ANALYZING THE BULLWHIP EFFECT IN AFTER-SALES SPARE PARTS SUPPLY CHAINS IN TELECOM FIRMS, A COMPLEX SYSTEM APPROACH

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ABSTRACT

Complex system science is a new field into the interdisciplinary disciplines. Different phenomena have been studied under this approach. In this paper, we analyzed the bullwhip effect in an after-sales spare part closed loop supply chain in telecom firms. The system is analyzed using tools of fractal analysis.

Keywords: Complex systems, bullwhip effect, supply chains, telecom industry

1. INTRODUCTION

With increased market globalization, budget limitation, short life cycle of products, competition, high quality and fast delivery customer expectations, the need of information sharing and coordination through each echelon of the network, etc. have forced companies to focus more attention in their supply chains. *"A supply chain is a goal-oriented network of processes and stock points used to deliver goods and services to customers"* (Hopp, 2008). The goal is to find the efficient frontier curve of a combination of cost versus quality, speed, service and product variety, considering a system approach (Hopp, 2008). However, the supply chain management becomes difficult because (i) it is challenging to design and operate a supply chain by minimizing the systemwide cost while maintaining the systemwide service and (ii) by coping with uncertainty in the demand process and in the supply process (Simchi-Levi, Kaminsky and Simchi-Levi, 2003).

The "bullwhip effect" refers to the phenomenon that experienced supply chains when replenishment orders generated by a stage exhibit more variability than the demand the stage faces. For instance, by examining the demand of Pampers disposal diapers, management people in Procter & Gamble realized that retail sales were fairly uniform, however the distributors' orders issued to the factory fluctuated much more than retail sales (Lee, 1997a). Because all variability must be buffered, the bullwhip effect has important consequences for the systemwide efficiency of the supply chain. Hence, it is necessary to understand what cause this phenomenon. Lee, Padmanabhan and Whang (1998b), identified four factors that lead to the bullwhip effect: batching, forecasting, pricing and gaming behavior, which suggested some options for mitigate it.

After-sales spare parts supply chains in telecom firms are use to support basically two services: Advance & Exchange (AE) of spare parts and Repair for Services (RfS).

This paper studies only the dynamics of the AE service in one particular firm[1]. The AE service is trigger when a critical network element of the carrier[2] fail, then the Telecom Equipment Manufacturer (TEM)[3] must send to the carrier a good circuit pack from their stock under a determined Service Level Agreement (SLA), once received, the carrier must return the faulty unit back to TEM's warehouse, so this one can be repair and return back to the pool of good stock (see figure 1).

