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INFORMATION BLACKOUTS IN A MULTI-ECHELON SUPPLY CHAIN SIMULATION

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ABSTRACT

Information blackouts, defined as sudden and short-duration failures of the information flow in a supply chain, amplify the bullwhip effect in supply chains. We develop a discrete-event simulation of a multi-echelon supply chain, utilizing Rockwell Automation's Arena software tool, to investigate this phenomenon. We investigate inventory order history blackouts of three different durations (1, 2, and 3 time periods). Based on the increased bullwhip effect observed as the result of an information blackout, managers may decide to "wait out" the amplification or to use an estimate to replace the missing inventory order history by utilizing the last known value. The latter choice employs the common manager's heuristic of trusting the recent past to be the best predictor of the future. Our results provide supporting evidence for such managerial decisions.

1 INTRODUCTION

Supply chain managers focus significant amounts of time and energy on inventory management. The costs incurred from holding too much inventory or from running short are, by no means, insignificant. In an effort to minimize both cases, inventory control systems are increasingly automated. Even with the increased use of automated inventory control systems, managers still have a heavy hand in inventory replenishment decisions. As such, an increased understanding of the characteristics of both up-stream and down-stream inventory in the supply chain can drive better, more informed, decision-making.

We wish to answer a basic question: what happens when an information blackout deprives the manager of necessary inventory information? We address this question in cases of information blackouts of one, two, or three periods in length occurring at the retailer, wholesaler, or distributor in a supply chain. We build a discrete-event simulation model of a multi-echelon supply chain utilizing Rockwell Automation's Arena simulation software package. The supply chain follows a serial structure commonly seen in the literature, often referred to as the Beer Game (Sterman, 1989), and consists of customer, retailer, wholesaler, distributor, and factory echelons. Using this supply chain structure gives us one stocking point, the wholesaler, that is not adjacent to an end point. This provides results that more closely reflect the supply chains being modeled.

2 RELEVANT LITERATURE

2.1 Discrete-Event Approach to Modeling Supply Chain Disruptions

Discrete-event simulation models are well-suited for studying supply chains. Supply chains are modeled quite naturally as a set of events acting on distinct entities representing the orders moving upstream and downstream within a supply chain. Prior literature supports the use of discrete-event analysis of supply chains. Cigolini et al. (2014) used a discrete-event analysis to explore how the configurations of supply chains can impact performance.

Chatfield (2013) investigate the decomposability assumption when modeling the bullwhip effect in supply chains by comparing the use of multiple node pairs to a single, "monolithic" model to represent a multi-echelon supply chain. Although the literature is predominantly made up of studies that use node pair based models, Chatfield (2013) notes that a monolithic model provides a better representation because, in part, it can represent nodes that do not interface with an end node (customer or supplier/factory). Our study uses a monolithic multi-echelon model which, we believe, allows us to study facets of disruption that we could not if we used a node pair approach.

Disruptions to supply chains are often difficult to predict or mitigate. Much research has been dedicated to this effort. One of the more common methods for studying supply chain disruptions is discrete-event simulation. There have been several such studies in recent years. They include Datta and Christopher (2011), Chatfield (2013), Chatfield and Pritchard (2013), and Cigolini et al. (2014). Each of these studies examines a different aspect of supply chains. Datta and Christopher (2011) investigated how uncertainty in supply chains can be managed through information sharing and coordination mechanisms. Chatfield (2013) used discrete-event simulation to look system decomposability. Chatfield and Pritchard (2013) studied the effect returns have on a supply chain. Cigolini et al. (2014) discovered that increasing the number of suppliers actually degrades the performance of the distributors and manufacturers.

2.2 Bullwhip Effect Measure of Supply Chain Performance

We use the well-known bullwhip effect (BWE) to measure the impact of information blackouts. The bullwhip effect represents order variance amplification, the tendency for orders placed in a supply chain to increase in variability as one moves upstream in the supply chain. Forrester (1958, 1961) is credited with the initial studies of order variance amplification (later to be called the "bullwhip effect" and in some cases the "Forrester effect"), employing a system dynamics approach.

