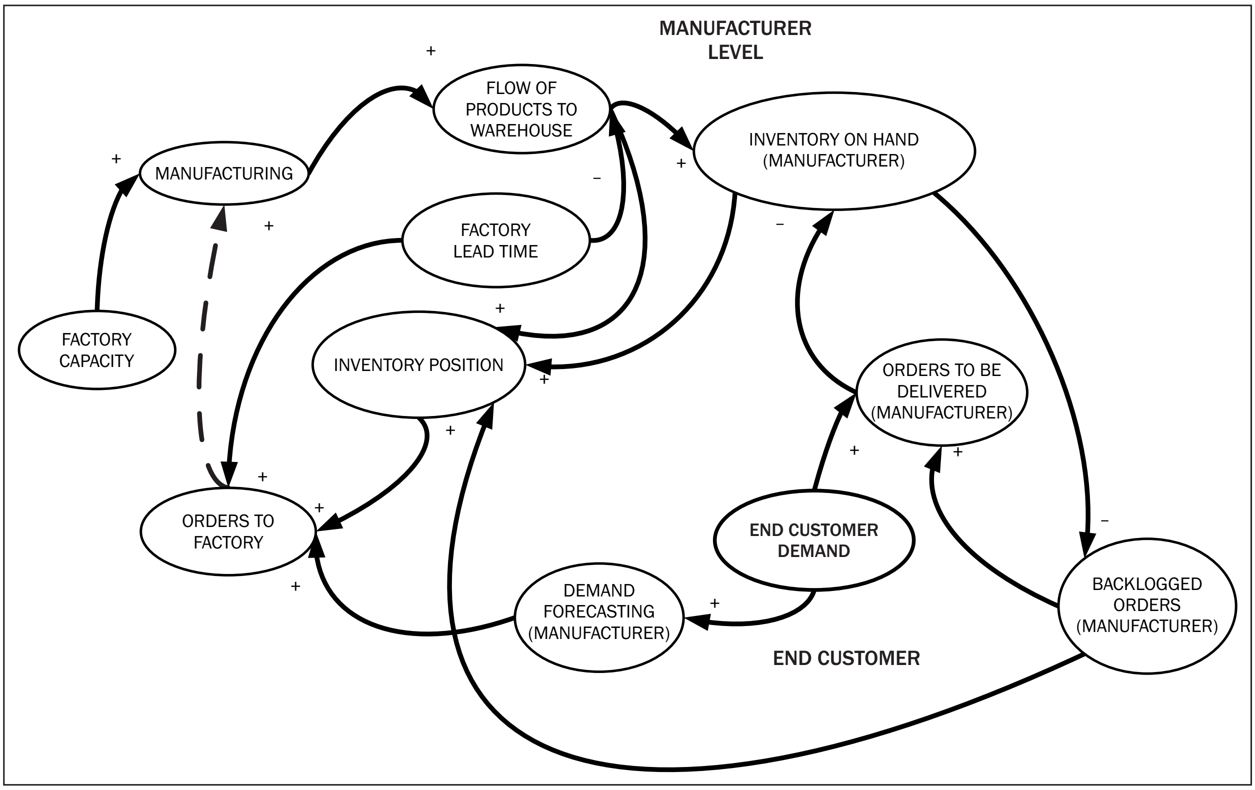

Figure 3 - The causal-loop diagram associated to our study

one that is being considered and of the backlogs of the concerned chain echelon.

c) Backlogged orders.
d) The on-hand inventory: this is the inventory that can be in the warehouse, and its on-hand amount can never be negative. This amount is important because it makes it possible to determine if the demand from a certain customer can be satisfied directly from the warehouse.
e) Demand Forecasting.
f) Inventory Position.
g) Orders to the factory. Manufacturing orders to be made according to the inventory policy chosen to manage the demand. Regardless of the policy followed, the variables Demand Forecasting, Inventory Position and Supply or Manufacturing lead time will be taken into account to trigger these orders.
h) On-order products: Made up of the inventory that has been served and will not be on hand until the stipulated lead time has elapsed and the inventory that will be on hand at the warehouse after completion of the manufacturing process.
i) Manufacturing capacity: To be expressed as the number of units that can be made in a period.
j) Manufacturing.
k) Manufacturing lead time.
l) Fill rates. Fill rates will be defined as the quotient between the number of units shipped to the customers on time and the total number of units demanded by them.