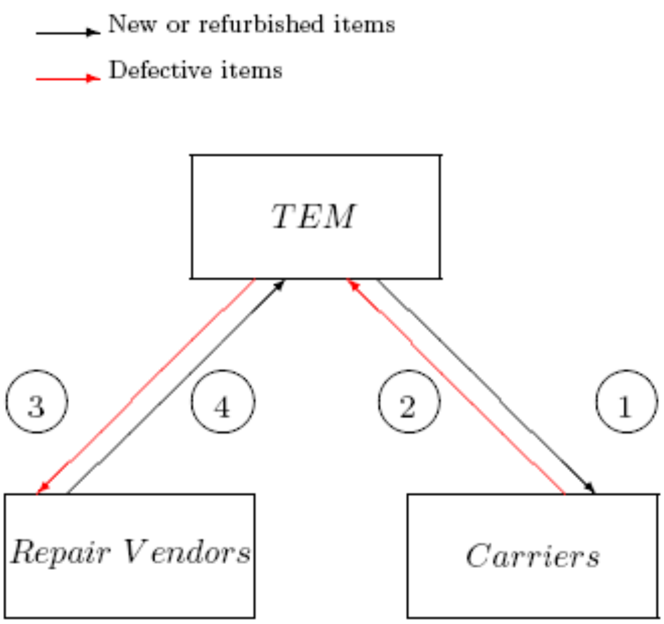

Fig. 1. Closed loop supply chain of repairable items

The activities that feed and consume the spare parts into the pipeline compose an enormously complex system. The study of complex systems in a unified framework has become recognized in recent years as a new scientific discipline. This approach studies how relationships between parts give rise to the collective behaviors of a system and how the system interacts and form relationships with its environment (Bar-Yam, 1997, 2004). The study of complex systems in a unified fractal framework has become recognized in recent years as a new scientific discipline. The fractal behavior study of complex systems consists in general, in three major approaches: theoretical, experimental and computational. The goal is to have the most parsimonious description of the phenomena under study and the most faithful representation of the observed characteristics (Morales et al, 2010).

The after-sales spare part system to support AE services will be characterized using a fractal analysis of the time series of each process described in figure 1 of the supply chain.

This article encompasses the following sections: in 2, some schools of complex systems and fractal tools are described. In 3, the literature around the phenomenon

[1] Because of confidentiality the name of the company and the customer is not shown in this paper.
[2] In the Telecom industry the carrier refers to the customer.
[3] In the Telecom industry the Telecom Equipment Manufacturer refers to the provider.

Bullwhip Effect is mentioned. In 4, the system is characterized with a fractal analysis approach and in 5 some conclusion remarks and future research are suggested.

2. COMPLEX SYSTEMS

Foote (2007) stated that complex systems share some common themes:(i) They are inherently complicated or intricate, in that they have factors such as the number of parameters affecting the system or the rules governing interactions of components of the system; (ii) they are rarely completely deterministic, and state parameters or measurement data may only be known in terms of probabilities; (iii) mathematical models of the system are usually complex and involve nonlinear, ill-posed, or chaotic behavior; and (iv) the systems are predisposed to unexpected outcomes (so-called emergent behavior). This new science has an interdisciplinary impact in the fields of physics, mathematics, information science, biology, medicine, sociology and economy (Morales et al, 2010), and recently, there is a new attention to apply these tools also to the management science (Amaral and Uzzi, 2007).

According with Zexian (2007), in recent years, different theories, methods, approaches and schools have appeared in the studies of complex systems: (i) complex systems dynamics, (ii) self-organizing, (iii) chaos theory, (iv) complex adaptive systems, (v) cybernetics of system evolution, (vi) complex system organization management, and (vii) the approach of the philosophy of complex systems. We add also (ix) the school of fractals (Morales et al 2010; Balankin, 1997) and (x) the school of complex networks (Newman et al, 2003).

2.1 Fractal Analysis

Taking into account the different schools of complex systems, this paper will be focus only on fractals analysis. A fractal can be seen as an object or phenomenon under an invariant structure in different scales. There is no universally agreed definition of exactly what we should mean by a fractal but tow points are central: it should be an object with some type of non-integer dimension, such as Hausdorff dimension[4] and it should be approximately (or statistically) self-affine (Mumford et al, 2002).

Definition 2.1.1 (Self-affine process). The standard definition of self-affine said that a process of continuous time $Y=\{Y(t), t>0\}$ is self-affine if the distribution probability of $\{Y(t)\}$ has the same distribution probability of $\{a^H Y(at)\}$ for $a>0$ (Gao et al, 2007).

The parameter H takes values between 0 and 1 and it is known as the Hurst exponent. This parameter measures the correlation persistence of data.

- For $0<H<0.5$, the process is said to have antipersistent correlation.
- For $0.5<H<1$, the process has persistence correlation and infinite variance.
- For $H=0.5$, the time series is said to be memoryless or short-range dependence.

[4] See the definition of Hausdorff dimensión in Barnsley (1988)

To estimate *H* in this paper we use the method rescale range (R/S) analysis. This method allows the calculation of the self-similarity parameter *H*, which measures the intensity of long-range dependence in a time series (Mandelbrot, 1982).

