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Managing Supply Systems with Partial Information on Shipment Locations

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Abstract

This paper studies a supply system for a retailer who orders a single product from one manufacturer. Orders filled by the manufacturer pass through multiple transportation stages before reaching the retailer. Each stage represents either a physical location or a step in the delivery process. The lead-time for a new order depends on the location of shipments against prior orders in transit. Shipments are not allowed to cross over in time. Thus, the movement of each shipment depends on the movements of shipments ahead of it and the resulting congestion. The retailer is able to track shipments as they move through the transportation channel.

The retailer adopts an ordering policy that minimizes the sum of his one-period holding and shortage costs, using available status information of shipments already in transit. The case where practical constraints prevent the retailer from obtaining a complete status of shipments at all stages in the transportation channel is considered. The methodology developed evaluates the value of partial shipment tracking information, and uses it to determine the optimal placement of a limited number of tracking devices. The methodology can also be used to evaluate the cost-benefit of placing additional tracking devices in the supply system.

Keywords: Stochastic processes, Markov chain, Stochastic lead time, Shipment tracking, Value of information

1. Introduction

In today's globalized supply chain environment many manufacturing companies ship their products, subassemblies, parts and raw materials over great distances. Transportation of these shipments might require multiple modes (rail, sea, air, and road) either using a single carrier or with multimodal transport operators. When transportation involves many sub-carriers, especially when the transportation channel goes through several countries, the process for tracking a shipment can become complex.

Advances in information technology make it possible to obtain data to track the status of shipments in the supply system in real time and such real-time tracking data can enable better supply chain management. Unfortunately, the value of this tracking information is not adequately understood. The lack of a firm understanding can lead to incorrect decisions on when, where, and to what extent these technologies should be deployed. It presents a challenge and an opportunity for analytical methods to model and evaluate the value of real-time information.

This paper considers a supply system in which a retailer places orders for a single product on a manufacturer. The manufacturer fills the orders immediately, but shipments against these orders pass through multiple stages of transportation before they reach the retailer. Each transportation stage represents either a physical location or a step in the delivery process. Shipments are not allowed to cross over in time. Thus, the speed of movement of each shipment depends on the movements of shipments ahead of it and the resulting congestion, if any. The lead time for a new order therefore depends on the location of shipments ahead of it in the transportation channel. Hence there is value in obtaining information on the location of shipments in the transportation channel, using available technology such as radio frequency identification (RFID) devices that are tagged with each shipment. A stochastic model is used to evaluate the value of shipment tracking information where the retailer adopts a periodic review, order-up-to-level inventory control policy. The order-up-to level (and correspondingly the order quantity) in each period explicitly depends on the number and position of the outstanding orders.

Due to budget or process constraints, however, it may not be feasible to have these technologies deployed at every stage in the transportation channel. When technology is not available to automatically locate shipments in the channel, additional processes are required at each stage to obtain tracking information. Even if location technologies such as RFID tags are used, the process capability depends on the type of RFID tags in use. For example, if a shipment uses a *passive* RFID tag (that only emits a signal when queried by an outside source), its location information can only be obtained if the RFID tag is physically scanned by a RFID reader at any given stage. Even if an *active* RFID tag (which can initiate wireless communication with an RFID scanning device located nearby) is used, location information can still be restricted depending on the type of wireless technology used. Furthermore, location information can be updated on an instantaneous basis only if the active RFID tag is able to communicate its location using more sophisticated capabilities such as global positioning systems (GPS). Installation of such active RFID tags adds additional costs and may not be always possible due to budget constraints.

As an example of how a process constraint only allows partial tracking of shipments, consider a case study presented in Prater, Markus, and Smith (2001). This case study describes the supply operations of VAI (a subsidiary of VA Technologie AG, Austria), a large international producer of steel products. Seeking an expansion of its production capabilities, VAI set up a joint venture with steel mills in the Ural Mountains of Russia. This operation is coordinated from VAI's offices in Austria. The joint venture allows VAI to deal with increased demand in steel while keeping costs fairly low. The steel is first transported by rail from the Ural in Russia to Odessa, Ukraine on the Black Sea, then by ship to Southeast Asia. However, VAI has to deal with limited information in the supply process. As stated in Prater *et al.* "To track the progress of shipments, VAI hires people to observe various points of the rail line. As each train passes by, the observer notes the apparent loads of the rail cars (in order to check for theft) and sends a telegram to VAI giving the train's location." In the context of the current paper, these observation points correspond to the stages in the transportation process of the supply system, where the shipment location information is tracked.

The implication of the preceding discussion is that full information on the supply status may not be available to the retailer at any given point in time. The contribution of this paper is to investigate the value of obtaining information on shipment locations from only select stages in the transportation channel. The methodology developed in this paper evaluates the value of such partial shipment tracking information, and also uses it to determine the optimal location of a limited number of tracking devices placed in the system for partial shipment tracking. Thus the model can help organizations such as VAI reduce cost by hiring fewer observers and placing them at more strategic locations. The methodology can also be used to evaluate the cost-benefit of placing additional tracking devices in the supply system.