In particular, the *inventory position* is defined by the following expression (see Silver et al. [31]):

$$\begin{gathered} Inv.\ position = Inv.\ on\ hand + orders\ placed \\ but\ not\ yet\ received - backlogged\ orders \end{gathered}$$

Moreover, *the manufacturer order at the end of period t*, O_t , is given by (Silver et al. [31]):

$$O_t = S_t - inventory\ position \quad (2)$$

where S_t is the *order-up-to level* used in period 't'. The *order-up-to level* is updated according to:

$$S_t = \hat{D}_t^L + k\hat{\sigma}_t^L \quad (3)$$

where L is the lead-time, k is the fill rate or safety factor, $\hat{D}_t^L$ is the estimated mean of the demand over L periods and σ_t^L is the estimated standard deviation over L periods.

In this work, $L = 2$, $k = 2$ and *initial inventory* = 100 units have been chosen.

Figure 3 presents the stock and flow structure for a two-stage supply chain system in its corresponding causal loop diagram. The arrows represent the relations among variables. The direction of the influence lines shows the direction of the effect. Signs "+" or "–" at the upper end of the influence lines indicate the type of effect. When the sign is "+", the variables change in the same direction, otherwise, these change in the opposite direction.

4. DESCRIPTION OF FORECASTING METHODS

One of the main causes of Bullwhip is the technique used to forecast the customer demand in a supply chain. This paper is focused on comparing the influence of different forecasting methods on the Bullwhip effect. For this, six forecasting techniques were selected: MA, SES with fixed smoothing parameter, SES with best parameter, ARMA, theta method and kernel regression.

In this section the six methods employed for the demand forecasting are briefly described, all of them commonly used in the context of time series. In the field of supply chains, the MA and SES with fixed smoothing parameter correspond to the most popular ones. The study of the SES with best parameter and ARMA techniques started recently. The other two, theta method and kernel regression, had not been used previously to quantify the impact on the Bullwhip effect as far as we know.

Below, let us denote by $\{d_1, d_2, \ldots, d_{720}\}$ the series of actual demands which were simulated in Section 2. Under the assumption that the demand series has been observed until time 't', the demand at time '$t+1$' can be predicted (through a forecasting method) that is denoted by $\hat{d}_{t+1/t}$.

The MA technique is commonly used in the context of time series to smooth out short-term fluctuations. Given a history of demand observations up to period t, $\{d_1, d_2, \ldots, d_t\}$, the MA method of order 'n', $MA(n)$, estimates the demand at time '$t+1$' as the average of the previous n periods:

$$\hat{d}_{t+1/t} = \frac{1}{n}\sum_{i=t-n+1}^{t} d_i \quad (4)$$

The $SES(\alpha)$ is another smoothing technique that works as a weighted moving average. That works by providing more weight to the most recent terms in the time series and less weight to older data. It is assumed that there is neither trend nor seasonality in the time series to apply this method. On the contrary, other exponential smoothing techniques should be used such as Holt and Winters methods. Given a history of demand observations up to period t, $\{d_1, d_2, \ldots, d_t\}$, the SES method of parameter α, $SES(\alpha)$, estimates the demand at time '$t+1$'as a weighted average among the last demand observation and the last demand prediction:

$$\hat{d}_{t+1/t} = \alpha \cdot d_t + (1-\alpha) \cdot \hat{d}_{t/t-1} \quad (5)$$

where $\alpha \in [0,1]$ is the smoothing parameter. The selection of $\alpha = 0.2$ is employed in this research.

Technically the SES model can also be classified as an ARIMA(0,1,1), an autoregressive integrated moving average model, with no constant term [32].

An alternative to SES with fixed parameter consists of determining the 'best' smoothing parameter that minimizes the mean square error of the residuals. This method is just called *SES with best parameter*.

The ARMA technique, also called Box-Jenkins methodology, tries to find the stochastic processes that could generate the time series in the study. The stationary of the series is assumed to apply this procedure and our simulated demands have verified this condition. The general model $ARMA(p,q)$ suggests that the time series at the current time can be explained by '*p*' previous observations and the residuals of '*q*' previous estimations. One of the simplest cases corresponds to the first-order autoregressive process denoted by $AR(1)$. Given a history of demand observations up to period *t*, $\{d_1, d_2, \dots, d_t\}$, the $AR(1)$ method estimates the demand at time '$t+1$' by:

$$\hat{d}_{t+1/t} = \hat{a} + \hat{\rho} \cdot d_t \tag{6}$$

where $\hat{a}$ and $\hat{\rho}$ are the estimations of the constant and correlation coefficients given by the ARMA method. When the demand series is an i.i.d. process, the prediction provided by the ARMA method at time '$t+1$' is given by the cumulative average of the previous periods:

