A System Dynamics Approach to Investigate The Effects of Disruption on The Supply Chain with A Mitigation Strategy

MA Abdullah1, a, H Hishamuddin2, b and NEN Bazin3, c

1, 2Department of Mechanical and Material Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, Malaysia
3Faculty of Computing, Universiti Teknologi Malaysia, Malaysia

Abstract. In this paper, a system dynamics approach is used to simulate a three stages supply chain system experiencing supply disruption. The supply chain system consists of single supplier, manufacturer and retailer. The model is developed suggesting backlogged and inventory as the primary performance measure. The model is tested under three conditions, which are normal condition, disruption condition and disruption with a mitigation strategy. The main findings from the study are lead time changes on the entire system directly impact the inventory of the entire stages in the system. Furthermore, the disruption occurrence produces an adverse effect on supply chain performance for a period longer than the actual period of the disruption and likewise, influence system performance. The study further identifies that by incorporating safety stock as a mitigation strategy in the event of a supply disruption, will significantly reduce the disruption impact. The proposed simulation model and experimental findings are important to assist management in their inventory and risk control decision-making in the event of disruptions.

Keywords: System dynamics simulation, supply disruption, safety stock mitigation strategy

1. Introduction

Supply chain management (SCM) consists of the information collection from downstream stages and be used for the upstream stages. Those information is transform to a physical or material flow from the upstream stages to the downstream stages, in addition to the integration of key business processes through the primary supplier to the end of customers [1]. Nowadays, most supply chains (SC) are vulnerable to various risks including disruptions. Disruption may be caused by a factory fire, transportation accident, natural or environmental disasters. It is inevitable that at some stage, some form of disruption will occur, and hence, it may occur at any point in time, to any entity in the SC network. As a result, the operations and functions of a regular SC will potentially be impacted and in severe cases, disabled [2]. For instance, in 2011 Tohoku earthquake that occurred in Japan caused the Toyota manufacturing company to incurred a considerable loss of almost US$ 250 billion dollars when one of its suppliers, Renesas Electronics, was unable to fulfil the demand from Toyota [3].

In reviewing wealth of the studies in this area, there were three main concerns identified that researchers incorporated into their models: inventory, lead time, and demand fluctuations. For instance, Hishamuddin et al. investigated a model to recover an inventory system from a disruption, to enable the
fulfilment of customer demands [4]. The study demonstrates just how disruption management for inventory-related decisions can satisfy customer demands with a shorter recovery period. Also, Qi et al. presented an inventory problem which was overcome by adjusting the ordering strategy by proposing a suitable sourcing strategy to mitigate the impact of a disruption. Also, a comparative study of multiple sourcing strategies as counter-action measures to demand disruption was explored [5].

There are wealth of System Dynamics (SD) studies have been used as references in this study. Several presented here are, Davarzani et al. developed a SD simulation in Closed-loop SCM that improved customer satisfaction. In a separate study, Golroudbary and Zahraee evaluated demand behaviour by integrating the methods of fuzzy estimation and SD models [6]. Campuzano-Bolarín et al. developed recovery and product exchange policies for a supply chain using an SD framework model [7]. Das and Dutta compared the performance of several models in a supply chain system (SCS) both with and without information sharing [8]. The method used bullwhip effect to investigate the effectiveness of information sharing, as compared to a more traditional model.

However, in the literature, there are a limited number of studies of SD application in the SC disruption context. For instance, Ozbayrak et al. demonstrated the resilience of the SCS by applying inventory placement methodology where proactive inventory placement is captured via SD modelling [9]. Schmitt and Singh used the SD approach to examine the effects of SC disruption. In their study, one model is constructed without a backup supplier, and another model is developed with a backup supplier [10]. Huang et al. studied SC performance impacted by a transportation disruption using the SD approach [11]. In their study, traditional and VMI models are constructed consisting of similar stages. The outcome of the study found that the worst impact resulting from a disruption was between the tier 1 supplier and the warehouse (stage 1).

Given the significant gap in this area based on the literature review, there is a definite need to investigate SC disruption using the SD approach. From the best of our knowledge, most of the existing studies using SD to manage disruption merely focus on recovery strategies instead of mitigation strategies. Therefore, in this study, the SD approach was used to suggest a mitigation strategy using safety stock to reduce the impact of a disruption.

The remainder of this paper is organised into the following sections. Section 2 details the methodology, Section 3 presents the simulation, results and discussion and lastly, Section 4 provides the conclusion, implications and directions for further study.

