IMPROVING DELIVERY PERFORMANCE IN A SUPPLY CHAIN

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ABSTRACT

It is essential for modern competitive organizations to improve delivery performance to the final customer through their serial supply chain. This research builds on contemporary management theories that advocate reducing variance as the means to improve process performance. This paper proposes a two-step optimization framework to improve supply chain delivery performance by reducing the variability in activity times of the upstream stages of the supply chain.

Keywords: Supply chain delivery performance, delivery improvement, variance reduction

INTRODUCTION

Today's modern competitive business environment made companies require and adopt a highly responsive supply chain. One factor for a highly responsive supply chain is to demand the supply base to maintain high levels of on-time delivery performance. Many studies indicate the high degree of importance that customers place on the on-time delivery performance of their suppliers [1], [2]. The logistics and delivery process is fundamental to supply chain management philosophy and is one of the five core components (plan, source, make, deliver and return) of the Supply Chain Operations Reference-model (SCOR). The strategic and tactical importance of establishing metrics to evaluate delivery performance is found in [3], [4].

Bushuev [5] provide a summary of delivery performance models appearing in the supply chain management literature . Overall, there are two common characteristics found in these models. First, a customer defines the on-time delivery window and classifies deliveries received by the customer. The classification is delivered early, on-time, or late. Consequently, early or late deliveries impose contractual penalty costs on the supplier (see for example [6]–[8]). These types of models translate the probability of untimely delivery (early or late) into an expected cost of failing to deliver the product within the on-time portion of the delivery window. A second feature found in the supply chain delivery models is the use of variance reduction to improve delivery performance. For a fixed delivery window, reduction in the variance of the delivery time distribution decreases the probability of early and late delivery and thus improves the expected cost of untimely delivery. This aspect of modeling the improvement in the delivery process is in line with the operations management literature where reducing the variability of a process is widely acknowledged as the key step to improving the performance of the process [9], [10].

In this paper, we extend above models. We propose two-step process to improve delivery performance in a serial supply chain. In the first step, the final customer sets the optimum variance level given a fixed delivery window. The outcome is the variance level that minimizes the expected cost of untimely delivery based on Gaussian normal distribution. In the second step, taking the overall variance level set by customer as given, the upstream suppliers optimize/improve their delivery performance. This means once the last stage of supply chain variance is set, the remaining stages simultaneously improves variances. There are two types of variance reduction cost. First is the investment cost characterized by diminishing returns. Second is the physical cost of reducing the per unit variance and is characterized by increasing marginal cost per unit of variance.

MODEL

We model *n*-stage serial supply chain where final delivery to the customer represented by a fixed delivery window. Table 1 summarizes the notation used. A delivery window is defined by the difference between an earliest acceptable delivery date and a latest acceptable delivery date, which is imposed by the final customer. Within the delivery window, a delivery can be classified as *early*, *on-time* or *late* as previously discussed.

Symbol	**Description**
d_1	Beginning of on-time delivery
d_2	End of on-time delivery
Q	Delivery lot size
K	Unit penalty cost for early delivery
H	Reduction rate/fraction of variance at stage
x_i	Reduction rate/fraction of variance at stage
η	Variance reduction cost coefficient
k	Scale economies coefficient
C_L	Investment cost coefficient
$C_i(x_i; v_i)$	Total cost to improve variance at stage
$I_i(x_i)$	Investment cost at stage
$R_i(x_i)$	Variance reduction cost at stage

In a serial supply chain, we assume that an activity duration of stage *i* is distributed according to Normal distribution with parameters (μ_i, v_i) and is independent of other activities. Hence, the delivery time to the final customer is defined as a convolution of all activity durations of stages, which yields a Normal distribution with parameters $(\sum \mu_i \equiv \mu_n, \sum v_i \equiv v_n)$. Figure 1 summarizes this concept of delivery window within *n*-stage supply chain.

