Impact of Early Forecast Information Sharing on Manufacturers with Capacity Uncertainty

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Demand patterns during seasonal sales and promotional marketing efforts can be considered 'atypical' behaviors; they are usually non-recursive and do not follow a discernible pattern over time. Compared to manufacturers facing stationary demand, manufacturers with capacity uncertainty and shortages facing atypical demands often incur higher holding costs if required to build inventory in anticipation of future demand. Advanced forecast information sharing between buyer and seller about these demand patterns could be beneficial to all players involved. To investigate, we model two information sharing scenarios: (1) manufacturers receive firm orders for seasonal or promotional events with a finite lead-time; (2) manufacturers receive an early rough forecast with a deterministic due date, however, forecast revisions are allowed at regular intervals. We have formulated optimal production schedules for manufacturers facing capacity uncertainty for these two scenarios using dynamic programming. We compare the two scenarios through extensive Monte Carlo simulations. Key managerial insights offered by this analysis pertain to the impact of early forecast sharing on manufacturers cost as a function of information sharing timing, forecast revision process, production capacity, capacity uncertainty, overage, underage, and holding costs.

Keyword: Supply chain management, information sharing, forecast evolution, atypical demand, manufacturing uncertainty.

1. Introduction

Modern information technology (IT) has enabled companies to engage in various information-sharing practices, including the commonly known Collaborative Planning, Forecasting and Replenishment (CPFR) initiative. One of the objectives of CPFR is to link sales and marketing practices with supply chain planning and execution processes to increase availability while reducing inventory (VICS 2004a).

Despite such initiatives, information sharing still suffers from problems in practice and there is room for research. To quote a recent study, Terwiesch et al (2005) points out that information such as demand forecasts change and are continually updated as the buyer receives new information about the demand it faces. In such cases, suppliers that act immediately (through production) on any given forecast might face significant future adjustment costs. If the supplier happens to be a manufacturer, apart from the uncertainty in forecast it faces during production decision making, it also needs to consider uncertainty in production capacity. Usually, safety inventory is used to protect firms against both sources of uncertainty. However, using inventory as a hedge against demand and capacity uncertainty can be an expensive proposition, especially when holding costs are high (Hu 2003). Compared to manufacturers facing stationary demand, manufacturers that face seasonal and promotional demand might have to incur even higher holding costs if sufficient capacity to meet such demand is not available and have to build inventory in anticipation of high demand later. Such demand patterns are normally considered “atypical” behaviors; they are usually non-recursive and do not follow a discernible pattern over time (Reinmuth et al 1986).

The supply chain literature is relatively vast regarding the benefits of sharing demand information (for a good review, see Chen, 2003 and Sahin and Robinson, 2002). However, we found little or no research pertaining to benefits associated with sharing information related to ‘atypical’ behaviors. Raghunathan (2001) found that ‘simplistic’ demand information sharing by retailer does not benefit manufacturer. He states, “Information sharing regarding retailer’s action such as promotion, price reduction, and advertising are beneficial to the manufacturer because such events can’t be inferred from past order history”. The motivation for this research is to address this gap in the literature.

Our research inquires whether sharing the timing of certain events such as promotional and/or seasonal sales and advanced demand forecast are beneficial to manufacturers with capacity uncertainty? We have developed a model to quantify the potential performance improvements for a particular manufacturing setting. In particular, we model a manufacturer under two information sharing scenarios: (1) manufacturer receive firm orders for seasonal or promotional events with a finite lead-time; (2) manufacturers receive an early rough forecast with a deterministic due date, however, forecasts revisions are allowed at regular intervals. We have derived optimal production-schedule for the manufacturer considering capacity uncertainty for both these scenarios. Detailed formulations of these two unique models are presented in section 3. Relevant existing literature is reviewed in section 2. The experimental framework for assessing the benefits is outlined in section 4. Section 5 presents results that illustrate and quantify expected manufacturer benefits from sharing early forecast information regarding atypical events. Section 6 offers some concluding remarks.