2. Literature Review

The value of sharing information in supply systems has been widely acknowledged and the literature on this topic is growing rapidly (see, for instance, Dejonckheere *et al.* (2004), Gaur *et al.* (2005), Kim *et al.* (2006), and Viswanathan *et al.* (2007)). Most of the work has focused on the value, to the manufacturer or to the entire supply chain, of retail demand or inventory information from downstream locations. For example, Lee *et al.* (2000) considers a manufacturer facing periodic demands from a retailer and quantify the value of external demand information. A small body of work studies the value of upstream information, such as information on the supplier's inventory status and order lead times (see, for example, Jain and Moinzadeh 2005, and Li *et al.* 2006).

Most of the papers that address the value of sharing supply information typically focus only on uncertainties caused by the production or inventory condition at the supplier. The above referenced papers, for example, do not consider how uncertainties in the shipping and/or transportation process affect lead times. Some papers such as Song and Zipkin (1996) and Chen and Yu (2005) implicitly consider congestion in the upstream transportation process using a Markov Chain to model lead time.

Liu *et al.* (2009) presents a model that explicitly considers shipment congestions, so that the lead time has different distributions depending on whether or not shipment congestion is present. Shipment movement is modeled using a Markov Chain modulated by the presence of other shipments that create congestion in the system. Shipments move downstream in the same sequence as the order in which they were

shipped and pass through K transportation stages before reaching the retailer, as shown in Figure 1. Thus the assumption is that shipments do not cross each other while in transit. Axsater (2000) notes that this assumption simply reflects common practice. For example a well-known automobile assembly facility in the US requires its seat suppliers to deliver seats in a set sequence to match up with the final assembly facility schedule. Such a sequencing requirement forces the supplier to disallow any crossovers during shipment.

[Figure 1 here]

In the Liu *et al.* paper, when order shipments from upstream stages move to the same downstream stage they are considered to be merged into a larger shipment, moving as one shipment from then onwards until the combined shipment reaches the retailer. Merging shipments is common practice, for example Oracle's transportation management software (Oracle 2010) uses a merge-in-transit feature to consolidate products shipped to the same destination. It is noted that while there may be some consolidation, these individual product shipments can still retain their unique identity while in transit. However, since they have arrived at the same stage, it is fair to assume that the actual physical processes (behind the Markov chain model) that govern their movements will make them move together in subsequent stages. Let the vector $\vec{s}(t) = [s_1(t), \dots, s_K(t)]$ define the supply status in the transportation process at the end of time period t where each binary variable $s_k(t)$ denotes the presence or absence of a shipment at stage k at time period t . Let $\mathbf{s} = \{\vec{s}(t), t = 1, 2, \dots\}$. It can be shown that the process \mathbf{s} is Markovian. Let the supply status vector at period t , $\vec{s}(t) = \vec{s}_j$, and let $W_j, j = 1, 2, \dots, 2^K$ represent denote the limiting distribution for \vec{s}_j . Let $IP(t)$ denote the inventory position after the order is placed in time period t . There is a holding cost, h , and a shortage cost, r , both assumed to be constant over time. Let $G(\vec{s}_j, IP(t))$ denote the one-period expected cost attributable to period t , and let $\bar{IP}_j^* = \underset{y}{\operatorname{argmin}} G(\vec{s}_j, y)$. It can be shown (see Liu *et al.* 2009 for details) that the minimum expected cost, C^* , with full real-time tracking information is

$$C^* = \sum_{j=1}^{2^K} W_j G(\vec{s}_j, \bar{IP}_j^*).$$

When no information about the supply status vector is known, the optimal base stock level can only be determined as one that minimizes the weighted average one-period cost over all realizations of the supply status vector. We term the cost, C_s^* , obtained with this base stock level as the *static* optimal expected cost. This cost is obtained, more simply, as

$$C_s^* = \min_y \sum_{j=1}^{2^K} W_j G(\vec{s}_j, y).$$

Our paper extends the work presented in Liu *et al.* (2009) to the case where practical constraints prevent the retailer from obtaining a complete status of shipments at all stages in the transportation channel.

3. The Model For Supply Systems With Partial Information

Suppose real-time tracking information is not available from all transportation stages. To track shipments, *tracking devices* are placed at $N < K$ unique stages. Each pair of adjacent tracking devices monitor shipments that have passed the transportation stage at which the first of these tracking devices is placed but are yet to reach the transportation stage where the next tracking device is placed. Therefore a pair of adjacent tracking devices can detect the presence or absence of shipments at the stages in between the two tracking devices. For ease of exposition, we will say that the transportation stages between two adjacent tracking devices are monitored by the tracking device at the lower-numbered transportation stage.

For instance, consider a system with $K = 5$ stages and $N = 2$ tracking devices, and suppose these devices are located at stages 2 and 4. In this example the tracking device at stage 2 monitors stages 2 and 3. The tracking device at stage 4 monitors stages 4 and 5, as illustrated in Figure 2. Clearly, shipments made by the manufacturer (at location 0) as well as shipments received by the retailer (at location $K+1$) will be monitored and accounted for. Therefore, it is implicitly assumed that a tracking device exists at location 0 (tracking device 0) and at location $K+1$, in addition to the N tracking devices.

