Supply Chain Cooperation by Agreed Reduction of Behavior Variability: A Simulation-based Study

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Abstract—Supply chain echelons normally base their operational decisions on average values of the parameters that depend on other members. However, in real-life operation the variability of said parameters decreases the link profits. Thus, a cooperative arrangement may be devised in which a link agrees to reduce the variability of its behavior to enhance the performance of other links, receiving compensation in return. This work shows the application of simulation and decision trees to assess the feasibility of this cooperation scheme, from the perspective of the central link of a three member supply chain. First, the operational parameters of the link are optimized for mean values of the variables set by adjacent members. Then, by simulating the system for different probability distributions of these variables, graphs of the expected link gain versus the variances of the distributions are plotted. The results are incorporated to decision trees to evaluate the collaboration feasibility. It was found that the increased variability of the behavior of one neighboring member decreases the benefit of lowering the variability of the behavior of the other. The manuscript closes with a discussion of the practical viability of this collaboration scheme.

Keywords—supply chain; uncertainty; collaboration; simulation

I. INTRODUCTION

A supply chain is the set of companies (named “links”, “members” or “echelons”) that participate in delivering a product to an end user, including activities ranging from raw material extraction, production, transporting and retail operations [1]. When the companies belong to different owners or parent organizations, each one doesn’t normally have detailed information on the variables that depend on neighboring members (i.e. its supplier and customer). Thus, each link designs its operational polices based on average values of variables like size and arrival time of customer orders and supplier delivery times [2]. However, the real-life variability of these variables causes the link profits to be lower than planned [3]. A collaboration arrangement can be devised to alleviate this: a link commits to decrease the variability of its behavior so to benefit a neighboring member, receiving a payment from the latter in exchange. For example, in a chain of supplier-retailer-customer, the retailer can offer reduced prices to the customer in exchange for his commitment to make his purchases with an even quantity and frequency. Similarly, additional payments can be offered to the supplier if he commits to less variable delivery times, which can be provided by prioritizing inventory and transportation for this retailer. In this collaboration mode, customers and suppliers benefit the retailer by making their behavior less variable, without changing their average behavior. The size of the incentives that the retailer may offer for this partnership, however, depends on the benefits he reaps when the other links decrease their behavior variability.

This work shows the usage of simulation [4] and decision trees to evaluate the feasibility of the collaboration between supply chain members through a compromise of reducing their behavior variability. Simulation is used to assess the effect of the variability in the behavior of the upstream and downstream members on the performance of an intermediate link. The results are incorporated into a tree representing the decision of said link on whether to participate in an agreement of intermediate link. The formulation than do the analytical expressions reported in the literature (for example in [3]).

II. LITERATURE REVIEW AND JUSTIFICATION

There is a vast body of research literature on supply chain collaboration. Empirical studies are shown in [5-7], dealing with the impact of inter-organizational systems on chain performance, and in [8], treating the effect of uncertainty and confidence. Collaborative supply chain performance has been analyzed in [9, 10], with the latter concluding that, in many cases, the collaboration only benefits the retailer. Planning and design models of the collaborative chain are shown in [11] for procurement planning, in [12] for cases in which the members have different manufacturing systems and in [13], where a link decision model incorporating cooperating members is shown. Meanwhile, the model of [14, 15] incorporated the internet to
Several authors deal with the division of the collaboration benefits. Side payment calculation is approached through bargaining theory in [28-31]. The special case of supply chains with re-work is covered in [32], while [33] treats the effect of lying and misrepresentations on the contracts and [34] deals with gain sharing through wholesale pricing. A form of collaboration is the sharing of information. The effect on performance of different information sharing degrees is treated in [35]. In [36], authors showed how a global firm can improve its performance by sharing information with retailers. In [37], a model in which information on customer demand and adjustments of inventory position are shared through the chain is presented. In [38], authors discussed the convenience of sharing innovations with other links. Game theoretical models for the convenience for the retailer to share demand information are shown in [39, 40], the latter finding that the retailer is inclined to increase the uncertainty of the other links and in [41] authors concluded that, only when there are product returns, it is beneficial for the producer to share demand information with the retailers. Additionally, in [42] authors demonstrated that complete information sharing does not guarantee performance improvement. Analytical results of the impact of information sharing on the supply chain bullwhip effect are presented in [43-45]. The issue is also addressed statistically in [46] and through process control theory in [47]. Meanwhile, in [48] authors treated the case of chains with work returns and in [49] authors showed that, even with total information sharing, a residual bullwhip effect remains. Finally, chain performance with information sharing is contrasted to that of a vendor-managed inventory policy in [50, 51].