1.1 Materials and Method
SD describes the interaction of information flows to a physical process, as well as managerial policies to identify a large number of variables associated with dynamic behaviour over time. The main purpose of SD is to understand and investigate the structural causes that influence the behaviour of a system and to prepare an improvement policy [12]. SD is well suited for investigating the behaviour of large integrated systems incorporating causal relationships, feedback loops and time [13].

1.2 Model Development
The three-stage SCS model developed for this study, incorporates the supplier, manufacturer and retailer. The retailer is the only stage having direct contact with the customer. The demand produced at the retailer site are similar to the demand from the customer. While for the other two echelons (the manufacturer and the supplier), the demand is created based on the neighbouring downstream echelon. Figure 1 illustrates the flow of materials (physical form) from upstream and the flow of information from the downstream stages.
Figure 1. Flow of information and materials.

1.3 Stock and Flow Diagram
The previous causal loop diagrams are then converted into stock and flow rate diagrams using Vensim® DSS 5.11 software. The model consists of important parameters that are related to performance measures, which they are selected among the variables. Each variable chosen is the stock variable, in which the performance of the SC is measured by identifying its dynamic behaviour versus time. The diagram have been constructed for the model is shown in Figure 2 for the stage 2 (manufacturer) and is identical to the other two stages.

Figure 2. Stage 2 of the SC model

1.4 Model Validation
Before conducting the experiments, it is necessary to conduct a dimensional consistency testing. The testing was undertaken to check whether the models perform realistically or not. According to (Forrester & Peter 2013), dimensional consistency testing is important to verify the model’s reliability. For example, when the input value changes (customer demand), the average value of inventory (output) for the entire stages also changes in-line with the input changes. Figure 3 illustrated the relationship between input value to the output value. From the relationship shown in figure 3 between customer (input) and average inventory (output) it is proven a consistent value between the input and output. Therefore, demonstrates that the model developed is reliable and realistic.
2. Results and Discussions

Four simulations have been conducted under four different conditions: normal condition, lead time adjustment, passive disruption and disruption with a mitigation strategy. The normal condition was performed earlier as it become the benchmark for another three simulations. The results presented, are the relationship between backlogged orders versus simulation time.

2.1 Simulation of Normal Condition

The system was first tested where the demand is constant for the entire simulation period. In this simulation, there are three setting made to the lead time for each stage. Figure 4 shows the relationship between the backlogged order amount and the simulation time. Since this study only considered backlogged orders at the manufacturer and supplier stages, Figure 4 shown is two lines representing backlogged orders for both stages. The line with number 1 and 2 represent the manufacturer and supplier respectively.

As shown in Figure 4, the highest amount of the manufacturer’s backlogged order is 243 units of inventory, while the supplier’s backlogged order amount is 182 units of inventory. During the initial 30 weeks, the backlogged order pattern is unstable for both the manufacturer and the supplier. After week 30 to the remaining 74 weeks, the pattern gradually becomes stable. This shows that the flow of material and information is stable after week 30.
2.2 Simulation of Normal Conditions with Lead Time Adjustment

In investigating the effect of a disruption (in form of time) on SC performance, the lead time was next adjusted by 20%, (both higher and lower) from the total lead time. Figure 5 shows the relationship between adjusted lead time with a 20% increase to the backlogged orders. The figure shows 4 lines, namely line 1, 2, 3, and 4 that represent (manufacturer backlogged-normal) MBN, (supplier backlogged-normal) SBN, (manufacturer backlogged-adjustment) MBA and (supplier backlogged-adjustment) SBA respectively. From the Figure, 5 the highest inventory level is reached during week 3, where MBN is 260 units and MBA is 367 units. Given the variation in value, the higher lead time (i.e. increased by 20%) will also produce a larger backorder amount. A similar pattern also occurred to the supplier, where an increase of 20% slightly increased the backlogged order quantity. From this pattern, it is shown that the higher the lead time, the higher the backlogged order and vice versa.
2.3 Simulation of Normal Condition Under Disruption

The main concern of this study is to investigate and examine the impact caused by the disruption. Supply disruption occurrence is incorporated into the developed SC model in earlier simulation. The disruption
model is designed by executing a variable to the flow of manufacturer incoming raw materials. The equation form regarding the disruption simulation shown in Equation.1 and in Figure 6.

\[ \text{Supply Signal} = 1 + \text{STEP}(1, 53) + \text{STEP}(1, 55) \]

Figure 6 shows that the disruption duration is defined by the supply signal of 0 value from week 53 until week 58. The variable is defined as the supply signal, in which, when the time reaches week 53, the incoming raw materials will be unavailable known as supply disruption. Therefore, the manufacturer incurs a material disruption (shortage of raw material) which is important to enable the production line in order to prepare finished goods required by the downstream stages. The disruption event is lasted for five weeks. This depicts a clear behavior and obtain significant effect of disruption.