[Figure 2 here]

Define a tracking device vector $\vec{b}(t)=[b_0(t),b_1(t),b_2(t),\dots,b_N(t)]$, where the variable, $b_i(t), i = 0, \dots, N$, is binary and indicates the presence or absence of shipments among the monitored stages for a tracking device. Let l_i denote the location of tracking device i , for $i = 1, \dots, N$, and set $l_0=0$ and $l_{N+1}=K+1$. Thus, for $i = 0, \dots, N$,

$$b_i(t)=\begin{cases} 1, & \text{if there is an occupied stage among the stages } l_i, \dots, l_{i+1} - 1 \\ 0, & \text{otherwise} \end{cases}$$

Therefore, there are 2^{N+1} possible values for the tracking device vector. Let $\vec{b}_q, q = 1, \dots, 2^{N+1}$, denote a tracking device vector. Let $\mathbf{b}=\{\vec{b}(t), t = 1, 2, \dots\}$ and let $\Theta=\{\vec{b}_1, \vec{b}_2, \dots, \vec{b}_{2^{N+1}}\}$ denote the state space of \mathbf{b} . To illustrate the relationship between the tracking device vector and the supply status in the transportation process vector, suppose there are $K = 4$ stages and $N = 1$ tracking devices located at stage 3 in addition to tracking devices at stage 0 and stage $K+1 = 5$. The tracking device vector values and the values of the corresponding supply status vector in the transportation process are shown in Table 1.

[Table 1 here]

Each tracking device vector, $\vec{b}_q, q = 1, \dots, 2^{N+1}$, thus accounts for (or covers) a set of supply status vectors. Let B_q denote the set of supply status vector indices covered by tracking device vector \vec{b}_q . Note that since tracking devices are placed at unique locations, no two tracking devices share a common stage in the transportation channel. Note that the limiting probability that the system is in state \vec{b}_q is $\sum_{l \in B_q} \omega_l$.

3.1. The Expected Cost with Partial Information

When the system is in state \vec{b}_q the one-period expected cost (the expected cost charged to an order placed in period t , given $\vec{b}(t) = \vec{b}_q$ and $IP(t) = y$) is

Let IP_q^* be the optimal order-up-to level that

minimizes the one-period expected cost, given that the system is in state $\vec{b}(t) = \vec{b}_q$ when an order is placed. That is, $IP_q^* \stackrel{def}{=} \arg \min_y GB(\vec{b}_q, y)$. Let C_p^* denote the optimal (myopic) expected cost with partial information on shipment locations. It can be

shown that this cost is $C_p^* = \sum_{q=1}^{2^{N+1}} \min_y \left(\sum_{k \in B_q} [\omega_k G(\vec{s}_k, y)] \right)$. It can also be shown that $C_p^* \geq$

C^* .

A comprehensive numerical study was performed to gain insights on the value of partial shipment tracking information under different scenarios. The value of partial tracking information was evaluated by varying the manufacturer's shipping process as well as the shipment congestion at the various stages in the transportation process. The next section presents the results from this numerical investigation.

4. Numerical Investigation

A wide range of parameters and settings was used to model and evaluate the manufacturer's shipping process and the transportation process. For each problem in the study the long run average cost with a different number of tracking devices (as well as different locations for the tracking devices) was evaluated to help determine the optimal positioning of the tracking devices. Consider first the effect of the transportation process.

For the transportation process, the shipment transition probabilities at stages k , $1 \leq k \leq K$, determine the level of transport congestion in the system. The congestion at transportation stages is modeled using two scenarios: low and high.

- For the Low-congestion scenario, a shipment in location $1 \leq k \leq K$ either stays in the same location during the next time period with probability $p_{k,k} = 0.1$, moves to the next stage with probability $p_{k,k+1} = 0.8$, or attempts to move two stages downstream with probability $p_{k,k+2} = 0.1$. As a shipment at the stage K

cannot move two stages downstream, the probabilities are as follows: $p_{K,K} = 0.1$ and $p_{K,K+1} = 0.9$.

- For the High-congestion scenario, $p_{k,k} = 0.5$, $p_{k,k+1} = 0.4$ and $p_{k,k+2} = 0.1$ for $1 \leq k < K$. And for the shipments at stage K the probabilities are as follows: $p_{K,K} = 0.5$ and $p_{K,K+1} = 0.5$.

It is noted that since orders are not allowed to cross over, in either scenario a shipment at stage k may not be allowed to proceed to stage $k+2$ if stage $k+1$ has a shipment.

As far as the manufacturer's shipping process is concerned, the numerical investigation assumes that the shipment from the manufacturer moves directly to the retailer with a probability $p_{0,K+1}$. If the manufacturer's shipment does not move directly from the manufacturer to the retailer, then it moves to stage 1, i.e., $p_{0,K+1} + p_{0,1} = 1$. Three different cases are considered.

- Case 1: $p_{0,K+1} = 0.9$ and $p_{0,1} = 0.1$.
- Case 2: $p_{0,K+1} = 0.7$ and $p_{0,1} = 0.3$.
- Case 3: $p_{0,K+1} = 0.3$ and $p_{0,1} = 0.7$.