The above mentioned reports do not address supply chain cooperation through a links’ agreement by which one member commits to decrease the variability of its behavior so to benefit another. While the benefits of this cooperation scheme may be lower than other cooperation forms treated in the literature, it has two qualities that render it appealing in practice. The first is that the member benefited by the variability reduction, does not need to disclose to the other the amount of this benefit. He just offers a payment for the variability reduction, which may or not be acceptable by the other. This makes it easy for the partners to find an agreement beneficial to both, without bargaining. The second advantage of this collaboration scheme is that, unlike other cooperation modes, it does not require the members to disclose information to each other. This is extremely important in practice, as many opportunities for cooperation between supply-chain members are hindered by the members’ fear that the revealed information can prompt the other member to become a direct competitor. For example, the retailer may reasonably believe that if he reveals to its wholesaler that some of the customer’s demand goes unsatisfied, the wholesaler may be tempted to launch a retail operation on its own. The collaboration scheme through payed reduction of behavior variability, with its minimal need for information revelation, allows an easy practical implementation, and thus may have a measurable impact on the operation of real supply chains.

III. CASE STUDY DESCRIPTION

A case study supply chain of supplier, retailer and customer is shown in Figure 1. The customers arrive to the retailer every \(\Delta_t\) time units and request the amount of product \(Q_c\). If \(Q_c\) is greater than the retailer’s current inventory (\(I_r\)), the sale is lost. The retailer’s inventory policy is a point-of-reorder, continuous review scheme: when the value of \(I_r\) is less than a minimum inventory \(I_{r,MIN}\), he asks the supplier for a load of product of size \(I_{r,MAX}\) which takes \(\Delta_t\) time units to arrive. For a given planning horizon, the retailer’s profit \(G\) can be calculated as

\[
G = P_r \times V_r - P_d \times V_d - C_E \times N_E - C_I \times \text{Max}(I_r)
\]

Where:
- \(P_r\) = Unitary product sale price to the customer.
- \(P_d\) = Unitary product purchase price from the supplier.
- \(C_I\) = Cost of retailer inventory, per unit.
- \(C_E\) = Shipment cost from the supplier, per trip.
- \(V_r\) = Total sale of the retailer.
- \(V_d\) = Total sale of the supplier.
- \(N_E\) = Number of deliveries from the supplier to the retailer.
- \(\text{Max}(I_r)\) = Maximum retailer inventory value during the planning horizon.

Equation (1) implies that the retailer pays the order delivery cost from the supplier. As mentioned in Section I, the retailer optimizes its operation parameters \(I_{r,MIN}\) and \(I_{r,MAX}\) so to maximize his profit \(G\), based on average values of variables \(\Delta_t\), \(Q_c\) and \(\Delta_t\), that depend on other chain members. However, the real-life variability of these parameters causes the retailer profit to be lower than the optimized value. Thus, the retailer can offer compensation to either supplier or customer (or both) for decreasing this variability. The maximum amount of this compensation depends on how much the variability reduction represents in increased retailer profits. In the following section, simulation is used to determine this maximum amount for a numerical case study.