2. Literature review

There is extensive literature regarding information sharing in supply chains. Chen (2003) and Sahin et al (2002) provide a good review of literature on information sharing and supply chain coordination. Most of the literature cited in these two surveys and elsewhere gives limited attention to the value of sharing information regarding events that we term here as ‘atypical’. It the case that in many product segments, promotional sales are higher compared to usual sales (Blattberg et al 2003). In addition, many studies have reported that out of stock problems are more severe during promotional events. For example, the retail out-of-stock study done by GMA/FMI (VICS 2004b) not only shows that out-of stock problem is much worse during promotional events but also finds that manufacturer bears 48% of the loss and retailer bears 59% of the loss due to stock out. In addition, it is generally the case that many manufacturers face capacity uncertainty (Lin et al. 1999, Hwang et al 1998).

Here we briefly review some closely related models that are similar in formulation to our model of production scheduling. Among the earliest of papers to incorporate a forecast revision process with production scheduling for seasonal demand goods is Housman et al (1972). It is a multiperiod capacitated model with terminal demand where the successive forecast update ratios follow a lognormal process. Kaminsky et al (2001) consider a forecast generation process that depends on forecast bands that get refined over time for a terminal demand capacitated case. Raman et al (2002) combine model features from Housman et al (1972) and Fisher et al (1996) and demonstrate the impact of holding cost and reactive capacity on manufacturer's profitability with a real world example. While, the above-mentioned papers primarily deal with the task of optimal production scheduling of seasonal goods with a forecast revision process, we have also shown the comparison between optimal production policies for two manufacturing processes, one that works with a forecast revision versus another that only receives just the order with no advanced information. In addition, none of reviewed papers considers capacity uncertainty, something very critical for many manufacturers. A dynamic programming formulation for deriving an optimal production schedule for single product manufacturer with inclusion of capacity uncertainty is another prime contribution of our research.

3. Problem formulation

This section will address the following issues: (1) The two scenarios considered for evaluating the benefits of information sharing, (2) The difference in information content between the scenarios considered, (3) Performance measures used to compare them, (4) Sources of uncertainty and constraints, and (5) Formulations of models that represent different scenarios

3.1 Two scenarios: Information sharing vs. no sharing

Sequence of events for the manufacturer's model is as follows. Future demand information for a single product is delivered by the customer (a retailer or another manufacturer) to manufacturer in one of the following two ways: (1) The 'no information sharing case', where manufacturer is provided with order quantity for the seasonal or promotional event with a finite lead-time; (2) The 'information sharing case', where manufacturer is provided with an early rough forecast with a deterministic due date, with forecasts being revised several times at regular intervals.

It is usual to model the customer's final orders to the manufacturer with identical randomness irrespective of whether advanced forecast information is shared or only final information is transmitted. To model the forecasting process, it is assumed that joint distribution of the successive forecasts follow a probability distribution $f(\alpha)$ with known parameter(s) α and that the ratios are independent (this is similar in spirit to Raman 2002). Mathematically, if Y_i and Y_{i+1} represent two successive forecasts, then their ratios denoted by (Y_{i+1}, Y_i) follows a joint continuous distribution $f(\alpha_i)$ such that (Y_{i+1}, Y_i) and (Y_{i+2}, Y_{i+1}) are independent. If the forecasts are updated N times, then, the forecasting process is characterized by N joint forecasts. It is evident that in the no information sharing case, manufacturer is only supplied with only the final order Y_F with a due date τ_d, whereas in the information scaring case, manufacturer is also supplied with several forecast updates from which it can estimate $f_i(\alpha_i)$'s with a due date τ_d supplied in advance

Comparisons between two scenarios will be based on manufacturer's total cost. It is assumed that the manufacturer makes one final shipment on the due date asked by the customer. Holding cost is incurred for keeping finished goods and overage and underage costs are incurred at the day of shipment. Overage costs are possible only when forecasts are updated; therefore, for no information sharing case, this cost component is not applicable. Costs are denoted as follows: c_0 for unit cost of overage, c_u for unit cost of underage, and h for holding cost per unit per a unit time-period.