Note that with no congestion in the transportation channel, a shipment dispatched directly to the retailer's site gets delivered in the next time period. However, if there is congestion in the transportation channel, this shipment merges with the shipment at the first occupied stage downstream since orders are not allowed to cross over.

Case 1, which has a relatively high value for $p_{0,K+1}$, will certainly have a higher probability of shipments reaching the retailer more quickly when no other shipments are in transit. However, congestion due to shipments in transit will affect the progress in general. Thus, while case 1 is more likely to have a lower expected lead time compared to cases 2 and 3, it is also likely to have a higher lead time variability or uncertainty. Similarly, case 3 for which $p_{0,K+1}$ is low should have a higher expected lead time relative to cases 1 and 2 but it should also have the lowest lead time uncertainty. Based on the experiments that were carried out, the average coefficient of variation (CV) of the lead time for cases 1, 2 and 3, were 0.77, 0.43 and 0.26, respectively. The three cases modeling the manufacturer's shipping process are henceforth referred to as *high lead time uncertainty* (Case 1), *medium lead time uncertainty* (Case 2) and *low lead time uncertainty* (Case 3).

Using these parameter settings for the transportation process and the manufacturer's shipping process, a series of experiments was carried out for values of K , ranging from 1 to 11. The effect of shortage cost was investigated by varying the shortage cost from $r = 5$ to $r = 30$ while keeping the holding cost fixed at $h = 10$. Demand was generated from a normal distribution with $\mu_d = 100$ and σ_d ranging from 10 to 30. The following discussion draws on the results of our numerical investigation.

4.1. A Baseline for the Expected Cost

When no information is available on the location of shipments in the transportation channel, the retailer can certainly work with the static optimal base stock level. However, even without any real-time tracking information, the retailer can further reduce his cost of operation using any available knowledge on outstanding orders as follows. Simply by keeping track of the order dispatches and receipts, the retailer can determine whether or not there are any outstanding orders in the transportation channel. The retailer can now use two base stock levels, one for when the supply status vector represents an *empty* state $\vec{s}_1 = (0,0,\dots,0)$, and another for when it is not. Let C_B^* denote the corresponding expected *baseline* cost. The expression for C_B^* is

$$C_B^* = \min_{y_1} W_1 G(\vec{s}_1, y_1) + \min_{y_2} \sum_{k=1}^K W_k G(\vec{s}_k, y_2),$$

where y_1, y_2 , are the optimal base stock levels corresponding to the supply status vector, $\vec{s}_1 = (0,0,\dots,0)$ and to the set of vectors $\vec{s}_j \neq \vec{s}_1$, respectively.

It should be clear that the baseline cost is always lower than the static optimal expected cost, C_s^* . The first set of experiments investigates the cost difference between the expected cost, C^* , with complete information on shipment locations, and the baseline cost, C_B^* . The difference between C^* and C_s^* is also calculated. Table 2 shows results for a supply system with $K = 8$ transportation stages, holding cost $h = 10$, and a normally distributed demand on the retailer with mean $\mu_d = 100$ and standard deviation $\sigma_d = 10$, for $r = 5$ and 15.

[Table 2 here]

A few general observations are made from this set of results. First, the potential cost savings provided by shipment tracking information is relatively low when the lead

time uncertainty is low. The cost savings increase with increasing levels of lead time uncertainty. Clearly, when the lead time uncertainty is low, knowledge on the locations of these downstream shipments does not provide as much value.

Second, the cost differences are more pronounced with a shortage cost of 5. The intuitive explanation for this is that as the shortage cost increases, the retailer tends to hold more inventories and the corresponding increased costs tend to dilute some of the benefits of real-time information on the shipment status.

Third, the Low-congestion scenario always gives better cost savings (in terms of the difference between C_B^* and C^*) than the High-congestion scenario. An intuitive explanation is that with high congestion, shipments move slowly, typically one or a few stages at a time, and so the value of information on shipment location status is less pronounced.

Finally, two important observations are made. The first is that the difference between C_B^* and C^* is sometimes as high as 19.1%, emphasizing the importance of real-time tracking information. The second observation is that the baseline cost, C_B^* , is often significantly lower than the static optimal cost, C_s^* , which highlights the benefits of just having knowledge on whether or not there are outstanding orders in the transportation channel.

Figure 3 shows the expected costs C^* , C_B^* , and C_s^* for the medium lead time uncertainty case with $h = 10$, $r = 5$ and different values of K . Figure 4 shows the corresponding cost savings. It is observed that as K increases the values of C_s^* and C_B^* approach each other. In other words, as the number of transportation stages increase, the knowledge that there are outstanding orders in the transportation channel does not provide much benefit since the uncertainty due to the congestion effects are higher with a longer transportation channel.