![Supply Signal Pattern](Image)

Figure 6. Supply signal pattern

Figure 7 shows the relationship between simulation time to the backlogged order level. The figure indicates that at week 53, the backlogged order for both the supplier and manufacturer suddenly increased to a double amount from 130 units to 300 units at manufacturer and from 120 units to 150 units at supplier. After the disruption period end, the backlogged order supplier shows a reduction to zero at week 62 to week 67. This due to excess inventory produced and shipped after the disruption was resolved.
2.4 Simulation of Disruption with Mitigation (Safety Stock)

The use of safety stock can be classified as a mitigation strategy, where the pro-active action is undertaken to address any abnormalities. The policy suggested in this simulation are, for every cycle, the safety stock is 20% of the downstream stage’s demand amount. Figure 8 illustrating the relationship between backlogged orders to the simulation time under disruption with safety stock. It can be observed that the safety stock not just lowered the number of backlogged orders but also reduce time to stabilize material-information flow by 4 weeks earlier which is 30 weeks at normal condition to 24 weeks at safety stock execution. The figure shows backlogged order at manufacturer is reduced from 300 units to 180 units at the same period. Besides that, backlogged order at supplier is reduced by 50 units from 150 units to 100 units.
Figure 8. Backlogged order behaviour versus time under supply disruption with safety stock integration.

Figure 9 shows the results obtained from the simulation and average inventory for the entire four stages. The normal condition is recognised as being the benchmark data. It can be observed that the reduction in lead time resulted in lower inventory levels as compared to the normal condition. Additionally, the disruption condition exhibits the highest inventory as compared to the condition before changing the lead time. This scenario demonstrates that a disruption has an adverse effect on the entire system. Furthermore, as shown in last the two rows of Figure 9, the use of safety stock was proved to reduce the negative impact of a disruption, where a reduction in inventory was found when safety stock exists in the system.
Based on the results and analysis performed earlier, normal simulation shows the average inventory is amplified to the upstream stages where supplier has the highest inventory per cycle followed by manufacturer and retailer. It is found that demand from customer amplified through the way up to upstream stages. The longer the distance of a stages to another stages the higher the demand and inventory or in other words the effect is ‘bullwhip’. In addition, the changes in lead time will significantly influence the inventory levels for all stages in the SC. It is found that a longer the lead time, will result in higher average inventory stocked per cycle.

The ‘under disruption’ simulation (with and without safety stock) showed a difference in the amount of inventory for all stages. For example, at the supplier and retailer site, the level of inventory is lower for the disruption with safety stock as compared to the disruption without safety stock. Disruption exhibits highest inventory as compared to the normal condition. This demonstrates that a disruption has an adverse effect on the entire system. Disruption also triggered all stages in the cycle to produce larger quantity of inventory after the disruption ended and significant delays in distributing inventory amounts. This make the average backlogged order amount become higher.

Use of safety stock was proved to reduce the negative impact of disruption. Safety stock helps to stabilize inventory per cycle at each stages to follow the demand from customer as compare to normal simulation. Besides that, reduction in inventory found to be with a significant for the entire simulation for each stages.

3. Conclusions
A mitigation strategy in the event of a disruption was developed using the SD approach. Two main achievements were evident from work performed. Firstly, a three-stage SCS was successfully developed, and secondly, a mitigation strategy was used to manage and safeguard against the occurrence of a disruption, which proved to be significant. In conclusion, lead time will affect SC performance, whereby a longer lead time, will result in much lower SC performance and vice versa. By using the...
same model, the experiment demonstrated that incorporating safety stock would reduce the impact of a SC disruption.

The findings are significant and beneficial to management within the supply chain and logistics segment which are vulnerable to disruption occurrences. Furthermore, the findings in this study will assist management to identify possible solutions and risk management strategies related to either for the backward information flow or forward material flow. The key findings will help industry and practitioners alike towards the application and usage of safety stock to reduce the impact of a disruption. There are several directions for future study that should be conducted, which is to enrich the model with multiple performance measures such as pricing and profit. Besides that, applying safety stock at multiple stages would be another interesting aspect to investigate further and analyse the effects on mitigating disruption. In addition, examining the inter-relationships and inter-dependencies between mitigation and recovery strategies could be another direction for future research.

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