It is assumed that the final forecast Y_F is provided with a lead-time of l. In case of advanced forecast sharing, updated forecasts are transmitted to manufacturer in an interval of Δl time-periods. Production capacity per period, denoted by C is assumed random. It follows a probability distribution function $\phi(\theta)$

3.2 Production model for no information sharing case

In this case, the underage cost $(Y_F - I_{l+1})^+$ is incurred during the day of shipment and the holding cost is based on the production schedule. Here I_{l+1} denotes final finished goods inventory position on the day of shipment. With the presence of capacity uncertainty, we can optimally schedule production for l periods using a dynamic programming approach. Let, I_i denote inventory at the beginning of i^{th} period and C_i denote capacity for i^{th} period, the following relationship holds on the day of shipment:

$$g_{l+1} = c_u[Y_F - (I_l + x)]^+ = c_u(Y_F - I_{l+1})^+ \tag{1}$$

Here, $x = I_{l+1} - I_l$ denotes the production quantity for a period. Working a period backward, the cost at the beginning of period l is:

$$g_l = \underset{R_l}{\text{Min}}\left(\int_{c_l=0}^{R_l} g_{l+1}(c_l).\phi(\theta_l)dc_l + g_{l+1}(R_l)\int_{c_l=R_l}^{\infty} \phi(\theta_l)dc_l \right) \tag{2}$$

The general recurrence relation for period i would be written as:

$$g_i = \underset{R_i}{\text{Min}}\left(\int_{c_i=0}^{R_i} \left(g_{i+1}(c_i).\phi(\theta_i)dc_i + hc_i(l-i) \right) + \left(g_{i+1}(R_i) + hR_i(l-i) \right) \int_{c_i=R_i}^{\infty} \phi(\theta_i)dc_i \right), \quad i \in [1,l] \tag{3}$$

Therefore, optimal production release quantity R_i for any period i is obtained by minimizing g_i. Note that this quantity for any period i depends on state vector (I_i, Y_F).

3.3 Production model for information sharing case

The dynamic programming formulation for this case is similar to the formulation above (from section 3.2) with inclusion of the following additional factors: the likelihood of incurring overage costs on the day of shipment and the uncertainty with forecast update process. The time-periods between successive forecasts and the time-period between final order and the due date is termed here as a 'stage'. For ease of expression, a stage here is defined as the time-periods between successive forecasts or the time-period between final order and the due date; thereby the term 'time-period' becomes the smallest resolution in time in our model. Let, I_i and Y_i denote inventory position and forecast of final order quantity, respectively, at the beginning of period i. Consider a forecast revision process where forecasts are revised N times (after the first forecast is made) with a time interval of Δl periods (leading to N stages with Δl periods). Due date is deterministic and transmitted with the first forecast. Final order is always given l periods in advance of the due date and this last period is denoted stage *N+1*.

The policy for this (*N+1*)th stage (of duration *l*) is similar to the production policy for the no information sharing case, except for the addition of overage cost term while calculating cost on the day of shipment. The sum of overage and underage cost on the day of shipment is denoted g_{t+1}:

$$g_{t+1} = c_o(I_{t+1} - Y_{t+1})^+ + c_u(Y_{t+1} - I_{t+1})^+ \quad (4)$$

where $t = N\Delta l + l$. I_{t+1} and Y_{t+1} represent the inventory position and order quantity respectively at the day of shipment, respectively, with $Y_{t+1} = Y_F$. Optimal production release order for the final production period can be determined by minimizing,

$$g_t = \underset{R_t}{\text{Min}}\left(\int_{c_t=0}^{R_t} g_{t+1}(c_t).\phi(\theta_t)dc_t + g_{t+1}(R_t)\int_{c_t=R_t}^{\infty} \phi(\theta_t)dc_t \right) \quad (5)$$