$$\hat{d}_{t+1/t} = \frac{1}{t}\sum_{i=1}^{t} d_i \tag{7}$$

The Theta model was described originally by Assimakopoulos and Nikolopoulos [33] and was simplified by Hyndman and Billah [34] years later. They showed that the forecasts obtained are equivalent to simple exponential smoothing with drift. Given a history of demand observations up to period *t*, $\{d_1, d_2, \dots, d_t\}$, the theta method of parameter θ estimates the demand at time '$t+1$' by:

$$\hat{d}_{t+1/t} = \tilde{d}_{t+1/t} + \frac{1}{2}\hat{b}_0\left(\frac{1}{\alpha} - \frac{(1-\alpha)^t}{\alpha}\right) \tag{8}$$

where $\tilde{d}_{t+1/t}$ is the forecasting point using the $SES(\alpha)$ method and

$$\hat{b}_0 = \frac{6(1-\theta)}{t^2-1}\left(\frac{2}{t}\sum_{i=1}^{t} i \cdot d_i - (t+1)\cdot\frac{\sum_{i=1}^{t} d_i}{t}\right) \tag{9}$$

The Kernel regression method was derived independently by Nadaraya [35] and Watson [36]. Given a history of demand observations up to period *t*, $\{d_1, d_2, \dots, d_t\}$, the kernel regression estimates the demand at time '$t+1$' by:

$$\hat{d}_{t+1/t} = \frac{\sum_{i=1}^{t} K\left(\frac{t-i}{h}\right) d_i}{\sum_{i=1}^{t} K\left(\frac{t-i}{h}\right)} \tag{10}$$

This procedure implies the use of function $K(x)$ to assign weights to near observations. Function $K(x)$ is the kernel function, which is traditionally chosen from a wide variety of symmetric density functions. Parameter '*h*' is called the bandwidth or smoothing parameter. The selection of an appropriate bandwidth *h* (a non-negative number controlling the size of the local neighbourhood) is key part of non-parametric regression fitting. In this paper, the Gaussian kernel was employed:

$$K(z) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}z^2\right) \tag{11}$$

The bandwidth was chosen using a data-based method for local linear regression developed by Ruppert et al. [37].

Note that the SES with best parameter, ARMA and Theta methods were carried out with package '*forecast*' (see Hyndman [38]), whereas the kernel regression method was developed using R package '*lokern*' (see Herrmann [39]). Other two simpler methods, MA and SES with fixed parameter, were easily implemented.

5. ANALYSIS OF RESULTS

In this section the forecasting methods in both aspects are compared, the accuracy of the forecast and the impact on some features of the supply chain (Bullwhip, NSAmp and Fillrate). The following definitions were used for the study:

– *Bullwhip*. According to Fransoo and Woute [40], the bullwhip effect at a particular level in a multi-level supply chain is measured as the quotient between the demand coefficient of variation at the level where the bullwhip effect is measured and the demand coefficient of variation received at this level. For a two-level supply chain, it can be reduced to:

$$Bullwhip = \frac{C_{orders}}{C_{demand}} \tag{12}$$

where:

$$C_{orders} = \frac{\sigma_{orders}}{\mu_{orders}} \qquad c_{demand} = \frac{\sigma_{demand}}{\mu_{demand}} \tag{13}$$

– *NSAmp*. The Net Stock Amplification was defined by Disney and Towill [17] as:

$$NSAmp = \frac{\sigma^2_{NS}/\mu_{NS}}{\sigma^2_{D}/\mu_{D}} \tag{14}$$

where NS represents the net stock and D is the customer demand. The authors proposed that this measure can be easily applied to quantify any fluctuations in the net inventory at each level.

However, this paper defines the NSAmp measure in a similar way to the Bullwhip, that is, as the ratio between two coefficients of variation (the net stock coefficient of variation and the customer demand coefficient of variation):

$$NSAmp = \frac{\sigma_{NS}/\mu_{NS}}{\sigma_{D}/\mu_{D}} \tag{15}$$

Note that the last definition provides a dimensionless measure. Moreover, the measure has no dimension either in the nominator or in the denominator.

– *Fill rate*: The fill rate is a popular metric used to measure customer service, see Zipkin [41].

$$\text{Fill Rate} = 1 - \frac{\text{expected number of backorders}}{\text{expected demand}} \quad (16)$$

On the other hand, it is assumed that the retailer uses the MA(5) technique to estimate the demand at time 't' based on the actual demands of the previous five periods. Second, it is assumed that the retailer uses the SES(α = 0.2) technique to forecast the demand at next time based on the history of demand observations. The assumptions continue in a likely pattern for other four forecasting methods.