The results are then introduced in a decision tree to evaluate the feasibility of paying for supplier collaboration. The following sections assume the values of \(P_r = $50/item\), \(P_d = $30/item\), \(C_E = $1000/trip\) and \(C_I = $50/item\) and a simulation length of 1000 h.
IV. METHODOLOGY AND RESULTS

A. Simulation results

The results presented were produced using a simple simulation model of the retailer’s inventory, such as that shown in [52], coded in MS-Visual Basic. The retailer chooses the values of \( I_{T,MIN} \) and \( I_{T,MAX} \) to maximize his profits, assuming that the variables \( \Delta t \), \( Q \) and \( \Delta G \) remain constant at their average values of, respectively, \( E[\Delta t] \), \( E[Q] \) and \( E[\Delta G] \). The values of \( I_{T,MIN} \) and \( I_{T,MAX} \) so determined are named, respectively, \( I_{T, MIN}^{\ast} \) and \( I_{T, MAX}^{\ast} \). The influence diagram of this decision is shown in Figure 2. In these diagrams, double-bounded circles indicate variables with known value, rectangles stand for decisions and the hexagon represents the objective to be achieved [53]. Figure 2 emphasizes that the retailer, when selecting \( I_{T,MIN} \) and \( I_{T,MAX} \), considers only the average values of \( \Delta t \), \( Q \) and \( \Delta G \).

Setting the values \( \Delta t = E[\Delta t] = 10h \), \( Q = E[Q] = 10 \) items and \( \Delta G = E[\Delta G] = 70h \) and using simulation to evaluate different options of \( I_{T,MIN} \) and \( I_{T,MAX} \), the optimal values of \( I_{T, MIN}^{\ast} \) = 60 and \( I_{T, MAX}^{\ast} \) = 200 items are found. These produce a profit, in a 1000 h operation length, of $12'000.

To evaluate the retailer loss due to the variability of \( \Delta t \), \( Q \), and \( \Delta G \), different probability distributions are defined for these variables. The distributions retain the expected values previously set (\( E[\Delta t] \), \( E[Q] \)) and \( E[\Delta G] \) = 70h, but differ in variance. For \( \Delta t \) and \( Q \), the probability distributions of Table I are defined, with Table II showing the corresponding distributions for \( \Delta G \). In the tables, the notation \( \text{var}( ) \) refers to the variance of the variables for a probability distribution. The retailer’s profit, when adhering to \( I_{T,MIN}^{\ast} \) and \( I_{T,MAX}^{\ast} \) and with \( \Delta t \), \( Q \) and \( \Delta G \) following a probability distribution of Tables I and II, is calculated through simulation.

### Table I. Probability Distributions for \( \Delta t \) and \( Q \)

<table>
<thead>
<tr>
<th>( x ) (value of ( \Delta t ) or ( Q ))</th>
<th>Dist. I</th>
<th>Dist. II</th>
<th>Dist. III</th>
<th>Dist. IV</th>
<th>Dist. V</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>0.1</td>
<td>0.1</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>10</td>
<td>0.8</td>
<td>0.8</td>
<td>0.3</td>
<td>0.4</td>
<td>0.2</td>
</tr>
<tr>
<td>14</td>
<td>0.1</td>
<td>0.1</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>18</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>( E[\Delta t] = E[Q] )</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>( \text{var}(\Delta t) = \text{var}(Q) )</td>
<td>3.2</td>
<td>10.66</td>
<td>19.2</td>
<td>32</td>
<td></td>
</tr>
</tbody>
</table>

### Table II. Probability Distributions for \( \Delta t \)

<table>
<thead>
<tr>
<th>( x ) (value of ( \Delta t ))</th>
<th>Dist. I</th>
<th>Dist. II</th>
<th>Dist. III</th>
<th>Dist. IV</th>
<th>Dist. V</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.05</td>
<td>0.2</td>
</tr>
<tr>
<td>60</td>
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<td>0</td>
<td>0.1</td>
<td>0.3</td>
<td>0.2</td>
</tr>
<tr>
<td>70</td>
<td>1</td>
<td>0.8</td>
<td>0.3</td>
<td>0.4</td>
<td>0.2</td>
</tr>
<tr>
<td>80</td>
<td>0</td>
<td>0.1</td>
<td>0.3</td>
<td>0.5</td>
<td>0.2</td>
</tr>
<tr>
<td>90</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.05</td>
<td>0.2</td>
</tr>
<tr>
<td>( E[\Delta t] )</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
</tr>
<tr>
<td>( \text{var}(\Delta t) )</td>
<td>0</td>
<td>20</td>
<td>100</td>
<td>200</td>
<td>200</td>
</tr>
</tbody>
</table>