Here, $x = I_{t+1} - I_t$ is the realized production quantity for a given state $[I_t, Y_t]$. The general recurrence relation for any period i in stage *N+1* can be written as:

$$g_i = \underset{R_i}{\text{Min}}\left(\int_{c_i=0}^{R_i} \left(g_{i+1}(c_i) + hc_i(t-i) \right) \phi(\theta_i)dc_i + \left(g_{i+1}(R_i) + hR_i(t-i) \right) \int_{c_i=R_i}^{\infty} \phi(\theta_i)dc_i \right), \quad i \in [t-l, t] \quad (6)$$

The N^{th} stage spans the time period from beginning of (t-l-Δl)th period to beginning of (t-l)th period. Optimal production target for the (t-l)th period can be obtained by computing $g_{i=t-l}(N+1)$. Policy optimizations for *N*th stage uses a structure similar to that used for computing $g_i(N+1)$ with the inclusion of the forecast revision process for the last period of that stage. Without the existence of capacity uncertainty, the optimal production quantity for the last period of stage N (i.e. the $(t-l-1)^{st}$ period of the overall process) could be found by minimizing the following cost function w.r.t. the production quantity x:

$$G_{t-l-1} = \underset{x}{\text{Min}}\left(\int_0^{\infty} g_{t-l} f(\alpha_N) \mathrm{d}Y_{t-l} | Y_{t-l-1} + hx(l+1) \right), \quad x = I_{t-l} - I_{t-l-1} \quad (7)$$

It is easy to show that the optimal release order for $(t-l-1)^{st}$ period with capacity $C \sim \phi(\theta_j)$ would become:

$$g_j = \underset{R_j}{\text{Min}}\left(\int_{c_j=0}^{R_j} G_j(c_j).\phi(\theta_j)dc_j + G_j(R_j)\int_{c_j=R_j}^{\infty} \phi(\theta_j)dc_j \right), \quad j = t-l-1 \quad (8)$$

$$G_j(x) = \int_0^{\infty} g_{j+1}(x) f(\alpha_j) \mathrm{d}Y_j | Y_{j+1} + hx(t-j), \quad j = t-l-1 \quad (9)$$

For the remaining $(\Delta l - 1)$ periods of stage *N*, ratios of the successive forecasts can be treated as one. Therefore, the optimal release can be found by minimizing a cost function that incorporates only the capacity uncertainty:

$$\begin{aligned} g_{j-k} = \underset{R_{j-k}}{\text{Min}}\Bigg(& \int_{c_{j-k}=0}^{R_{j-k}-1} \left(g_{j-k+1}(c_{j-k}) + hc_{j-k}(t-j-k) \right) \phi(\theta_{j-k})dc_{j-k} \\ & + \left(g_{j-k+1}(R_{j-k}) + hR_{j-k}(t-j-k) \right) \int_{x=R_{j-k}}^{\infty} \phi(\theta_{j-k})dc_{j-k} \Bigg), \quad k = [1, \Delta l] \end{aligned} \quad (10)$$

Optimal release orders for other stages with length Δl can be computed in a similar way

4. Experimental framework for assessing the benefits of early forecast sharing

In this section, we briefly outline an experimental framework for quantifying the benefits of early forecast information sharing in terms of manufacturer's expected cost. The manufacturer's cost base on optimal production policy for the information sharing case and the no information sharing case strictly depends on the following factors: (i) Costs: holding cost, underage cost and overage cost, (ii) Randomness: Capacity uncertainty and randomness in successive forecast ratios, forecast quantities and final order, (iii) Constraints: Lead times and capacity constraint. Through Monte Carlo simulation, we show that certain combinations of these parameters result in higher cost effectiveness. Here, we have selected the parameter set in a systematic way to illustrate the point that under certain conditions, advanced forecast information sharing can lead to substantial reductions in manufacturing cost.