The following tables show the mean square error (MSE) and the maximum error (ME) obtained for the five samples of the simulated demand patterns using each forecasting method. The lowest values of MSE and ME for each sample have been marked using bold fonts.

Note that for the i.i.d. demand patterns, the SES, theta, ARMA and kernel regression methods provide quite similar values of MSE. Specifically, the ARMA technique has the minimum MSE in nine of the fifteen samples, whereas the kernel regression gives the other six lowest values. Besides, the lowest ME is reached by all techniques in similar proportions.

Table 1 - MSE and ME for the five simulated Gaussian patterns

MSE (ME)	Sample 1		Sample 2		Sample 3		Sample 4		Sample 5	
MA(5)	67.24	(22.43)	61.91	(26.55)	57.18	(23.42)	61.19	**(23.49)**	58.15	(26.46)
SES(0.2)	59.29	(20.57)	55.30	(23.84)	51.28	(24.05)	55.40	(25.13)	52.13	(24.83)
SES	52.98	**(20.44)**	51.06	(22.16)	46.41	(22.39)	50.72	(26.75)	47.66	(24.54)
Theta	52.60	(20.69)	50.95	**(21.93)**	45.81	**(21.71)**	50.37	(27.45)	47.56	(23.96)
ARMA	52.25	(20.67)	50.54	(22.11)	**45.35**	(22.35)	**49.88**	(27.25)	47.24	**(23.86)**
Kernel	52.39	(20.48)	**49.72**	(22.15)	45.66	(22.05)	50.13	(26.92)	**46.85**	(25.05)

Table 2 - MSE and ME for the five simulated Beta patterns

MSE (ME)	Sample 1		Sample 2		Sample 3		Sample 4		Sample 5	
MA(5)	81.06	(35.75)	76.65	(40.28)	73.97	**(29.31)**	83.70	(36.32)	80.08	(36.71)
SES(0.2)	76.41	(36.49)	72.93	**(38.72)**	70.03	(30.15)	75.05	(36.61)	75.32	(33.72)
SES	69.42	(33.95)	65.31	(38.89)	62.80	(31.09)	67.61	(34.40)	67.79	(29.64)
Theta	68.92	(34.48)	64.96	(39.09)	62.61	(31.53)	66.61	**(34.05)**	67.24	(29.27)
ARMA	**68.47**	**(33.75)**	64.46	(38.85)	**62.11**	(31.39)	**65.93**	(34.15)	**66.52**	(29.33)
Kernel	69.37	(34.70)	**64.40**	(39.47)	62.14	(31.14)	66.53	(34.06)	66.94	**(29.14)**

Table 3 - MSE and ME for the five simulated Extrem patterns

MSE (ME)	Sample 1		Sample 2		Sample 3		Sample 4		Sample 5	
MA(5)	53.83	(24.45)	50.48	(24.53)	53.65	(24.47)	52.03	(24.34)	51.86	(23.23)
SES(0.2)	49.50	(23.34)	46.96	(22.62)	50.84	(24.04)	48.95	(25.10)	48.56	(22.73)
SES	44.85	(20.86)	42.01	(20.20)	46.41	(19.86)	44.58	(20.50)	44.13	(19.94)
Theta	44.46	**(20.22)**	41.56	(19.84)	46.20	**(19.32)**	44.41	**(19.87)**	44.01	**(19.76)**
ARMA	**44.10**	**(20.22)**	**41.17**	(19.96)	45.81	(21.77)	44.15	(20.67)	43.71	(20.23)
Kernel	44.25	(20.54)	41.40	**(19.83)**	**45.69**	(19.82)	**43.99**	(20.15)	**43.21**	(20.02)

Table 4 - MSE and ME for the five simulated AR(1) patterns with coefficient 0.25

MSE (ME)	Sample 1		Sample 2		Sample 3		Sample 4		Sample 5	
MA(5)	52.54	(28.02)	57.61	(22.93)	56.97	(22.87)	61.19	(33.26)	54.62	(21.79)
SES(0.2)	48.98	(24.07)	52.57	(22.45)	51.28	**(21.36)**	53.78	(27.75)	50.55	(20.62)
SES	46.93	(22.05)	50.56	(24.84)	48.75	(24.56)	53.54	(25.54)	47.29	(20.98)
Theta	46.93	**(22.04)**	50.23	(23.42)	48.52	(24.70)	52.76	**(22.62)**	46.94	(20.71)
ARMA	**45.97**	(22.69)	46.93	(23.42)	46.41	(23.88)	47.54	(22.74)	45.68	(19.84)
Kernel	49.27	(23.00)	**45.34**	**(21.92)**	**45.43**	(23.64)	**42.94**	(26.90)	**45.43**	**(19.63)**