Many other methods for studying the bullwhip effect have been used since Forrester's initial work. There have been many discrete-event analyses as well as agent-based modeling studies and the use of differential equation-based models. Varied approaches to measuring the bullwhip effect have been proposed, such as those provided by Baganha and Chen (1995), Kahn (1987), and Metters (1996).

The most common measurement of the BWE is referred to as total variance amplification, which represents amplification at an echelon with a ratio defined as the order variance at that echelon over the variance of the customer (echelon 0) demand. As such, the following expression represents total variance amplification:

$$\text{Bullwhip} = \frac{\text{Variance of orders}}{\text{Variance of demand}} = \frac{\sigma^2_{\text{orders}}}{\sigma^2_{\text{demand}}}.$$

As Chen et al. (2000) explain, "most of the previous research in the bullwhip effect has focused on demonstrating its existence, identifying its possible causes, and providing methods for reducing its impact". Our work uses the bullwhip effect to investigate another phenomenon occurring in supply chains, information blackouts. The impact of information blackouts can be observed by comparing the bullwhip effect at the same location (echelon) when simulated with and without blackouts. The baseline model represents the situations where no information blackouts ever occur. The alternate (blackout) scenario includes the possibility of information blackouts occurring. If the bullwhip effect observed for the two scenarios is the same or very close (statistically insignificant difference), then we can conclude that the blackouts were so short that they did not affect the demand history enough to impact system performance. If the bullwhip effect levels observed are different, then an information blackout of a long enough duration to impact the demand history took place.

3 METHODOLOGY

3.1 Conceptual Model

The inventory system we used has been utilized in a number of previous studies, such as Chen et al. (2000) and Chatfield (2013). The five-stage serial supply chain, as depicted in Figure1, has stocking points (retailer, wholesaler, distributor) that utilize a periodic, order-up-to (R, S) inventory policy. Every R time periods, the inventory level is checked and if needed, a replenishment order is placed with the upstream partner to increase the inventory position to the order-up-to level S. As with Chen et al. (2000) and Chatfield (2013), the period is one day (R=1). A single, aggregate customer order is placed with the retailer each day. All stocking points in the supply chain use the same R, S inventory policy. The retailer orders once a day from the wholesaler. The wholesaler orders once daily from the distributor and the distributor orders once daily from the factory. The factory fulfills all order received from the distributor without capacity (stockout) concerns.

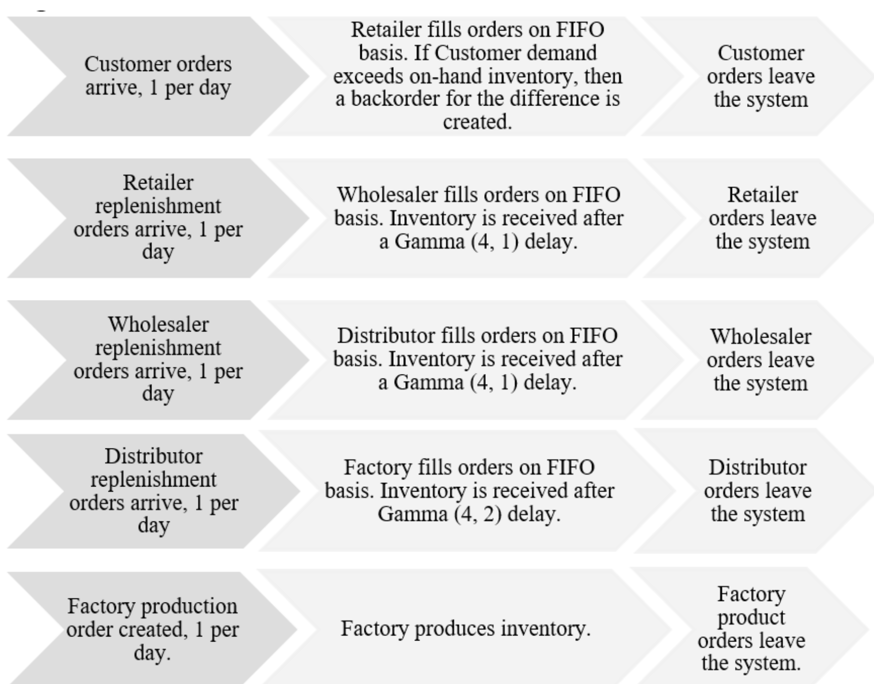

Figure 1: Model flow chart (Rasnick 2016).