The analysis begins with dividing a time series of length *L* into *d* subseries of length *n*. Next for each subseries $m = 1, ..., d$: 1° find the mean (E_m) and standard deviation (S_m); 2° normalize the data ($Z_{i,m}$) by subtracting the sample mean $X_{i,m} = Z_{i,m} - E_m$ for $i = 1, ..., n$; 3° create a cumulative time series $Y_{i,m} = \Sigma^{i}_{j=1} X_{j,m}$ for $i = 1, ..., n$; 4° find the range $R_m = \max\{Y_{1,m}, ..., Y_{n,m}\} - \min\{Y_{1,m}, ..., Y_{n,m}\}$; and 5° rescale the range R_m/S_m. Finally, calculate the mean value $(R/S)_n$ of the rescaled range for all subseries of length *n*.

It can be shown that the R/S statistics asymptotically follows the relation $(R/S)_n \sim cn^H$. Thus the value of *H* can be obtained by running a simple linear regression over a sample of increasing time horizons (Weron, 2001).

$$\log(R/S)n = \log c + H \log n.$$

The time series are plotted using cumulative data of each echelon of the process of the supply chain (Daganzo, 2003) (see fig. 2). The vertical difference between two curves represents the queue of material which exists in the process and the horizontal difference means the elapse time one unit use to go from one echelon to the next one.

In order to avoid the bullwhip effect the value of *H* might be almost statistically the same in each echelon into the supply chain, i.e. that each curve in graph shown below might be statistically symmetric.

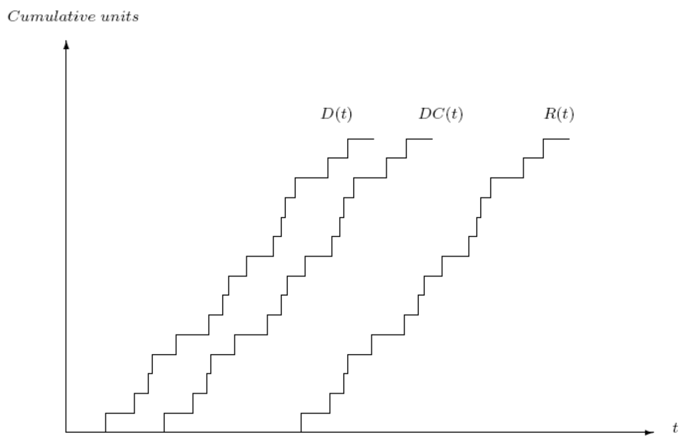

Fig. 2. Supply chain cumulative data of demand, collect and repair process

3. LITERATURE

Bullwhip effect has been analyzed in academic for some time. This phenomenon suggests that demand variability increases as one move upstream in a supply chain. Forrester (1961) observed that factory production rate often fluctuates more widely than does the actual consumer purchase rate and stated that this was consequence of industrial dynamics. Sterman (1989) reported an experiment of a simulated inventory distribution system played by four people who make independent inventory decision without consultation with other chain members, just relying on orders from the other players instead. This experiment was call “Beer Distribution Game” and shows that the variance of orders amplify as one moves up in the supply chain i.e. bullwhip effect. Sterman attributes this phenomenon as misperceptions of feedback of the players.

Lee et. al. (1997b) analyzed the demand information flow in a supply chain and identified four causes of the bullwhip effect: demand signal processing, rationing game, order batching and price variations. By identifying these causes, the authors concluded that the “combination of sell through data, exchange of inventory status information, order coordination and simplified pricing schemes can help mitigate the bullwhip effect".

Chen et. al. (2000) quantified the bullwhip effect in a simple supply chain of two stages. The model includes the demand forecasting and order lead time, which are commonly factors that cause the phenomenon. The work is extended to multiple stage centralized and decentralized supply chains. The study demonstrates that the bullwhip effect can be mitigate but not eliminated.