Table 5 - MSE and ME for the five simulated AR(1) patterns with coefficient 0.50

MSE (ME)	Sample 1		Sample 2		Sample 3		Sample 4		Sample 5	
MA(5)	49.53	(22.44)	53.99	(22.73)	53.11	(27.13)	52.40	(24.18)	51.02	(24.64)
SES(0.2)	43.81	(20.63)	45.20	(19.56)	46.92	(25.11)	46.48	(21.33)	44.86	(21.72)
SES	41.83	(19.87)	44.17	(20.11)	45.45	(25.97)	44.09	(21.86)	43.97	(22.52)
Theta	41.83	(19.86)	44.17	(20.10)	45.45	(25.97)	44.09	(21.86)	43.97	(22.51)
ARMA	35.57	(20.19)	36.27	(19.79)	38.80	(22.12)	37.28	(22.44)	37.32	(20.57)
Kernel	**25.15**	**(16.02)**	**20.27**	**(14.44)**	**25.80**	**(16.80)**	**24.08**	**(16.04)**	**26.11**	**(16.93)**

Table 6 - MSE and ME for the five simulated AR(1) patterns with coefficient 0.75

MSE (ME)	Sample 1		Sample 2		Sample 3		Sample 4		Sample 5	
MA(5)	36.38	(20.20)	39.36	(21.12)	37.29	(21.08)	45.13	(22.66)	36.63	(20.02)
SES(0.2)	35.53	(17.84)	37.36	(18.13)	34.06	(20.51)	40.59	(20.35)	32.60	(20.45)
SES	23.86	(16.18)	24.87	(16.50)	24.03	(16.12)	26.96	(14.53)	23.95	(14.50)
Theta	23.86	(16.18)	24.87	(16.50)	24.03	(16.12)	26.96	(14.53)	23.95	(14.50)
ARMA	21.70	(16.19)	22.25	(14.57)	21.44	(16.24)	23.74	(13.12)	21.36	(14.97)
Kernel	**9.08**	**(9.88)**	**8.41**	**(9.20)**	**7.72**	**(8.53)**	**8.22**	**(8.71)**	**7.47**	**(8.39)**

However, when the demand patterns with dependences are used, the kernel regression method provides the best accuracy of the forecasts in both aspects, the lowest MSE and the lowest ME. Furthermore, the difference among the forecasting methods increases with the correlation coefficient of the AR model.

As mentioned in Section 3, the performance of the supply chain was simulated according to the work of