[Figure 3 here]

[Figure 4 here]

4.2. Placement of Tracking Devices

The next set of experiments investigates the impact of tracking device placement on expected cost as well as the optimal location of the tracking device(s). It is assumed that all stages upstream from the first tracking device are monitored by tracking order dispatches and receipts to determine whether or not there are outstanding orders in the transportation channel. (Thus the baseline cost can be achieved without using any tracking devices.) For these experiments, the optimal location for the tracking device(s) is determined by exhaustive enumeration of the cost, C_p^* , for all possible tracking device placements. The results for the optimal placement of one tracking device is provided in Table 3.

[Table 3 here]

In general, as the lead time uncertainty increases, the optimal location of the tracking device tends to move further downstream. With the high lead time uncertainty scenario, (and especially with low-congestion), there is a high probability that the shipment moves directly or very quickly from the manufacturer to the retailer (or a location close to the retailer) provided there are no blocking shipments along the way. The shipment tracking information is therefore more valuable if we know that there are several stages at the beginning that are empty. Hence it makes sense to have the tracking device closer to the retailer (or further downstream). By the same token, as the scenario changes from Low-congestion to High-congestion, one would expect the optimal location of the tracking device to move upstream away from the retailer, and this appears to be the case especially for the scenario with high lead time uncertainty.

4.3. Impact of the Number of Tracking Devices on the Cost

When K is large enough for positioning several tracking devices, a natural question that arises is what should be the optimum number of tracking devices? Clearly, one would expect the marginal value (cost savings) of an additional tracking device to decrease as the number of tracking devices increase. This problem is investigated for those settings that give rise to the largest difference between C^* and C_B^* .

In general, as observed earlier, with low lead time uncertainty, there is not much value gained from tracking information on shipment locations. Therefore we only

investigate the impact of the number of tracking devices on the costs for medium and high lead time uncertainty with the next set of experiments. These experiments were run by adding one tracking device at a time, starting with just one tracking device placed at the manufacturer site, until the cost difference between the optimal expected cost using limited tracking devices and the optimal expected cost with complete information on shipment locations was less than one percent (the *tolerance level*).

The results show that in most cases no more than five tracking devices are needed to realize costs that are within one-percent of that achievable with perfect information on shipment locations. For the case with high lead time uncertainty and with a shortage cost of 15, it is enough to have only three tracking devices. The case with medium lead time uncertainty and with a shortage cost of 5 required five tracking devices to achieve the desired tolerance level for $K = 10$ and 11. Table 4 shows the expected costs and corresponding cost savings for the low-congestion scenario with medium lead time uncertainty for $K = 11$, the shortage cost $r = 5$, the holding cost $h = 10$ and normally distributed demand with mean $\mu_d = 100$ and standard deviation $\sigma_d = 10$. Note that the cost difference (cost saving) drops significantly when moving from three tracking devices to four tracking devices, and four tracking devices are adequate if the tolerance level is relaxed (to 1.3 percent).

[Table 4 here]

To summarize the results of the numerical study,

- With low lead time uncertainty, the optimal locations for the tracking devices are relatively closer to the manufacturer. There is relatively less benefit obtained from the information on the location of shipments.
- With larger lead time uncertainty, the optimal locations for the tracking devices move further downstream. In particular, with high lead time uncertainty, the optimal location for the last tracking device is very close to the end of the transportation channel.
- In most cases, for larger K , placing four to five tracking devices achieved close to 99 percent of the benefit of having full shipment tracking.

5. Summary And Conclusions

A stochastic model was developed to evaluate the value of partial real-time information on shipment locations for a supply system where delivery lead times depend on locations of shipments against orders in transit. The resulting shipment congestions are explicitly modeled. The paper develops a methodology to calculate the expected cost of operating the supply system with only limited information on the status of shipment locations.

The results of the numerical study show that partial information on shipment locations can be beneficial for the retailer especially with higher lead time uncertainty. We find that the optimal location of the tracking device(s) depends on the lead time uncertainty and the level of congestion in the system. We find that a limited number of tracking devices provide nearly the same benefit as that obtained by tracking the status of shipments at every transportation stage. The numerical study shows that in most cases, even for a supply system with as many as eleven transportation stages, no more than four tracking devices are needed to realize costs that are within one-percent of that achievable with perfect information on shipment locations. For such cases where obtaining real-time tracking information is difficult or involves more investments, the above result can be used by a carrier or logistics service provider to argue that providing real-time tracking information from a limited number of tracking devices should be sufficient for the retailer to lower his expected cost to within one percent of that realizable with full real-time tracking information.

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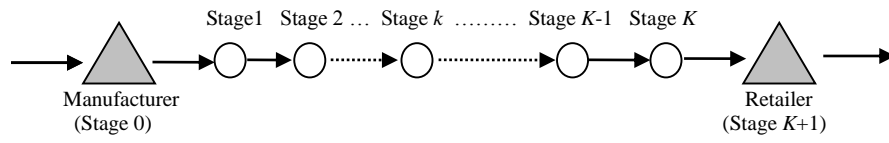