Daganzo (2003, 2004) has been studied the bullwhip effect in the frequency domain. He argued that the bullwhip effect is trigger with all operational inventory control policies, independent of demand process but showed that advance demand information in future order commitments can eliminate the bullwhip effect without giving up efficiency under a family of orderup-to policies. Dejonckheere et. al. (2003) used control theory to analyze and illustrate the bullwhip effect for a generalized family of order-up-to policies.

The study of supply chain from the point of view of complex dynamical systems theory has started only recently (Helbing, 2008). Concepts from statistical physics and nonlinear dynamics have recently been used for the investigation of supply networks (Radons and Neugebauer (ed.), (2004)).

Helbing (2003) generalized concepts from traffic flow to describe instabilities of supply chains. This work remark how small changes in the supply network topology can have enormous impact on the dynamics and stability of supply chains. In order to stabilize the supply chain, some strategies are mention on Radons and Neugebauer (ed.) (2004).

By simulation a supply chain model, Larsen et al (1999) showed a wide range of nonlinear dynamic phenomena that produce an exceedingly complex behavior in the production distribution chain model. Hwarng and Xie (2008) used chaos theory through the Lyapunov exponent across all levels of a specific supply chain. They showed that chaotic behaviors in supply chain systems can be generated by deterministic exogenous and endogenous factors. They also discovered the phenomenon “chaos amplification”, i.e. the inventory becomes more chaotic at the upper levels of the supply chain.

4. RESULTS

The time series encompassed one year of failures (demand of spare parts) of 4217 units. Unfortunately not all defective units were collected and/or repaired. Then, only 3617 units completed the entire process, i.e. since they were demanded until repaired. Figure 3 shows the cumulative data of the real time series of each process of the supply chain. We can observe on this graph that there is some symmetry between each process. However, some simple statistics of these time series (see table 1) show an increased in the variance between the demand and the other processes. This suggests the presence of the bullwhip effect in the supply chain[5].

Table 1. Simple statistics of the time series of the supply chain

	Demand	Defective Collect	Inboud Repair	Outbound Repair
Media	9.909589041	8.334101382	8.334101382	7.795258621
Desviación estándar	7.087757678	8.592998291	11.46805537	9.128734872

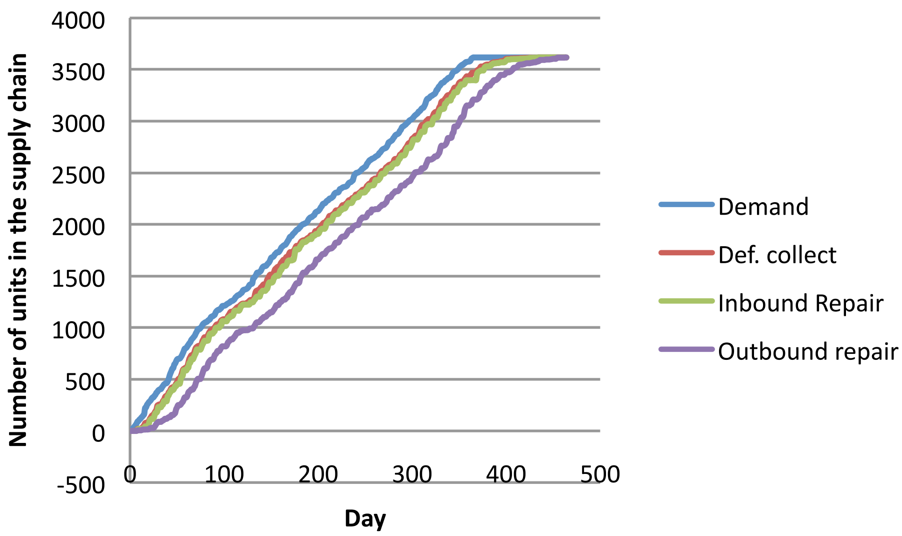

Fig. 3. Cumulative real data of the supply chain of spare parts

Another way to look at the data is by calculating the difference among two cumulative curves of the process, i.e. the queue of material pending to be process by the following steps of the supply chain.