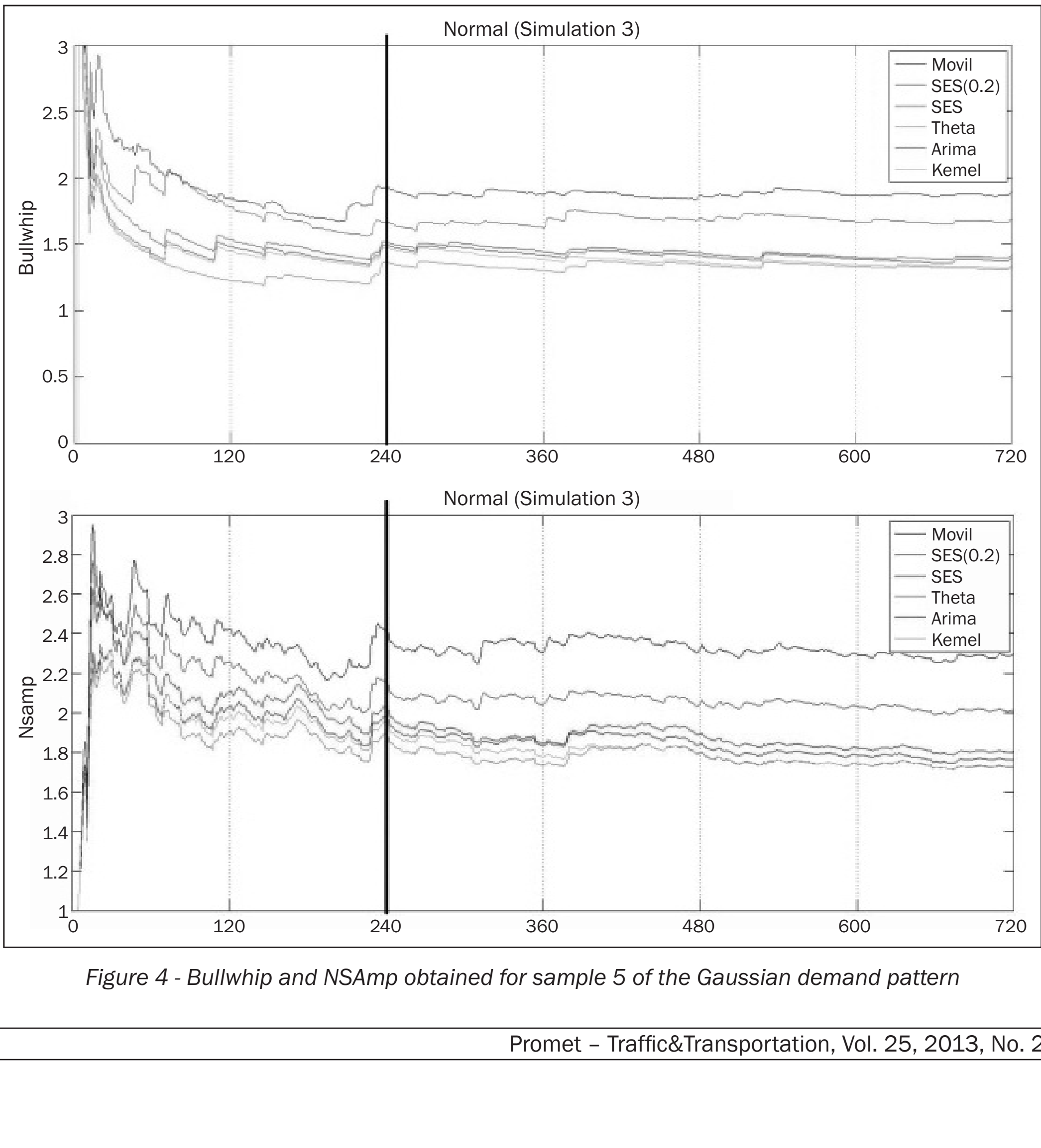

Figure 4 - Bullwhip and NSAmp obtained for sample 5 of the Gaussian demand pattern

Campuzano et al. [9], which was implemented using the software Vensim© by Ventana Systems. From each demand series (simulated) and its forecasting points, the simulation program provided, among others, the Bullwhip, NSAmp, and Fillrate quantities.

The simulation was carried out over a period of 720 days, which is three years at a rate of five observations per week. The results obtained for the first 240 data (first year) were disregarded in each model in order to avoid the transitional state and stabilize the Bullwhip effect and NSAmp of each simulation. Work continued with the data obtained from that moment on. *Figure 4* shows the result obtained in simulation number 3 using Normal demand pattern.

The figures below show the box plots of the Bullwhip, NSAmp, and Fillrate values (sample size = 5) of each of the simulated demand patterns using each forecasting method.

Note that for the i.i.d. demand patterns, the SES, theta, ARMA and kernel regression methods provide quite similar values of Bullwhip, NSAmp and Fillrate. Thus, when the demand series is purely random, none of these forecasting methods provides the 'best' results.