Figure 1. The K transportation stages between the manufacturer and the retailer

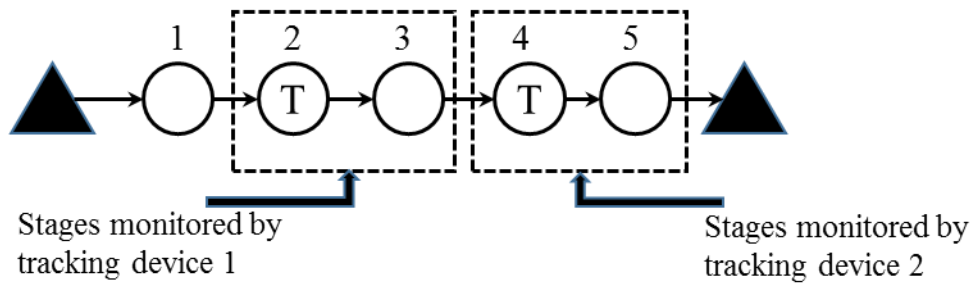


Figure 2. Example with two tracking devices for $K = 5$.

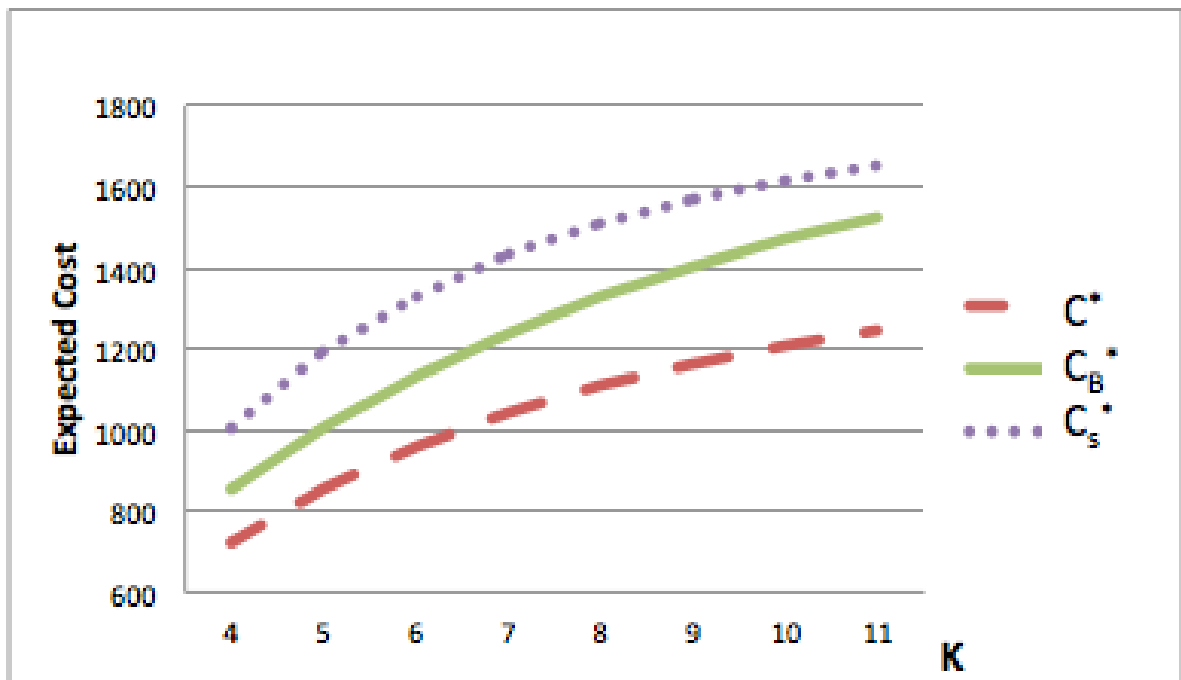


Figure 3 (a). Expected costs for medium lead time uncertainty case with $h = 10$, $r = 5$; $\sigma_d = 10$; Low-congestion scenario