[5] This analysis considers a different perspective of traditional definition, where the creation of the orders is considered in the analysis and in this paper is the completion of them.

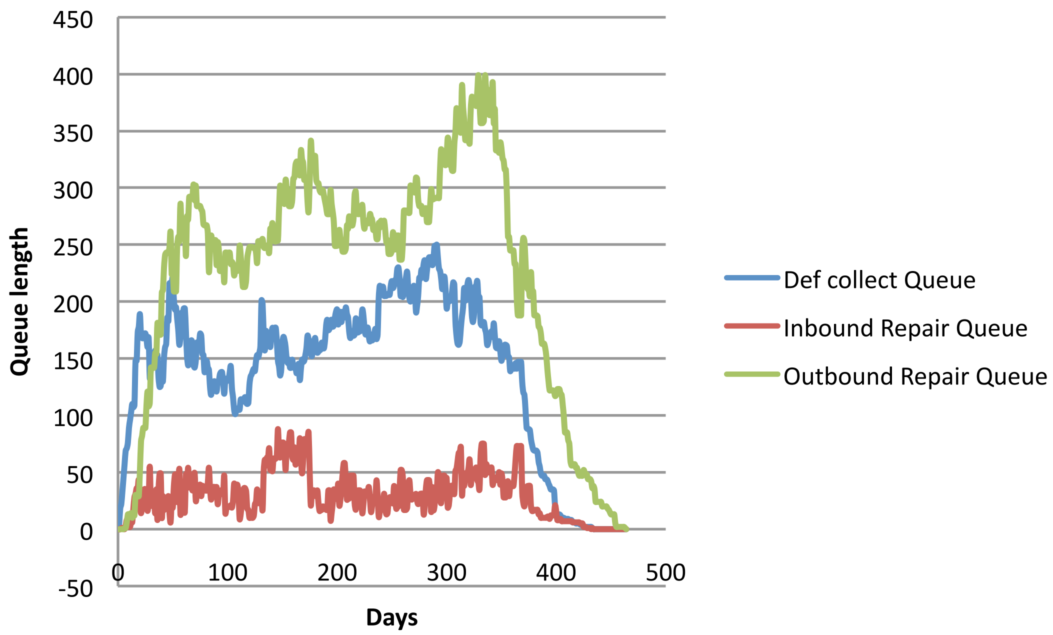

Fig. 4 Queue of parts pending to process in each echelon.

Figure 4 illustrates the difference among each queue length. The repair queue has an average of 223.42 units and standard deviation of 105.03 units, which is the largest queue. The defective collect queue has an average of 147.70 units and a standard deviation of 60.91 units, which is the second largets queue. An the small one, is the queue related with the units pending to be inbound in the repair process with an average of 32.40 units and a standard deviation of 19.49 units. The formation of these queues are closely linked to the time and uncertainty of each process.

To conclude this analysis, the Hurst exponent estimated through the R/S method, suggests that the demand process in the AE service shows persistence with a Hurst exponent value of 0.8449, and the defective collect process indicates still the presence of persistence with a Hurst exponent value of 0.6481. However in the following steps of the processes, the value of the Hurst exponent decreased with a value close to 0.5, which suggests that they follow a Brownian Motion process (see figures 5-8).In other words, it is notorious in this analysis that the system started to have strong long-range dependence but at the end it became almost memoryless.

Table 2. Hurst exponent value of each process of the supply chain

Summary	H
Demand	0.844
Defective collec	0.648
Inbound repair	0.516
Outbound repai	0.564