Numerical evaluation involves the following steps. First, optimization models for all the selected combinations are computed and optimal policies are stored. Then, the Monte Carlo simulation is performed that primarily involves two tasks: (i) generation of forecasts and final order quantities based on selected forecast evolution process. To make a fair comparison between the two cases, the final orders generated through simulation for information sharing case are used to compute the cost for the no information sharing case as well. (ii) Simulated forecasts and order quantities are used to obtain optimal production release orders based on stored optimal policies, and in turn, manufacturer's expected cost is computed.

5. Simulation results

This section presents results from numerical analysis to develop insights into the benefits of advanced forecast information sharing for a manufacturer. The primary focus of this section is two fold. Firstly, we show that advanced forecast information sharing provides significant cost savings compared to no information sharing. Secondly, we demonstrate the effect of capacity uncertainty and holding cost on total manufacturing cost.

For ease of simulation, we have taken a computationally efficient method to derive the production schedule. We observed that modeling capacity randomness for a stage (that comprises several periods) instead of a period provides significant advantage in terms of computing time. Firstly, we derive the capacity per stage from the capacity per period model. Then, we compute an optimal release order for every stage of production instead of every period of production. We assume that capacity for each stage, C , as *i.i.d* random variable. We then compute the optimal release order R for that stage. For a given release R and a realized capacity C in a stage of length Δl , we approximate the holding cost. For $R<E(C)$, we use a holding cost function $\frac{h}{2}\frac{Rl}{E(C)}R + hR(l + k\Delta l)$ and for $R \geq E(C)$, we use a holding cost function $\frac{h}{2}lR + hR(l + k\Delta l)$. In both the expressions, the first term is the holding cost for that stage and the second term is the holding cost for remaining periods (with due date $l + k\Delta l$ periods into the future). Subsequent modifications to equations (1) to (10) are straight forward and not presented her due to space constraints.

It is a commonly accepted notion that longer the forecast horizon more uncertain the forecast will be. We have modeled this notion using a linear model of forecast uncertainty degradation. Standard deviation σ_j of the forecast distribution Y_j is used as a measure of forecast uncertainty. Mathematically the linear model is written as $\sigma_j = \sigma_d + m_\sigma(l + \Delta l)$, where σ_d is the actual demand uncertainty and m_σ is the slope of the degradation model. Given that our formulation models the joint density of the successive forecasts, it is necessary to address the effect of correlation between two successive forecasts. For the purpose of numerical evaluation, we have assumed that correlation between two successive forecasts depends on the time period between

	Information Sharing (IS) Case	No-IS Case
Forecast revision process	N=3 $f(Y_1, Y_2) \sim N(\boldsymbol{\mu}_{12}, \Sigma_{12})$ $f(Y_2, Y_3) \sim N(\boldsymbol{\mu}_{23}, \Sigma_{23})$ $f(Y_3, Y_F) \sim N(\boldsymbol{\mu}_{3F}, \Sigma_{3F})$	N.A.
Capacity	$C \sim N(\mu, \sigma)$ $\overline{C} = \mu + 4.5\sigma$	Same as IS-Case
Final order	Y_F	Y_F

Table 1: Common framework for all simulations

the updated, i.e. Δl and we assume that this dependence is also linear: $\rho_{\Delta l} = 1 - m_\rho(\Delta l)$, where, $\rho_{\Delta l}$ is the correlation coefficient between successive forecasts. The formula implies the following: Correlation coefficient is one if two successive forecasts are made at the same time and it increases linearly with time with a slope of m_ρ.