3.2 System Description

Customer demand orders follow a normal distribution with a mean of 50 units and a standard deviation of 10 units, and we use the notation $N(50, 10)$ as a compact expression of the distribution. Orders from stocking points are based in the order size necessary to increase the inventory position to order-up-to level S, as dictated by the R,S inventory policies being used. Orders are filled in a first-in, first-out (FIFO) manner and are filled as soon as they arrive. We allow orders of negative size, using them to indicate a return of inventory. If a stocking point does not have enough on-hand inventory to fill an order, all on-hand inventory is used to partially satisfy the order and the remainder is backordered. The factory fills incoming orders (from the distributor) but does not generate orders of its own.

A replenishment order is received after a gamma distributed lead time with a mean of 4 days and a standard deviation of 1, or $G(4,1)$. The lead time distribution is the same for all echelons. When a replenishment order is received the on-hand inventory level for that node increases and the on-order decreases. In addition, each stocking point updates the order-up-to value (S) each period, attempting to adapt to the demand it sees, by using demand estimates generated with a 15-day moving average of previous demands.

The experimental variable in the model is the length of the information blackout. A control model (baseline scenario) is run with no information blackouts to which we can compare the experimental model data. Three experimental scenarios were chosen. They consist of information blackouts lasting for 1, 2, or 3 periods. These information blackout lengths were chosen because they most closely reflect the periods of information disturbance experienced by supply chain managers. For example, most businesses will have recovered power after a natural disaster within a day or two. Running models for information blackouts lasting longer than three days will represent what we consider to be rare event situations that are best studied separately. A supply chain that is, in part or wholly, experiencing an information blackout is, by definition, under distress by a disaster of some sort and it is unlikely that missing demand information will be a high priority in such cases.

3.3 Verification and Validation

For purposes of verification and validation, the baseline model, having no information blackouts, was run with the supply chain specifications used by Chen et al. (2000). We utilized a customer demand of $N(50, 20)$ and a constant lead time of 4 time units. The resulting data matched those obtained when applying the expressions developed by Chen et al. (2000) to those demand and lead time situations. We also compared our model to the work of Chatfield (2013). The customer demand distribution was $N(50, 10)$ while the lead time utilized was $G(4,1)$ distributed. Matching results were achieved here as well. The models used to perform our blackout simulations conform to the basic specifications used by Chatfield (2013), with the addition of information blackouts, of course.

3.4 Model Assumptions

We note the assumptions made during the modeling process as these are important to understanding the what is (and isn't) represented in the models we utilize. First, we assume there is a single product in the system, which is a common assumption with bullwhip effect related research. Second, we assume there is a single, aggregate order each day at each echelon. Third, we assume echelons have perfect reliability. There is never downtime for maintenance. They are always running at full capacity and never run out of material. Fourth, we assume all customer orders are identical and have the same priority. These are all common assumption when modeling supply chains based on the beer game structure. These assumptions, or some in the same vein, have been used in supply chain research by Chen and Lee (2017), Chatfield et al. (2013), Pacheco et al. (2015), and Chen et al. (2000).

4 RESULTS

Our experimental runs utilize a $N(50, 20)$ distributed customer demand and $G(4,1)$ distributed lead times for all order fulfillments. The time units for the replications are days. Each experiment was run for a period of 2200 days including a warm-up period of 200 days. The warm-up period allows the system to initialization and then stabilize before the experimental scenarios are run. This reduces the usable data to 2000 days. Each model was run for one hundred replications.

The experimental parameter in this investigation is blackout period length. A pattern emerged in the T-test results and can be seen in Table 1. As expected, echelons with no information blackout occurring, have scores of 1.0. All echelons where an information blackout occurred show significant results at the 0.025 level. A ripple effect can be seen in the stages following those where the information blackout occurred.