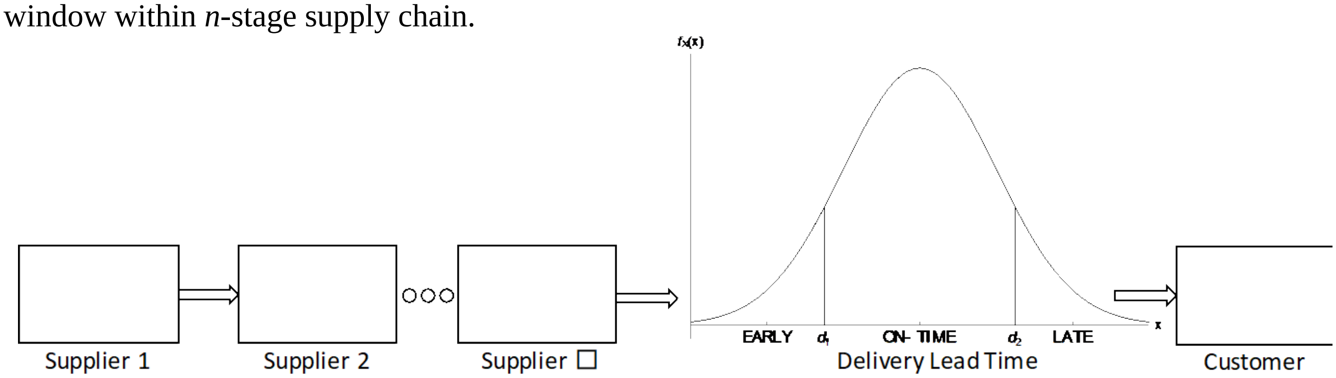

Figure 1: An *n*-stage supply chain with delivery window

Next, consider a supply chain operation over a time horizon of length *T*, where a demand requirement of the final customer single product is met with a constant delivery lot size *Q*. It is also expected for a final customer to charge suppliers for untimely deliveries; those either early and late as dictated by the delivery window. When a delivery is early, a firm incurs an extra cost of holding it. While if a delivery is late, the cost can be in terms of lost sales or disruptions in the production or service. Thus, there are both earliness and lateness penalty costs for a firm for untimely delivery. In this paper, we adopt the expected penalty cost for untimely delivery from [7] and we refer our readers to it for more details. For a fixed mean and delivery window, penalty cost for untimely delivery can be written as a function of variance as

$$Y(v_n) = QH\left[\sqrt{v_n}\,\phi\left(\frac{d_1-\mu_n}{\sqrt{v_n}}\right) + (d_1-\mu_n)\ \Phi\left(\frac{d_1-\mu_n}{\sqrt{v_n}}\right)\right] + K\left[\sqrt{v_n}\,\phi\left(\frac{d_2-\mu_n}{\sqrt{v_n}}\right) + (d_2-\mu_n)\ \left(1-\Phi\left(\frac{d_1-\mu_n}{\sqrt{v_n}}\right)\right)\right] \qquad (1)$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the probability density and cumulative distribution functions respectively. It can be shown that, Eq.\1 is convex function of variance provided that $v_n < \ min\{(d_1-\mu_n)^2, (d_2-\mu_n)^2\}$ (for details see [7]). One can solve cost function defined in Eq.1 as long as above condition is satisfied. Hence,

$$\frac{\partial Y}{\partial v_n} = 0 \Rightarrow \frac{QH\ \phi\left(\frac{d_1-\mu_n}{\sqrt{v_n}}\right) + K\ \phi\left(\frac{d_1-\mu_n}{\sqrt{v_n}}\right)}{2\sqrt{v_n}} = 0. \qquad (2)$$

Subsequent to the final customer's decision to set target variance level (i.e. optimum v_n^*), the upstream suppliers now take this variance as given and improve the supply chain. The upstream channel performance is characterized by x_i, the reduction rate of variance from the supplier *i*. x_i, denotes the fraction of variance reduced from current one, i.e., $0 \le x_i \le 1$. We model x_i as a function of the variance reduction effort, which is denoted by I_i , the investment in improvement activities. Such investments can be considered as six-sigma deployment, JIT and lean practices. Hence, the structure $I_i(x_i) = C_L x_i^2$, which would be expected to exhibit diminishing returns; the increase in $x_i = \sqrt{\frac{I_i}{C_L}}$ is slower than the increase in the total investment I_i. This characterization is widely adopted in supply chain literature and suits a wide range of scenarios that response in variability decreases in each additional investment [11]–[14].

Another component to variance improvement is the physical cost of reducing the variance. We define $C(x_i) = \eta\ (x_i v_i)^k$, which is in terms of variance reduction volume. In this setting, *k>1* captures diseconomies of scale in the operational cost of variance reduction at a particular stage of the supply chain. To see how a concave cost setting with *k<1* can emerge, consider a case where a company learns from the delivery process each time it invests to improve the performance. Thus, for a company, the marginal cost of reducing an additional unit of variance can be decreasing, such that economies of scale can be observed. Alternatively, a convex cost structure with *k>1* is the most commonly used and observed setting in the practice indicating that the marginal cost is increasing in the variance reduction. Hence, in this setting, cost of reducing variance can outweigh the benefits from the reduction implying diseconomies of scale such that a company is not required to reduce the entire possible reduction in variance. In this particular paper, we assume *k>1*. Therefore, after the final firm sets v_n^*, the remaining suppliers simultaneously set optimum reduction in variance x_i^*. Therefore, the objective is to minimize

$$Minimize\ \sum_{i=1}^{n}\left(I_i(x_i) + C(x_i; v_i)\right)$$

$$\begin{aligned} &such\ that \\ &0 < x_i \leq 1 \\ &\sum x_i v_i \leq v_n^* \end{aligned} \quad (3)$$

Proposition 1: *Under diseconomies of scale (k>1), there exists values x_i^* that minimize the total cost of improvement in variance as defined in Eq. 3.*

Proof: Total cost of improvement in variance is the sum of two convex functions in the same domain. Hence, it is a convex function and there exists values for x_i^* $ that ensure global minimum.

CONCLUSION

In this paper we have presented a framework for reducing the variability in the delivery time distribution to the end customer in a serial supply chain. Improvement (reduction) in the variability of the delivery time distribution of the end customer of the supply chain is directly integrated with the variability found in activity times of the upstream stages of the supply chain which additively defined the end customer delivery time.

We have proposed two-step optimization model where in the first step end customer sets the optimum delivery variance whereas in the second step upstream suppliers improve the variability.

In our future research we will examine a more formal investigation of the sensitivity of model parameters such as the penalty and scale economies coefficients. Also, we will investigate the behavior of the optimization model presented herein with real industry specific parameters. Finally, it will be interesting to study the characteristics of

the delivery time defined by other forms of probability density and mass functions which are reproductive under addition such as the Gamma and Poisson.

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