All the numerical evaluations are based on 1.5 million simulation runs. Table 1 provides the common framework (i.e., the numerical values of those factors that remain constant) for all the simulations while each subsection separately provides the framework for studying the effect of the above three factors. The joint distribution of successive forecasts are modeled as bivariate-Gaussian with parameters shown in Table 1. Capacity is modeled as Gaussian distributed. During optimization and simulation of various scenarios, we approximate the continuous probability distributions functions with probability mass functions defined over a set of discrete values. Capacity is assumed to be non-negative (i.e., the lower bound is zero) and with a definite upper bound. The upper bound (i.e., the maximum capacity per period/stage) is computed as $\overline{C} = \mu + 4.5\sigma$, where μ is the expected capacity per period/stage and σ is the standard deviation of capacity per period/stage

5.1 Effect of rate of information distortion on expected total cost to manufacturer

Rate of information distortion is modeled as liner. For the purpose of numerical evaluation we have used different values of m_σ and m_ρ, and demonstrated the effect of linear degradation in information on the total cost of manufacturer. To access the effect of m_σ, we have used the following design: mean forecasts $\boldsymbol{\mu} = [150,150,150,150]$, $m_\sigma = 0.6$ and $m_\rho = [-0.001, -0.021, -0.041, -0.061, -0.100]$. For accessing the effect of m_ρ, we have used: $\boldsymbol{\mu} = [160,160,160,160]$, $m_\sigma = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6]$ and $\rho = 0.75$. Following parameters are common for both the experiments: standard deviation of actual demand as $\sigma_d = 10$, $E(C) = 10$, $\sigma(C) = 2$, $c_u = 1.5$, $c_o = 1$ and $h = 0.05$. Figure 1 illustrates the effect of m_ρ. It is evident that as the slope increases, the co-relation between successive forecasts decreases and this in turn increases the cost. A clear implication is that higher correlation is always better, however, the relationship is non-linear in the region of experiment. Figure 2 shows that increase in forecast uncertainty is detrimental. The relationship is linear in this experiment.

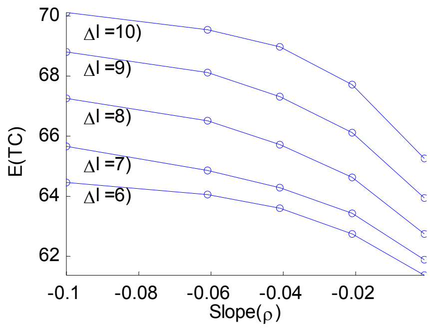

Figure 1: Effect of linear rate of change of correlation coefficient between successive forecasts on manufacturer's cost. (for information sharing case)

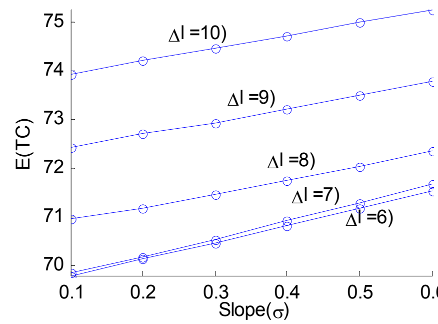

Figure 2: Effect of linear rate of change of forecast uncertainty on manufacturer's cost. (for information sharing case)

5.2 Effect of l and Δl on expected total cost to manufacturer

To assess the effect of Δl on expected total cost, we have used c_o=1, c_u=3, h=0.08, Δl=(1,3,5,7), $\boldsymbol{\mu} = [160,160,160,160]$, $m_\sigma = 0.6$, $\rho = 0.75$ for information sharing (IS) case and c_u =3, h =0.08 for no information sharing (no-IS) case. For both cases, we used l=(1,3,5,7,9) and $C \sim N(\mu = 5, \sigma = 2)$, $\sigma_d = 10$, and $m_\sigma = 0.6$. In total, 20 simulations are carried out for the IS case and compared against 5 scenarios of no-IS case. Expected costs for these scenarios are illustrated in Figure 3 and Figure 4.