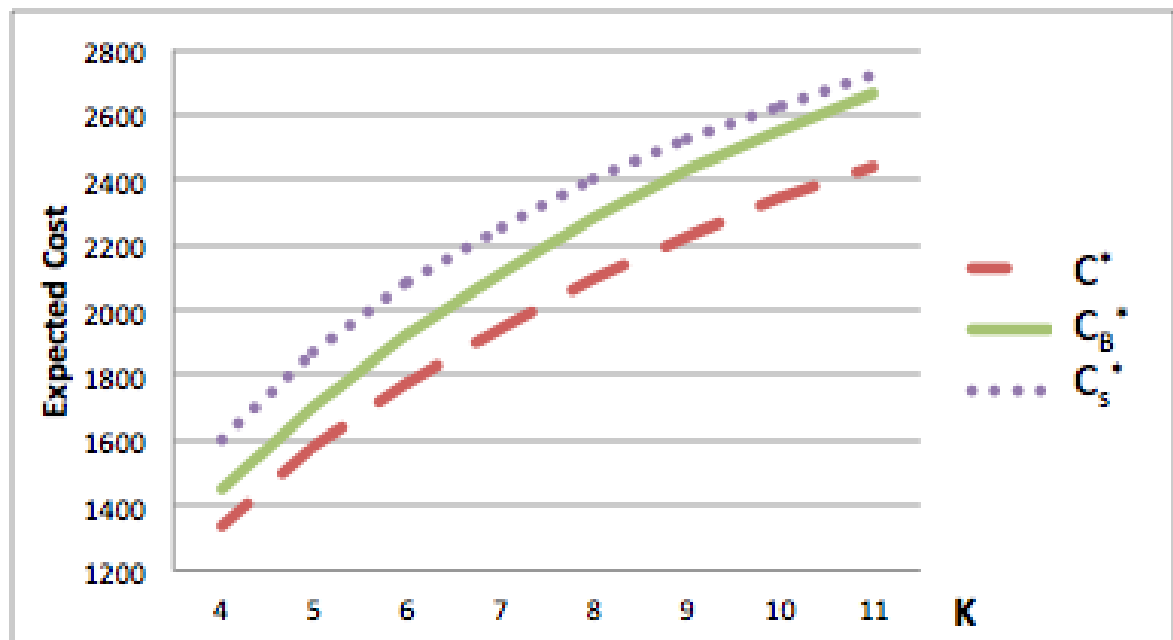


Figure 3 (b). Expected costs for medium lead time uncertainty case with $h = 10$, $r = 5$; $\sigma_d = 10$; High-congestion scenario

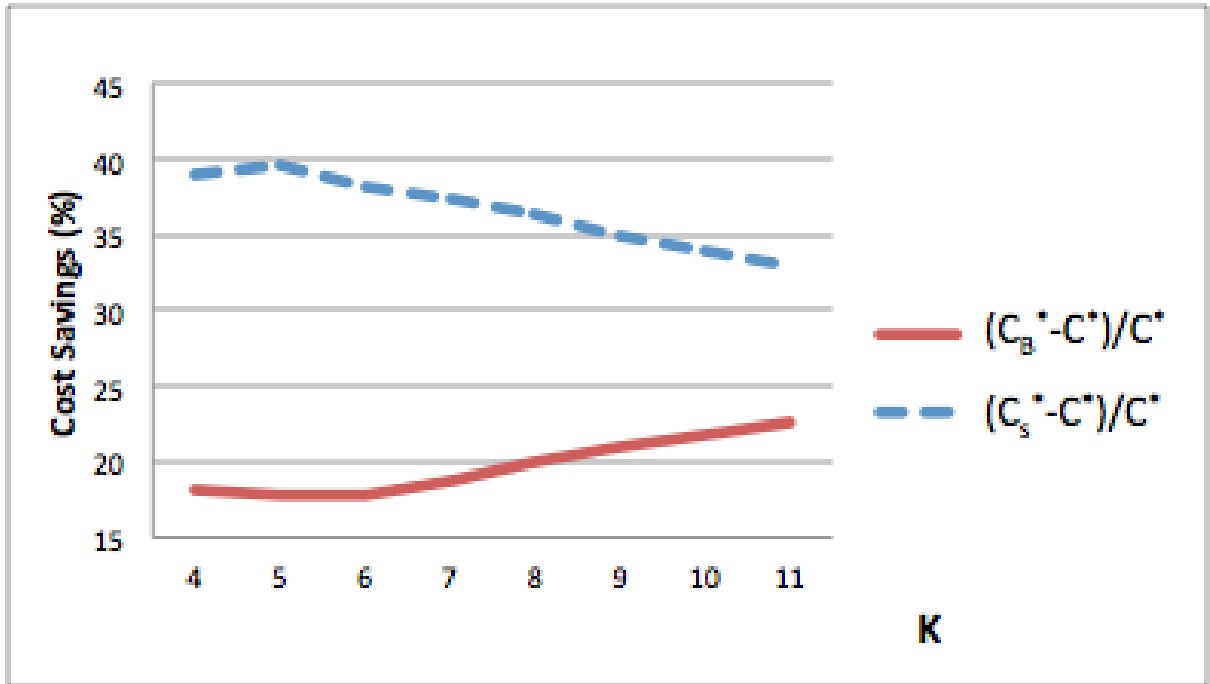


Figure 4 (a). Costs savings for medium lead time uncertainty case with $h = 10$, $r = 5$; $\sigma_d = 10$; Low-congestion scenario