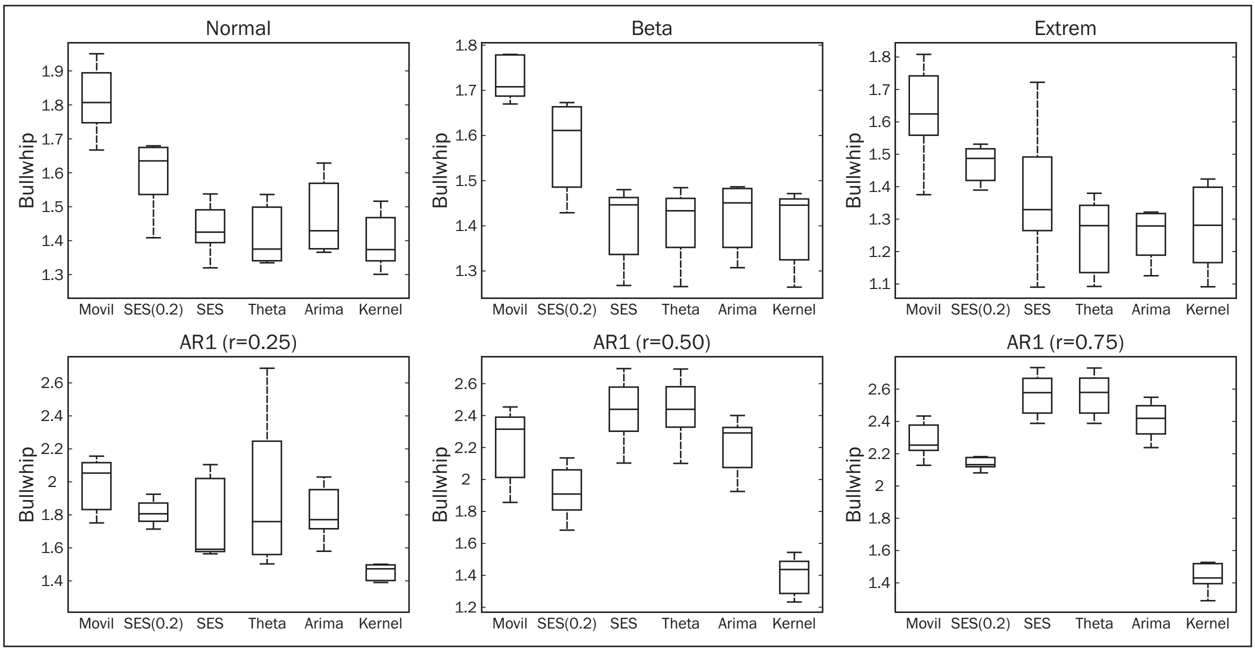

Figure 5 - Results obtained by Bullwhip

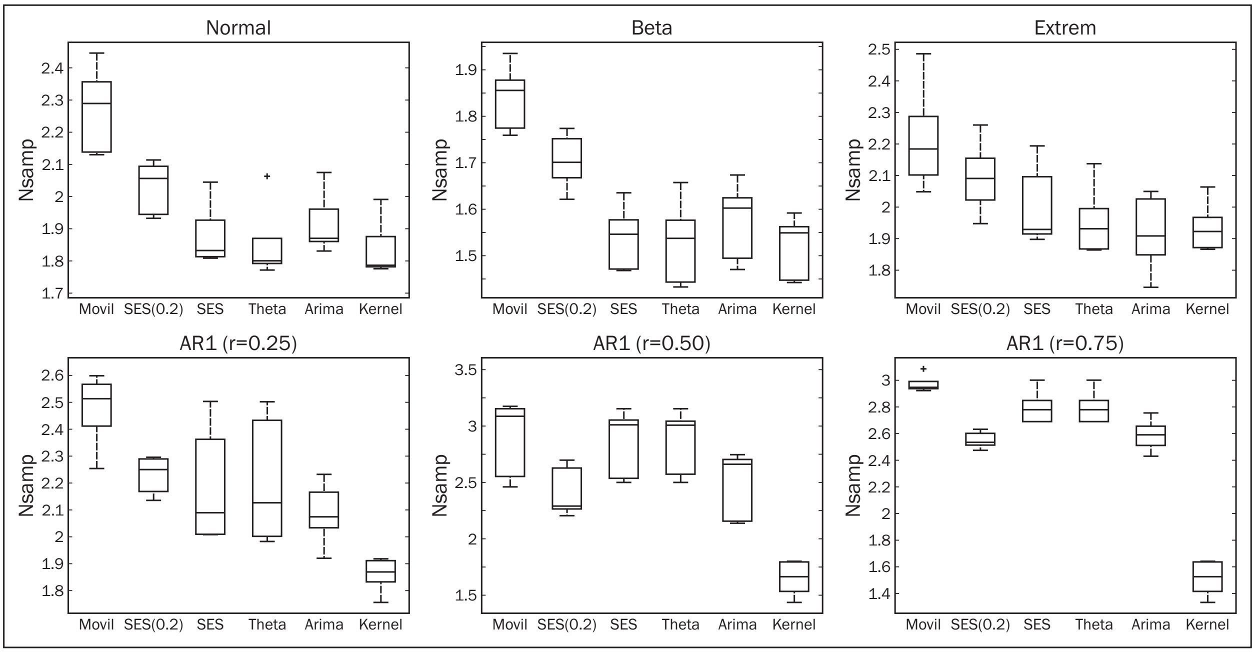

Figure 6 - Results obtained by NSAmp

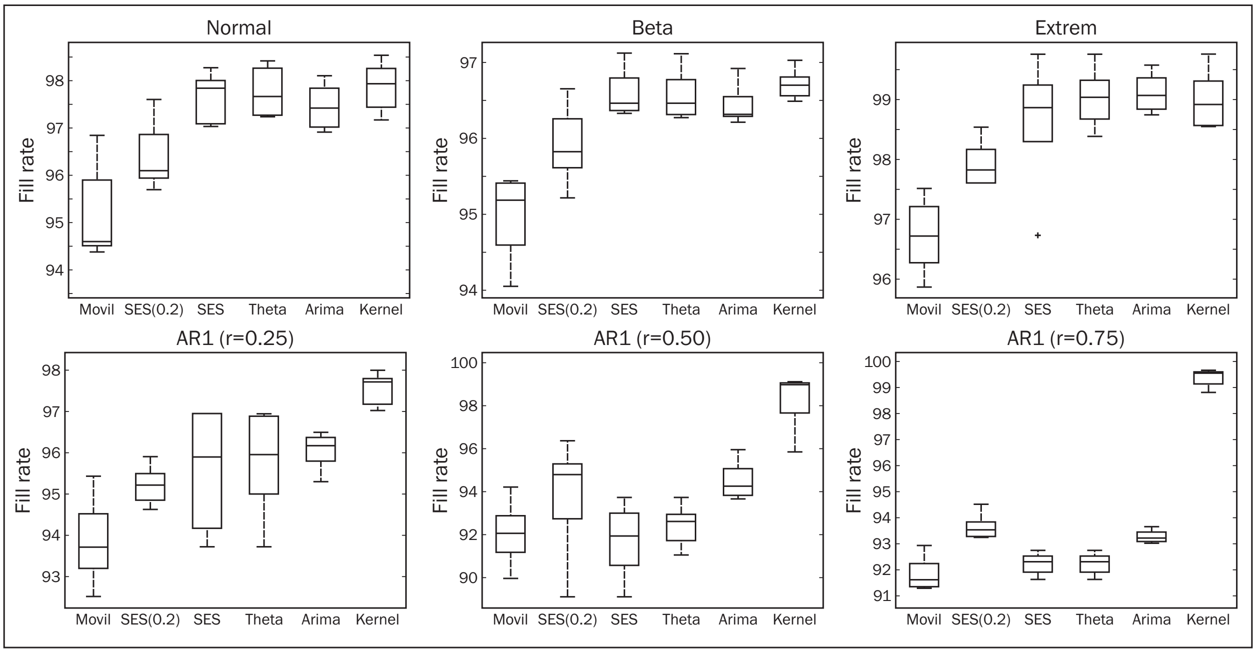

Figure 7 - Results obtained by Fillrate

However, when the autoregressive demand patterns are used, the kernel regression method provides lower Bullwhip and NSAmp (and higher Fillrate) than other forecasting methods. Besides, the difference among the forecasting methods becomes greater as the correlation coefficient increases.

On the other hand, *Figure 7* reveals that the SES(0.2) method gives lower Bullwhip than SES, theta and ARMA techniques in spite of their having more accurate forecasts than the former one (see *Table 6*). This fact corroborates the findings of Chaharsooghi et al. [28].

6. CONCLUSION

The impact of the forecasting method on the Bullwhip effect has been studied in several papers. However, just the simplest forecasting techniques were considered.

In this research, the influence of alternative forecasting methods on several features of a supply chain has been tested: Bullwhip, NSAmp, and Fillrate.

The findings show that when i.i.d. demand patterns are used, nearly all forecasting methods provide similar results, for symmetric or asymmetric demand shapes. However, for autoregressive demand patterns, the kernel regression method is a good alternative to reduce