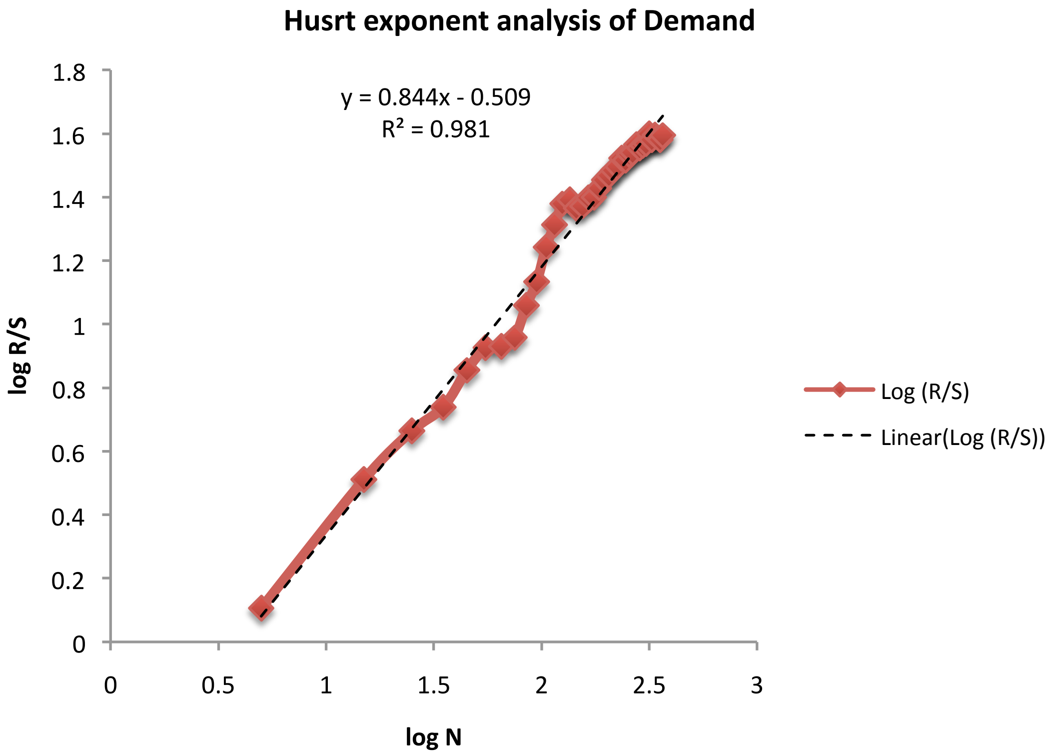

Fig. 5. R/S analysis of demand data (H=0.8449).

