Minimizing the Bullwhip Effect by Forecasting Supply Chain Demand: Case Study of the Argentine Automotive Sector

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December 25, 2020

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Summary: This article studies the uncertainty caused by the Bullwhip effect in the supply chain. The supply chain evaluated in this study is made up of a manufacturer, a distributor, and a retailer, and we studied the effect of demand between the links in the supply chain. The research uses data from the demand for Argentine automotive parts for 48 months and compares the forecast using the Holt-Winters and ARIMA methods over 4 years to minimize the Bullwhip effect.

Key Words: Bullwhip effect, Supply chain, ARIMA models, Time Series, Holt-Winters Method, Automotive Industry.

Introduction

Global markets require modern logistics chains to improve productivity and sustainable growth of international trade. In the same sense, each of the different actors in the supply chain must be coordinated to guarantee good customer service, ensuring a balance between the demand and supply chain. A simple supply chain is made up of independent organizations such as manufacturers, distributors, and retailers [1,2]. The efficiency of the supply chain can be evaluated using the total cost of services [3], the average inventory [4], and the bullwhip effect [5].

The bullwhip effect can be caused by several factors, including; demand forecast, lot order, price fluctuation, rationing measures, and shortages [6]; waiting times [7,8,9], inventory policies [10,11]; replacement policies [12,13,14]; poor control systems [15]; the number of participants in the supply chain [16]; distortion of information in the supply chain [17,18,19,20,21]; company processes [22]; capacity limits [16]; erroneous feedback perception [22]; lack of synchronization in the chain [23]; local optimization without global vision [22]; multiplier effect [15]. Also, the whip effect can be affected by members of the supply chain due to the delay of decision-making, lack of learning and/or training, and for fear of having an empty stock [24,25,26]. Other aspects have been reported by [27].

The bullwhip effect is a phenomenon that makes administrative management of the supply chain difficult; This effect generates a growing distortion of the demand transmitted by the different agents participating in the flow management of tailor-made products from the market to the producer. In other words, the Bullwhip effect reflects increased uncertainty as orders are transmitted upstream in the supply chain; It is an amplification phenomenon of the demand between the different elements that make up a supply chain.

This article evaluates the impact that the Bullwhip effect has on a supply chain made up of a manufacturer, distributor, and retailer: specifically studying the uncertainty caused by the manufacturer due to the demand variability in each market retailer.

1.1 Demand Forecast

The whip effect makes operational management of the supply chain difficult, in particular, forecasting demand. There are several methods to determine the demand forecast transmitted from the customer to the producer. The various forecasting methods existing in the literature can be classified into the following categories:

- **Time series forecasting techniques**
- **Automatic learning models.**
- **Agent based models**
- **Control engineering models**

The time series forecasting techniques are the moving average (MA), exponential smoothing (ES), auto-regression (AR), and auto-regressive moving average (ARIMA) [28, 29, 30, 31]. These techniques minimize total cost by optimizing the optimal inventory level and the number of orders. We conducted a comparative demand forecast study using the Holt-Winters and ARIMA methods to reduce uncertainty in the supply chain.

2 Methods

Forecasting of the demand time series will be approached using the Holt-Winters method by the seasonal characteristics and the systematic component of the demand. The implementation of the Holt-Winters method is:

For the systematic component of demand [(level + trend) x seasonal factor] with periodicity p of the data. L0, T0, and seasonal factors (S1, S2,… Sp) are obtained using the static forecasting procedure. For period t, the forecast for future periods is given by:

$$F_{t+1} = (L_t+T_t)(S_{t+1}) \text{ y } F_{t+n} = (L_t + nT_t)S_{t+n} \quad (1)$$

After observing the demand for period t + 1, the estimates for the level, trend, and seasonal factors expressed in equations (2 - 4) were revised:

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1- \beta)T \quad (2)$$

$$L_{t+1} = \alpha(D_{t+1}/S_{t+1}) + (1- \alpha) (L_t+T_t) \quad (3)$$

$$S_{t+p+1} = \gamma(D_t+1/L_{t+1}) + (1- \gamma)S_{t+1} \quad (4)$$

With α = smoothing constant for the level, β = smoothing constant for the tendency and γ = smoothing constant for the seasonal factor.