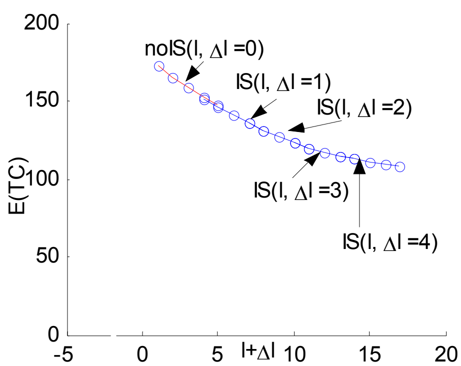

Figure 3: Effect of lead-time and time between forecast revisions on manufacturer's cost.

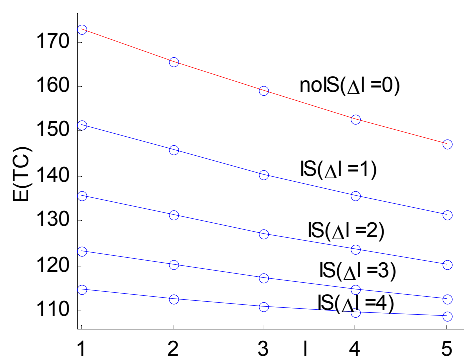

Figure 4: Effect of advanced forecast information sharing on manufacturer's cost.

The figures demonstrate the following insights:

- Expected cost of manufacturing decreases if final order is given with a longer lead-time. This is valid for both information sharing and no information sharing cases.
- Figure 3 demonstrates that under no circumstance would an uncertain forecast be better than a final order if both are transmitted at the same time instant. It makes the point clear that if some cost benefit is sought by sharing forecasts, then it has to be shared in advance in time compared to the lead-time usually given with final order. Although graph in figure 3 seems like a single continuous graph, in reality it contains five different graph segments. (It will be clear if we observe figure 3 and 4 together)

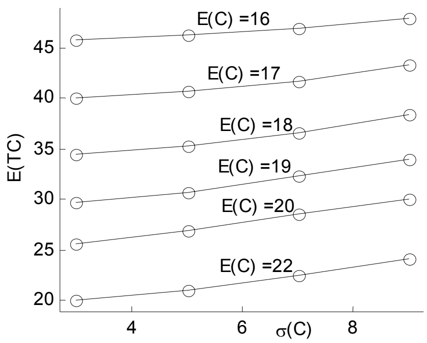

Figure 5: Effect of expected capacity on manufacturer's cost when early forecast is not shared.

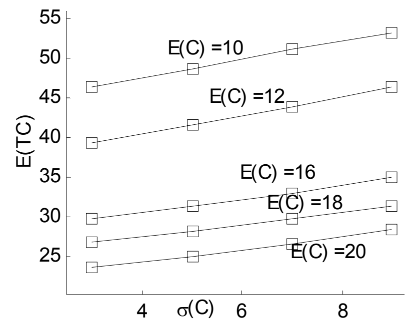

Figure 6: Effect of expected capacity on manufacturer's cost when early forecast is shared.

- Figure 4 shows the effect of advanced demand forecast sharing on manufacturer's cost. The plot clearly illustrates that there is value in issuing the final order with longer lead-times (if capacity is a constraint). The figure also shows that the manufacturer can always benefit from advanced forecasts of actual orders.

We notice that all the graphs in Figure 4 'fan-in'. This is due to the reason that as l increases, manufacturer will have enough capacity in its final stage to manufacture a large fraction of final order. Therefore, if capacity is not a constraint, advanced forecasts have lesser value.

5.3 Effect of capacity uncertainty on expected total cost to manufacturer

Capacity uncertainty is also studied through a simulation experiment for different levels of expected capacity and uncertainty (measure used here is standard deviations). Parameter values used for the IS-Case are: c_o=1, c_u=1.5, h=0.08, l = 5, Δl =3, E(C)=(10,12,16,18,20) and σ(C)=(3, 5, 7, 9), $\mathbf{\mu} = [100,100,100,100]$ and $\rho = 0.75$. For no-IS-Case, the values used for the parameters are: c_u=1.5, h=0.08, l = 5, E(C)=(10,12,16,18,20), σ(C)=(3, 5, 7, 9). For both the experiments $m_\sigma = 0.2$ and $\sigma_d = 10$. Figures 5 and 6 illustrate the results. Following insights can be obtained from the illustrations:

Figures 5 and 6 show that an increase in the expected capacity decreases the expected manufacturing cost. This is because increasing capacity increases manufacturer's responsiveness to forecast/demand fluctuations and hence reduces expected underage cost.