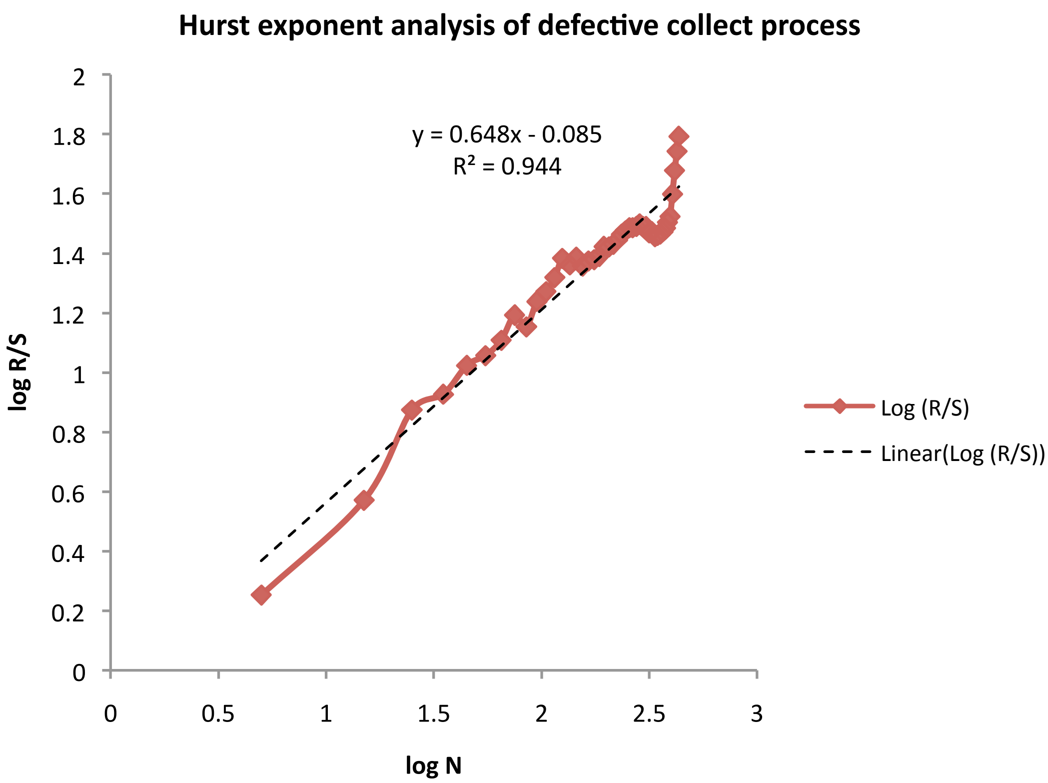

Fig. 6. R/S analysis of defective collect process data (H=0.6481).

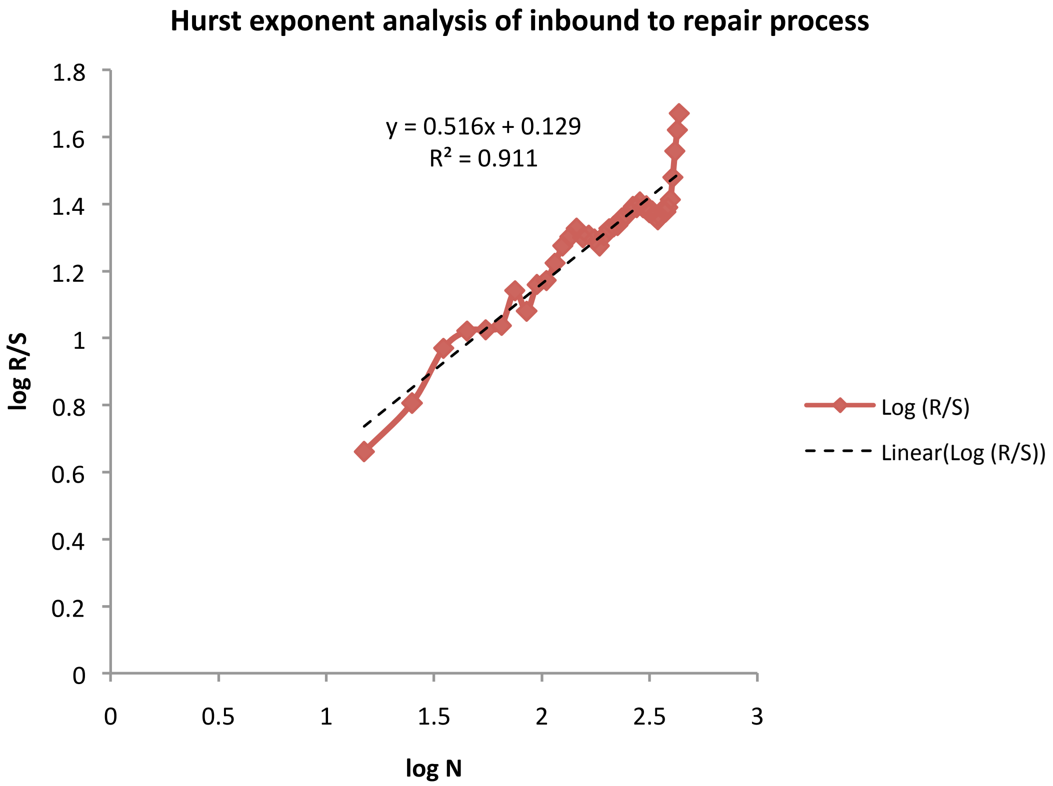

Fig. 7. R/S analysis of inbound to repair process data (H=0.5164).