Figure 3 shows the expected value of the retailer’s profit (\( E[G] \)), derived from 10'000 simulation replications, for all combinations of the probability distributions of Tables I and II; \( E[G] \) is plotted against the variance of \( Q \), with the variance of \( \Delta t \) shown parametrically for the curves. In Figures 3a-d, the variability of customer behavior is lower for the top curves (which are for probability distributions of low variance of time between arrivals) and for points closer to the left side of the figure (with low variance of the probability distribution of amount purchased). Similarly, the progression from Figure 3a to 3d shows \( E[G] \) values for increasing variability in the behavior of the supplier (increasing variance of the probability distribution of supplier delivery times). The following observations can be done by perusing Figure 3:

1. In Figures 3a-d, the bundle of curves is wider to the left (where there is less variability of \( Q \)) than to the right. This means that decreasing the variability of \( \Delta t \) (i.e. shifting from the lowest curve to the highest), has a greater impact the less variable \( Q \) is. This is illustrated by comparing lengths \( a \) to \( a' \) in Figure 3a.

2. In Figures 3a-d, the vertical distance between the highest and lowest points of a curve, is greater for the top curve (for \( \text{var}(\Delta t) = 0 \)) than for the bottom one (\( \text{var}(\Delta t) = 32 \)). This is illustrated in Figure 3b by comparing the dimensions \( b \) and \( b' \). This indicates that the decrease in variability of \( Q \) has a bigger effect on \( E[G] \) the lower the variability of \( \Delta t \).

These points are synthesized by stating that, regarding \( \Delta t \) and \( Q \), the value of decreasing the variability of one is greater the lower the variability of the other is.

The transit from Figure 3a to 3d shows the effect of increasing the variability in supplier delivery time, \( \Delta t \). From the curve bundle shape in these graphs, it can be noticed that, for an increased variability in \( \Delta t \), the effect of changing the variability of \( \Delta t \) and \( Q \) becomes smaller. This can be measured quantitatively by calculating, for Figures 3a to 3d, the difference in \( E[G] \) between the point with the least variability in \( Q \) and \( \Delta t \) (\( \text{var}(\Delta t) = 0 \) on the curve var(\( \Delta t \)) = 0) and that of the point with greatest variability in these variables (\( \text{var}(\Delta t) = 32 \) on the curve var(\( \Delta t \)) = 32). This difference is the impact of a reduced variability in the customer behavior. Doing this calculation for the four graphs of Figure 3, and plotting against the variance of \( \Delta t \), produces Figure 4. This plot shows that, as \( \text{var}(\Delta t) \) increases, the effect of reducing the variability of \( Q \) and \( \Delta t \) decreases.
Similarly, Figure 5 shows the change in $E[G]$ when the variability of $\Delta t_E$ drops from $\text{var}(\Delta t_E) = 200$ to $\text{var}(\Delta t_E) = 0$, for points with the same $\text{var}(\Delta t_C)$ and $\text{var}(Q_C)$ values. For example, the value for $\text{var}(\Delta t_E) = \text{var}(Q_C) = 0$ is calculated by subtracting from the $E[G]$ value of the point $\text{var}(Q_C) = 0$ on curve $\text{var}(\Delta t_E) = 0$ in Figure 3a, the value of $E[G]$ of the analogous point of Figure 3d. A trend similar to that of Figure 4 can be seen in Figure 5: the greater the value of $\text{var}(\Delta t_C)$ and $\text{var}(Q_C)$, the smaller the worth of decreasing $\text{var}(\Delta t_E)$.