Figures 5 and 6 also show that marginal benefit of increasing capacity decreases as we keep increasing capacity. It is also clear that increase in uncertainty hikes manufacturer's cost. They clearly show that adding less variable capacity is more beneficial.

5.4 Effect of holding cost on total cost to manufacturer

This subsection will analyze the impact of unit holding cost on the manufacturer's cost. Parameter set selected for simulation of IS-case is c_o=1, c_u=(1,2,3,4,5), h=(0.08,0.2,0.8,1.2), l = 4, Δl =3 and E(C)=6, σ(C)=2, $\mathbf{\mu} = [90,90,90,90]$. Parameter set selected for No-IS case is c_u=(1,2,3,4,5), h=(0.08,0.2,0.8,1.2), l = 13 and μ(C)=5 and σ(C)=2. For both the designs we have set: $\sigma_d = 10$, $m_\sigma = 0.3$ and $\rho = 0.75$. Figures 7 and 8 illustrate the relationship between h and E(TC) for different values of cu. We get the following insights:

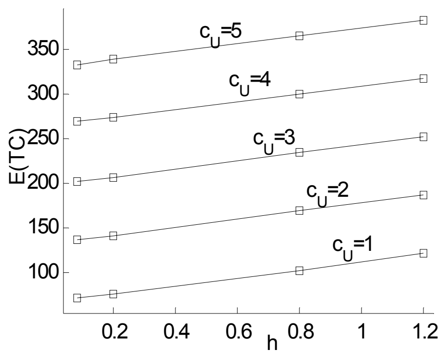

Figure 7: Effect of holding cost on manufacturer's cost when early forecast is not shared.

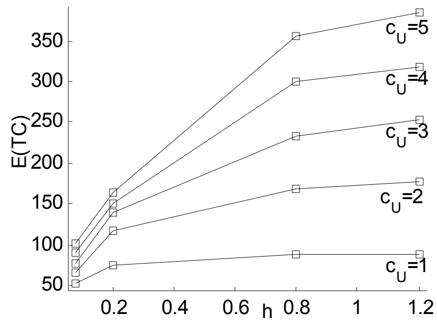

Figure 8: Effect of holding cost on manufacturer's cost when early forecast is shared.

As expected, the figures demonstrate that an increase in holding and/or underage costs increases the total cost for both forecast sharing and no information sharing cases.

With the presence of capacity uncertainty, increasing holding cost postpones production and in turn increases the probability of underage, thereby expected underage cost would increase and hence the total cost.

Effect of underage cost on manufacturer's cost is dramatic as illustrated. Product stock out during different stages of a product life cycle have different implications.

6. Concluding

For a make-to-order (MTO) manufacturer, receiving the order for a promotional or a seasonal sale with a higher lead-time would require lesser investment in capacity. Forecasts that are made very early in time are based on preliminary information and face substantial uncertainty about the sales. Usually, timings of promotion and seasonal sales are known with certainty. Therefore, a rough forecast of the order quantity with a definite due date can be transmitted in advance. We have mathematically modeled a MTO production schedule coupled with a forecast revision process and compared the benefit of advanced forecast sharing with the case of no forecast sharing. Through extensive simulation, we have found that advanced forecast sharing between buyers and manufacturers has the potential to improve manufacturers' cost performance. In this case, capacity uncertainty and holding cost play crucial role on the benefit that can be derived through information sharing. The model also investigates the effect of degradation of information as forecasts revisions are made with different lead times.

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