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The bullwhip effect in capacitated supply chains with consideration for product life-cycle aspects

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A B S T R A C T

This paper presents an analysis of the bullwhip effect and net-stock amplification in a three-echelon supply chain considering step-changes in the production rates during a product's life-cycle demand. The analysis is focused around highly complex and engineered products (e.g., automobiles), that have relatively long production life-cycles and require significant capital investment in manufacturing. Using a simulation approach, we analyze three stages of the product life-cycle including low volumes during product introduction, peak demand, and eventual decline toward the end of the life-cycle. Parts of the simulation model have been adopted by a major North-American automotive OEM as part of a scenario analysis tool for strategic supply network design and analysis. The simulation results show that performance of a system as a whole deteriorates when there is a step-change in the life-cycle demand. While restriction in production capacity does not significantly impact the bullwhip effect, it increases the net stock amplification significantly for the supply chain setting under consideration. Furthermore, a number of important managerial insights are presented based on sensitivity analysis of interaction effect of capacity constraints with other supply chain parameters.

1. Introduction

The bullwhip effect is one of the most widely investigated phenomena in the modern day supply chain management research. It is the tendency to see an increase in variability in the replenishment orders with respect to true demand due to distortion in the demand information as we move upstream in the supply chain. While Lee et al. (1997) first introduced the term "bullwhip effect" to explain this phenomenon, it was first described by Forrester (1961) to demonstrate the demand and variance amplification in an industrial system. His idea has been studied further and illustrated through the "Beer Distribution Game"—a simulation based teaching tool to explain the economic dynamics of stock management problem (Sterman, 1989). Lee et al. (1997) identified the following four reasons for the bullwhip problem: *demand signal processing, the rationing game, order batching, and price variations.* Since then, there have been a significant number of studies on this problem with respect to all the major causes of the bullwhip effect (Chen et al., 2000a; Dejonckheere et al., 2003; Disney and Towill, 2003; Moyaux et al., 2007; Boute and Lambrecht, 2007). Recently, third-party warehousing has also been cited as one of the causes of the bullwhip effect (Duc et al., 2010).

Classical inventory management models for multi-echelon supply chains require that the product demand process be fairly smooth in order to make it mathematically tractable (Williams, 1982). In comparison, simulation models are well suited to study complex supply chains with non-smooth demand process (e.g., lumpy demand during life-cycle) and allows for transient analysis. It is therefore widely used in the bullwhip effect analysis as well (Disney et al., 2004a; Wanphanich et al., 2010; Coppini et al., 2010). While simulation based games like "Beer Game" have helped researchers and practitioners understand dynamics of order and inventory fluctuations in a supply chain (SC) system, very few examples can be found that incorporate the life-cycle demand aspects into those dynamics (Disney et al., 2004b; Reddy and Rajendran, 2005). It is a well-known fact that every product has its own life-cycle demand curve—slow market growth at introduction, rapid growth during peak, and sluggish demand during saturation (maturity) or decline phase (Mahajan and Muller, 1979). Kaipa et al. (2006) discuss the nervousness of demand planning and its impact on bullwhip in an electronic SC in the face of changing demand at various life-cycle phases. Hoberg et al. (2007) also argue that the conventional approach of using a lower smoothing constant in forecasting will take a significantly long time to detect step-changes in demand.

While the notion of a product life-cycle is not new and somewhat witnessed in all industries (e.g., see Kaipa et al., 2006; Berry

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and Towill, 1982), the "signature" of the production life-cycle is unique to industries that produce complex engineered products (e.g., automobiles). During the first few months of introduction, the vehicle is typically produced at low volume to address any production quality and supply issues. Given the complexity of the assembly and other production facilities, it is not practical to change the production volume continuously due to the need to "balance" the assembly line and the supply chain. Instead, the production volume typically undergoes step changes at distinct epochs as the demand picks up for the product in the market place, e.g., in the form of additional production shifts and step changes in volume per shift (Kisiel, 2008). For example, most original equipment manufacturer (OEM) automotive products in the North-American market undergo a four to five year life-cycle (with some product "refreshing" every year), with demand typically waning after couple of years due to introduction of more competitive products in the market place with better functions, features, and option content.