The ARIMA technique models the regular part and the seasonal part of the time series using the autoregressive component (AR) and moving averages (MA).

3 Analysis of the results

Graph (1) shows the initial descriptive analysis of the time series with a level, a trend, and a certain cyclical seasonality for the three series. This pattern is repeated as shown in figure N°1.

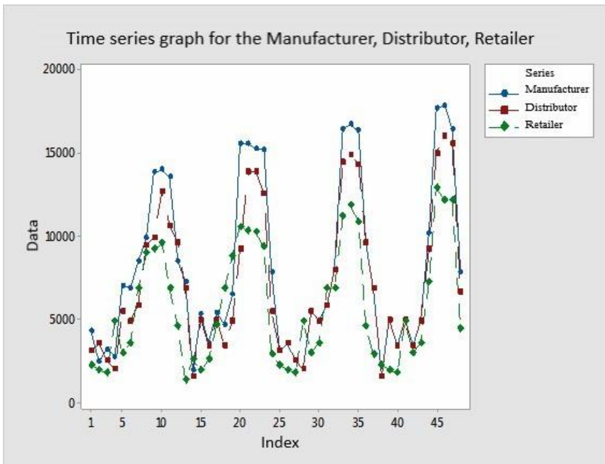

Fig. 1. Time series for the Manufacturer, Distributor, Retailer

For the Holt–Winters method, a smoothing constant was used for the α and β level in the range between (0.1-0.3). The adjustment of the parameters of this model was through simulations; the variation of the parameters had a differential of 0.01 for each iteration. Subsequently, a level of variation of the seasonal factor was determined at a range below 0.21. The best fit was achieved with the values of α = 0.21; β = 0.21, γ = 0.21 for the case of the manufacturer (figure 2).

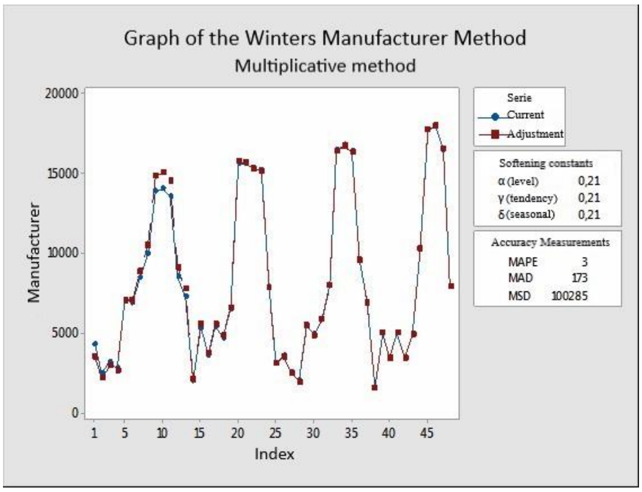

Fig. 2. Manufacturer Forecast

The forecast when using this technique obtained a mean absolute percentage error (MAPE) for the manufacturer, the distributor, and the retailer of 3%, 3%, and 2.7% respectively.

For the ARIMA analysis, the behavior of the time series was identified. The data do not have a normal distribution, as seen in figure Nº3 for the manufacturer's data.

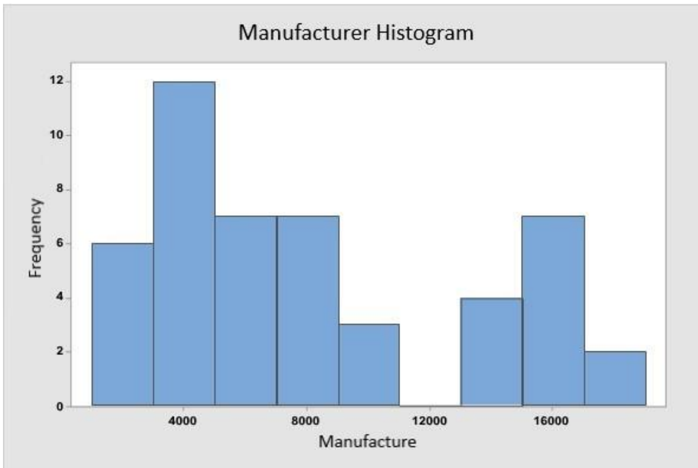

Fig. 3. Manufacturer's Histogram.