4.1 Model Results

The model was run with the one experimental parameter, the information blackout period. Blackouts are represented by replacing the order quantity with zero when a blackout occurred. The zero becomes part of the replenishment order calculation and thus effects more than just the single order that was wiped out. For the information blackouts of two or three periods, multiple replenishment orders are replaced with zeroes. This has an impact on the replenishment orders for several of the following periods. For example, an information blackout lasts two periods. The replenishment order quantities for two consecutive periods are replaced with zeroes. These zeroes become part of the demand history of the upstream node and are used in determining the 15-day moving average needed to update the order-up-to level. An information blackout of one period has some impact, however, any information blackout longer than a period has greater impact. With two of fifteen values being zeroed out, a substantial change in the average is expected and is seen in the results. When the information blackout is greater than three periods, the demand estimation becomes unrealistic. Any manager's heuristic would be a better method.

Table 1: T-statistics for information blackout models.

Model	T-Statistic, 1 period blackout	T-Statistic, 2 period blackout	T-Statistic, 3 period blackout
Information Blackout at Retailer	0.000549	0.000000	0.000000
Retailer	0.000019	0.000000	0.000000
Wholesaler	0.000209	0.000000	0.000000
Distributor	0.000020	0.000000	0.000000
Information Blackout at Wholesaler	0.004169	0.000000	0.000000
Retailer	1.000000	1.000000	1.000000
Wholesaler	0.003413	0.000000	0.000000
Distributor	0.000000	0.000000	0.000000
Information Blackout at Distributor	0.016903	0.000002	0.000000
Retailer	1.000000	1.000000	1.000000
Wholesaler	1.000000	1.000000	1.000000
Distributor	0.258121	0.028789	0.029887
Information Blackout at Retailer & Wholesaler	0.000000	0.000000	0.000000
Retailer	0.000019	0.000000	0.000000
Wholesaler	0.000000	0.000000	0.000000
Distributor	0.000000	0.000000	0.000000
Information Blackout at Retailer & Distributor	0.000000	0.000000	0.000000
Retailer	0.000019	0.000000	0.000000
Wholesaler	0.000209	0.000000	0.000000
Distributor	0.000000	0.000000	0.000000
Information Blackout at Wholesaler & Distributor	0.000000	0.000000	0.000000

Retailer	1.000000	1.000000	1.000000
Wholesaler	0.003413	0.000000	0.000000
Distributor	0.000406	0.000000	0.000000
Information Blackout at All Echelons	0.000000	0.000000	0.000000
Retailer	0.000019	0.000000	0.000000
Wholesaler	0.000000	0.000000	0.000000
Distributor	0.000000	0.000000	0.000000

Table 1 presents a comparison of demand data from the specified echelon for the model with no information blackouts and the model with information blackouts at the identified stage. The significance level was set to 0.025. As one would expect, we find no difference between the data sets of echelons where information blackouts did not occur. For instance, in the model where and information blackout occurred at the Wholesaler and Distributor stages, there is no difference in the demand data between the Retailer in the test model and the Retailer in the baseline model. This pattern holds true for all the experimental models.

5 FINDINGS AND CONTRIBUTIONS

This study builds on prior supply chain research in three ways. The first contribution is providing empirical evidence of the phenomenon of information blackouts in supply chains. Supply chain disruption literature is extended with this addition. The second contribution is the multi-echelon supply chain simulation model we developed. Few previous studies have explicitly modeled a multi-echelon supply chain. The third contribution is making supply chain managers aware that when they are experiencing an information blackout of greater than one day, they can reduce the bullwhip effect by replacing the missing demand information. If the information blackout lasts less than a day, the best strategy is, generally, to wait it out. If the information blackout is greater than a day, managers should create replenishment orders even if they use flawed calculations.

6 CONCLUSIONS AND FUTURE WORK

This study provides evidence of the impact information blackouts can have in a supply chain and adds to the supply chain disruption literature. Furthermore, by realizing that these events will occur and the potential impact, managers can plan in advance how to handle them. Understanding that the longer the information blackout, the greater the effect on inventory data, managers can decide at what length of time in an information blackout they wise to act. A manager's heuristic for replacing missing demand information will help soften the exaggerated bullwhip effect resulting from the information blackout.

Information blackouts can be further examined by using different demand order calculations, such as a moving average, running average or the last known order quantity, to replace the missing information. A preference for one over the other based on industry or product type is another consideration. A study could look at when managers should start replacing the missing demand information. This could determine a point at which manager's should replace missing demand data.

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