These life-cycles however tend to be different from industry to industry, with complex engineered product typically experiencing longer life-cycles due to complexity, costs, and risks associated with product development and launch. Another characteristic, at least typical of the North-American automotive OEMs, is that they predominantly operate in a "build to stock" production mode rather than a "build to order" mode. This is also attributable to complexity of the product, production facilities, challenges associated with coordination of the supply chains to support the "take rates" for the different options/features, and the long order-to-delivery lead-times. Accordingly, the companies rely heavily on dynamic pricing strategies (in the form of dealer or customer incentives) and marketing to influence demand while adjusting supply in the long-run to match demand. Hence, this study focuses more on modeling and control of the bullwhip effect in the supply networks as a function of fluctuations in the OEM final-assembly (FA) line production volume rather than end customer "demand". Fig. 1 shows a typical production pattern life-cycle for an automobile. In such a case, adopting a "one size fits all" production and inventory management policy results in a chaotic situation especially in multi-echelon SC settings. It is necessary to investigate how inventory and order variances propagate as a product passes through different phases of the life-cycle. Capturing such transient trajectories of different SC performance measures will be very helpful especially in designing or configuring a SC network for future products, such as the automotive industry example addressed in this paper.

The unique contributions of this paper are several-fold. First, we extend the work of Chen et al. (2000b) and present analytical expressions of the bullwhip effect and net-stock amplification for OEM using a different sequence of events in a replenishment period. These results confirm the bullwhip effect results developed in the literature for slightly different ordering policy. The analysis is then extended via simulation to a three-echelon SC consisting of OEM, Tier 1, and Tier 2 suppliers. Through simulation based models, we investigate the transient and steady-state impact of step-changes in OEM production volume on the bullwhip effect and net stock amplification. These analyses are performed for both with and without capacity constraint scenarios. For ease of presentation, we approximate different phases of the product life-cycle with three stationary phases (labeled, "introduction", "peak", and "end-of-life" stages) corresponding to the three stages of Fig. 1. Various sensitivity analyses are performed to explore the impact of interaction between capacity constraint and other SC parameters on the bullwhip effect and inventory variance (or net-stock amplification). Several insights of managerial importance are drawn based on the sensitivity analyses.

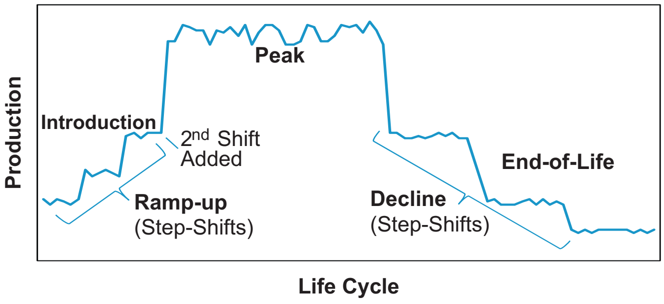

Fig. 1. Typical production pattern life-cycle for an automobile with introduction, peak, and end-of-life stages.

The remainder of the paper is organized as follows. A brief review of related literature on the bullwhip effect analysis is presented in Section 2. Section 3 describes the model and the undertaken SC policies. In Section 4, we present the analytical expression for inventory variance and bullwhip effect (from the literature) for OEM. Section 5 describes the simulation model and sensitivity analysis results for a three-echelon SC with and without capacity constraints. Finally, conclusions and directions for future research are outlined in Section 6.

2. Review of related literature

The bullwhip effect related research in supply chains has a long tradition which can be broadly divided into three streams. The first stream of research focuses on determining the impact of forecasting techniques employed by SC players on the bullwhip effect. Chen et al. (2000a) have analytically derived a quantitative measure of the bullwhip effect and demonstrated via simulation the impact of forecasting, lead-time and information. The authors used simple moving average (MA) forecasting techniques to determine the lower bounds of the bullwhip effect in simple single and multi-echelon supply chains. They later extended their work by studying impact of other forecasting techniques, in particular exponential smoothing (ES) under both auto-correlated demand and demand with linear trend (Chen et al., 2000b). Zhang (2004) compared the bullwhip effect under three different forecasting methods for a simple inventory system with a first-order autoregressive, AR(1), demand process. Zhang (2004) found the minimum mean square error (MMSE) to be the optimal forecasting method for stable AR(1) demand processes. In comparison, the MA or ES methods were more flexible and adapted better to the demand shifts over time. Disney et al. (2006) have developed exact methods to quantify the bullwhip effect for different demand processes including AR, MA, and auto-regressive moving average (ARMA). Holweg et al. (2005) discussed the challenges in implementing a Build-to-Order (BTO) production system given current SC network structures, in light of the bullwhip effect and scheduling issues especially in automotive industry. Hosada and Disney (2006) presented a control theoretic approach to quantify the bullwhip effect under the MMSE forecasting. The authors also derived an analytical expression for another important performance measure of supply chains, the "net-stock amplification". It is defined as the ratio of the net-stock variance over the variance of demand, which, just like the bullwhip effect, gets worse as we move up the chain. In addition to AR(1), attempts have been made to determine an upper bound for the bullwhip effect for two stage SC with first and second order autoregressive demand process (Luong, 2007; Luong and Phien, 2007). Duc et al. (2008) analyzed on a two-stage SC including one supplier and one retailer with a mixed autoregressive-moving average model, ARMA(1, 1) for