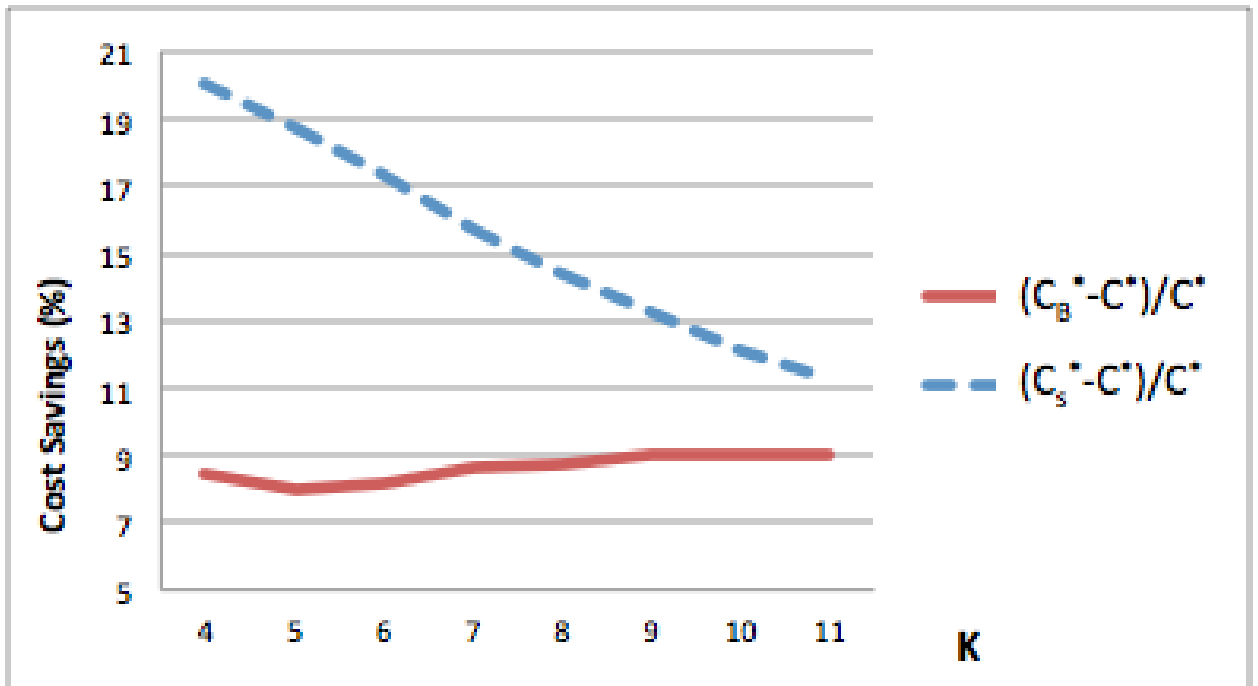


Figure 4 (b). Costs savings for medium lead time uncertainty case with $h = 10$, $r = 5$; $\sigma_d = 10$; High-congestion scenario

Table 1. The tracking devices and the total supply status vectors.

Tracking device vector (\vec{b})	Supply status vectors in the transportation process (\vec{s})
[0,0]	(0,0,0,0)
[0,1]	(0,0,0,1)
	(0,0,1,0)
	(0,0,1,1)
[1,0]	(0,1,0,0)
	(1,0,0,0)
	(1,1,0,0)
[1,1]	(0,1,0,1)
	(0,1,1,0)
	(1,0,0,1)
	(1,0,1,0)
	(0,1,1,1)
	(1,0,1,1)
	(1,1,0,1)
	(1,1,1,0)
	(1,1,1,1)

Table 2. Comparison of Expected costs with $K = 8, h = 10, \mu_d = 100, \sigma_d = 10$.

Congestion Scenario	Lead Time Uncertainty	r	C^*	C_B^*	C_s^*	$\frac{(C_B^* - C^*)}{C^*}$	$\frac{(C_s^* - C^*)}{C^*}$
Low	Low	5	765.0	786.5	786.9	2.8%	2.9%
Low	Low	15	1372.9	1386.7	1386.9	1.0%	1.0%
Low	Medium	5	1127.7	1342.8	1524.6	19.1%	35.2%
Low	Medium	15	2100.1	2249.8	2371.7	7.1%	12.9%
Low	High	5	1099.2	1289.6	1503.5	17.3%	36.8%
Low	High	15	2827.8	2980.3	3525.6	5.4%	24.7%
High	Low	5	2043.7	2058.6	2058.7	0.7%	0.7%
High	Low	15	3905.2	3922.5	3922.6	0.4%	0.4%
High	Medium	5	2218.3	2398.4	2507.2	8.1%	13.0%
High	Medium	15	4238.4	4427.9	4520.2	4.5%	6.6%
High	High	5	2340.8	2534.0	3273.9	8.3%	39.9%
High	High	15	5198.8	5378.3	6088.3	3.5%	17.1%

Table 3. Optimal location of the tracking device with $h = 10$, $r = 15$, $\mu_d = 100$, and $\sigma_d = 30$.

K	Low lead time uncertainty		Medium lead time uncertainty		High lead time uncertainty	
	Low Congestion	High Congestion	Low Congestion	High Congestion	Low Congestion	High Congestion
6	3	3	4	4	6	6
7	3	3	4	4	7	7
8	3	3	4	4	8	7
9	3	3	5	5	9	7
10	3	3	5	5	10	7
11	3	3	5	5	11	7

Table 4. The expected cost values and cost savings for $K = 11$; Low-congestion scenario with medium lead time uncertainty; $h = 10, r = 5; \mu_d = 100, \sigma_d = 10$.

	Expected Cost	Difference from C^*
No information (C_s^*)	1655.6	32.8%
“Baseline” cost (C_B^*)	1527.3	22.5%
Cost with 1 tracking device	1476.8	18.5%
Cost with 2 tracking devices	1440.7	15.6%
Cost with 3 tracking devices	1404.7	12.7%
Cost with 4 tracking devices	1262.5	1.3%
Cost with 5 tracking devices	1255.6	0.7%
Full information (C^*)	1246.5	