the Bullwhip and NSAmp, providing also high Fillrate. Although having a more accurate forecasting method is not equivalent to creating less bullwhip effect, the kernel regression has the two desired properties.

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ABSTRACTO

MÉTODOS ALTERNATIVOS DE PREDICCIÓN QUE REDUCEN EL EFECTO BULLWHIP EN UNA CADENA DE SUMINISTRO: ESTUDIO DE SIMULACIÓN

El estudio del efecto Bullwhip ha dado lugar a numerosos artículos de investigación, tanto analizando sus causas como proponiendo estrategias para su corrección, ya que se considera uno de los problemas críticos en la gestión de la cadena de suministro. Este artículo estudia una de sus prin-

cipales causas: los errores en la predicción de la demanda. Mediante el uso de patrones de demanda simulados, se proponen nuevos métodos predictivos que suponen una mejora en la reducción del efecto Bullwhip en una cadena de suministro en comparación con los métodos predictivos tradicionales (medias móviles, alisado exponencial simple y procesos ARMA). Este estudio muestra que la regresión núcleo es una buena alternativa para mejorar aspectos importantes en una cadena de suministro, como son Bullwhip, NSAmp (Distorsión del inventario neto) y niveles de servicio.

PALABRAS CLAVE

Efecto Bullwhip, cadena de suministro, regresión núcleo, dinámica de sistemas

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