A bimodal normal distribution was observed, to carry out the transformation using the Box-Cox method, transforming the data series into a normally distributed model, with $\lambda = 0.5$.

The autocorrelation functions (ACF) and Partial autocorrelation function (PACF), have a mixed model AR and MA structure (Figures 4 and 5).

A bimodal normal distribution is observed, to make the transformation using the Box-Cox method, changing the data series into a normally distributed model, with (lambda) = 0.5.

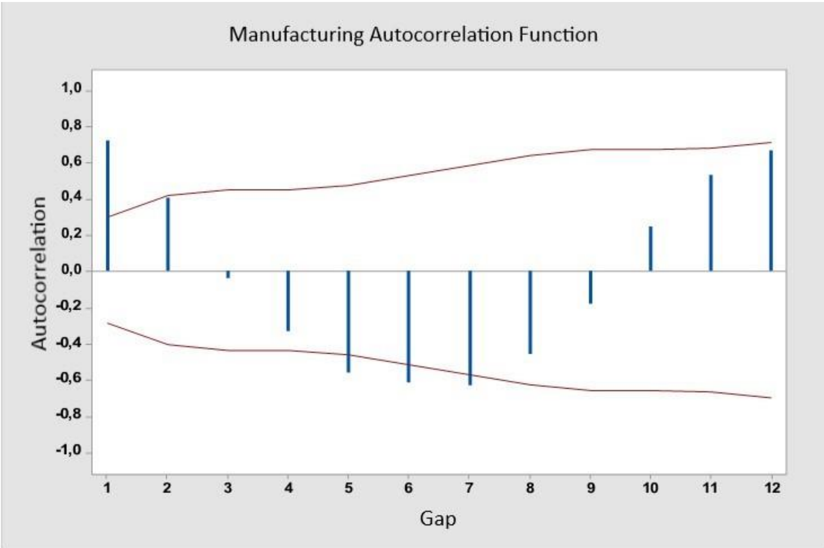

Fig. 4. ACF Producer.

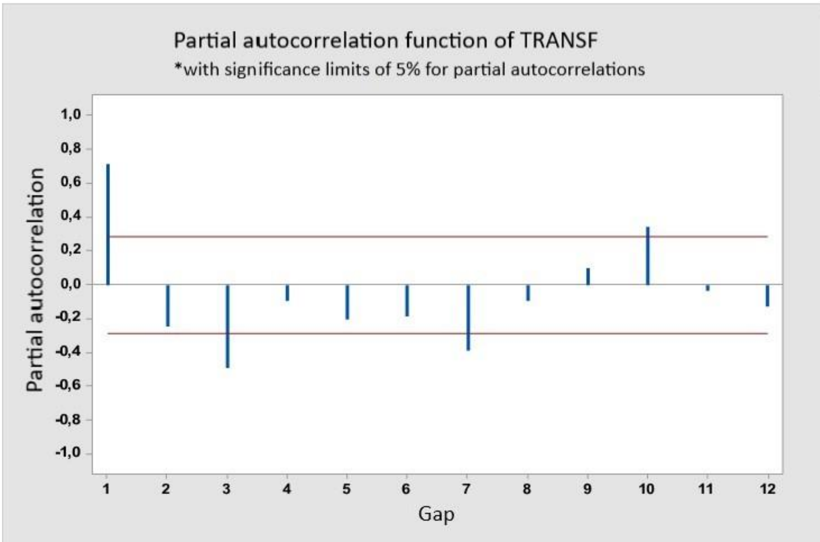

Fig. 5. PACF Producer.

Finally the following models were tested:

- ARIMA (1,0,0) x $(0,1,0)_{12}$
- ARIMA (1,0,1) x $(0,1,0)_{12}$
- ARIMA (1,0,2) x $(0,1,0)_{12}$
- ARIMA (1,0,3) x$(0,1,0)_{12}$
- ARIMA (0,0,3) x $(0,1,0)_{12}$
- ARIMA (1,1,1) x $(1,1,0)_{12}$

All models, except the last one, use a constant term. Figure 6 presents the model with the best prognosis.