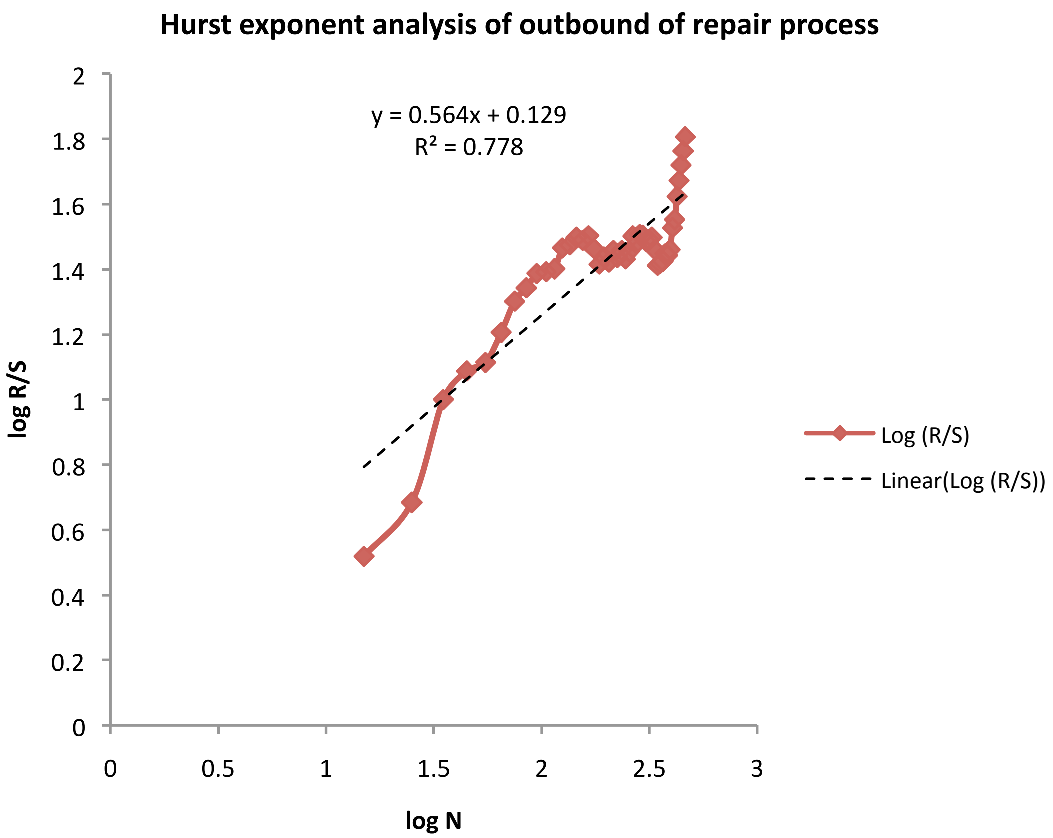

Fig. 8. R/S analysis of outbound of repair process data (H=0.5649).

These results come up with a different way of detecting the bullwhip effect. By intuition, the bullwhip effect would not occur if a statistical symmetry between each time series of each process in the supply chain is not broken, but unfortunately in this case, current models in the literature has this assumption (Sherbrook, 2004; Muckstadt, 2005).

5. CONCLUSION AND FUTURE RESEARCH

Bullwhip effect is a phenomenon experienced by supply chains when demand at the top tends to exhibit more variability than demand at the bottom. This work provides new insights to develop a new model of the spare part management which capture the characterization of the supply chain found in this paper. However, we use only one technique to determine the Hurst parameter and other ones need to be included in the analysis, to confirm the long-range correlation of the demand and collective defective processes and the Brownian Motion of the Inbound and Outbound processes. Moreover, a multifractal analysis is suggested to be done related with the Outbound process, because the graph of the Hurst exponent does not look adjusted with a line equation.

Other potential field to analyze the bullwhip effect is through the complex network discipline. The idea is to verify the impact of different topologies in the bullwhip effect. For example, what is the impact of having a supply chain which has a small-world phenomenon or scale free property?

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