It can be concluded that the more variable the behavior of the customer is, the smaller the benefit to be reaped from a reduction in the variability of the supplier’s behavior. The same applies the other way around: as the supplier behavior grows variable, the benefit of decreasing the variability of the customer behavior shrinks. Thus, the potential benefit of getting the compromise of one member to reduce its behavior variability depends drastically on the variability of the other member’s behavior.

### B. Feasibility of negotiating with the supplier

The previous results are used to evaluate, from the retailer’s perspective, the feasibility of negotiating with the supplier a payed reduction in the variability of the delivery time $\Delta t_E$. The retailer’s decision of whether to pay the supplier for reducing the variability of $\Delta t_E$ is shown as a tree in Figure 6. In these trees, squares stand for decisions and circles represent
uncertainties [53]. At the first decision square, "Negotiate with supplier" the retailer can choose either 'Yes' or 'No'. The alternative chosen influences the variability of $\Delta E$: [Dist. $\Delta E_{|\text{Yes}}$] represents the original (i.e. not negotiated) probability distribution of $\Delta E$ while [Dist. $\Delta E_{|\text{NE}}$] stands for the probability distribution of $\Delta E$ that the supplier agrees to maintain as a result of the deal with the retailer. It is understood that the variability of $\Delta E$ implied by [Dist. $\Delta E_{|\text{Yes}}$] is greater than that of [Dist. $\Delta E_{|\text{NE}}$]. The retailer’s profit is written to the extreme right of the tree. It can be seen that this profit is affected by the probability distributions of $Q_C$ and $\Delta C$, whose variability depends on the customer. The deal between the retailer and supplier implies that the former pays the latter an amount $c_N$ ($\$$), so the retailer’s profit for the top branch is $G-c_N$.

![Retailer’s decision tree on whether to negotiate a reduction in the variability of $\Delta E$](image)

The greatest value of $C_N$ that the retailer can pay for the supplier’s cooperation can be determined by substituting in the tree the relevant data from Figure 3. For example, for a low variability in customer’s behavior ($\text{var}(Q_C)=\text{var}(\Delta C)=3.2$), the highest value the retailer can pay for reducing the variability of $\Delta E$ from $\text{var}(\Delta E)=200$ to $\text{var}(\Delta E)=20$ is $323$. If, on the other hand, there is a high variability in the customer’s behavior ($\text{var}(Q_C)=\text{var}(\Delta C)=32$) the maximum value of to pay for such variability reduction is only $109.

V. CONCLUSIONS

Normally the links of a supply chain design their operation based on average values of the parameters set by other chain members, and, as a result of the real variability of said parameters, their profits are diminished. The aim of this work is to explore the feasibility of a form of supply chain collaboration, consisting of the links reducing the variability of their behavior so to benefit another, in exchange for a monetary compensation. A key factor for the operability of this cooperation scheme is how much the profit of the members improves by such variability reduction. This work shows the use of simulation to determine this improvement, for a case study of supplier-retailer-customer. The retailer designs its operation using average values of the variables depending on other members and then, by simulating different probability distributions for these variables, the variability impact on the retailer’s profits is calculated. For the central link, the value of reducing the variability of the behavior of one neighboring member (upstream or downstream) is strongly related to the variability of the behavior of the other. Reducing the variability of the behavior of either member is more valuable when the behavior of the other isn’t widely variable. If both members show a very variable behavior, a collaboration scheme with only one of them appears to be of little value. In this case, some reduction of the variability of both members’ behavior should be sought. While the feasibility conditions of this scheme seem somewhat restrictive, it should be noted that, given the practical advantages of this collaboration scheme (i.e. natural way of cutting win-win contracts, no information disclosure needed), a situation in which the retailer can get behavior variability reduction commitments from both neighboring links, is not farfetched. However, as the retailer must pay for the collaboration of both neighbors, an analysis via simulation and decision trees, such as presented here, can be done to determine how much he can pay while still coming ahead.

VI. REFERENCES