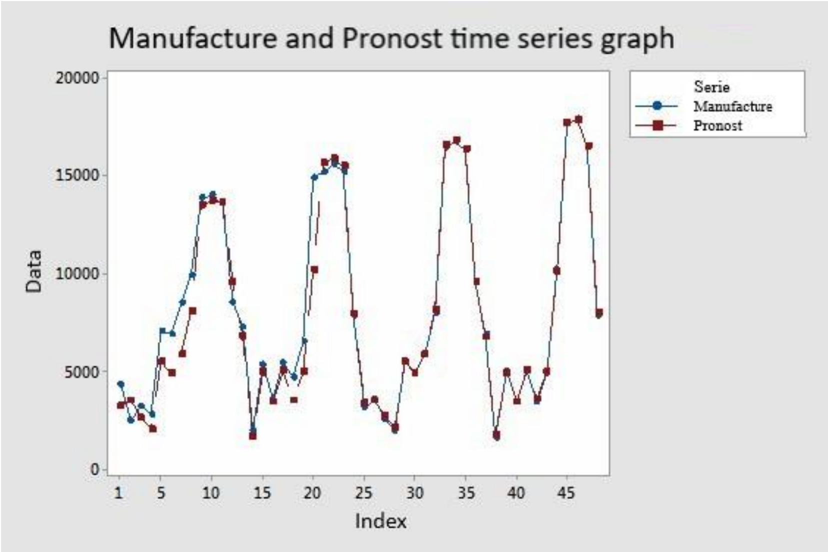

Fig. 6. Manufacturer's forecast using ARIMA model.

For the distributor and distributor series, the transformations were made using the Box-Cox method. However, no correlations were found for the time series using the ARIMA model (table 1). The time series used correspond to the demand for spare parts in the Argentine automotive industry (see annex table 2).

Table 1. The final parameters obtained by the model.

Type	Coefficient	SE Coefficient	Value T	Value P
AR 1	0.385	0.195	2.18	0.056
SAR 12	-0.974	0.102	-9.50	0.000
MA 1	0.942	0.127	.41	0.000

4. Conclusion

This study focused on minimizing the Bullwhip effect by forecasting the demands of the manufacturer, distributor, and retailer based on historical data from the argentine automotive sector. The results obtained were consistent with the theorical literature that refers to the bullwhip effect for the demands at different levels, providing the decision maker with an appropriate methodology for seasonal demands.

Two methods were used, the Holts-Winters method which obtained optimal values for α, β, and γ for the manufacturer, distributor, and retailer. The values for the three stages are $\alpha = \beta = \gamma = 0.21$, with a forecast error of less than 5%.

The ARIMA model for the manufacturer's time series was ARIMA$(1,1,1)x(1,1,0)_{12}$ without a constant term, and was validated with the T contrast test and p-values. However, ARIMA models could not be found for the other two series after the transformations made with the Box-Cox method.

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Annex

Table 2. N°1 Historical Data of the demand level of a Manufacturer, Distributor, Retailer.

Months	Manufacturer	Distributor	Retailer
1	4320	3125	2254
2	2458	3548	1967
3	3214	2548	1789
4	2771	1987	4887
5	7054	5487	3015
6	6879	4898	3594
7	8461	5874	6874
8	9902	9450	8990
9	13850	9909	9201
10	13975	12694	9586
11	13534	10654	6874
12	8506	9574	4589
13	7251	6874	1345
14	1985	1587	2597
15	5324	4987	1937
16	3587	3456	2597
17	5416	4987	4687
18	4698	3456	6874
19	6487	4897	8794
20	14900	9205	10587
21	15150	13855	10364
22	15550	13871	10234
23	15190	12548	9354
24	7856	5481	2897
25	3125	3125	2254
26	3548	3548	1967
27	2548	2548	1789

28	1987	1987	4887
29	5487	5487	3015
30	4898	4898	3594
31	5874	5874	6874
32	7987	7987	6871
33	16446	14444	11201
34	16694	14897	11856
35	16335	14326	10874
36	9574	9574	4589
37	6874	6874	2897
38	1587	1587	2254
39	4987	4987	1967
40	3456	3456	1789
41	4987	4987	4887
42	3456	3456	3015
43	4897	4897	3594
44	10205	9205	7208
45	17665	14985	12871
46	17865	15995	12201
47	16450	15544	12186
48	7856	6671	4437