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Engineering Value Chain Coordination and Optimization

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1 Introduction

Increasing competitive pressures and market globalization are forcing firms to develop engineering chain that can quickly respond to customer needs. Historically, have been managed independently, buffered by large inventories. Therefore, effective engineering management requires coordination among the three fundamental stages of the engineering chain: procurement, production, and distribution.

Coordination can be visualized in different functions such as logistics, inventory management, forecasting, and transportation. Similarly, various interfaces such as supplier—manufacturer and manufacturer—retailer can be effectively managed using coordination. The members of engineering chain are often separate and independent economic entities. Even though

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coordination improves the performance of the engineering chain, it may not always be beneficial to coordinate the engineering chain members. Hence, a key issue in engineering chain coordination is then to develop specific mechanisms that align the objective of independent members and coordination, their decisions, and activities so as to optimize engineering system performance. By utilizing coordination mechanisms, the performance of engineering chain value may improve. There are four different types of coordination mechanisms as discussed (see Fig. 1).

With the advances in logistics and engineering chain management technology in recent years, there has been an explosion of interest in the topic of "engineering Chain Optimization". Optimization is the application of processes and tools to ensure the optimal operation of manufacturing and distribution chain. This often involves the application of mathematical modeling techniques using optimization techniques (see Fig. 2).

Typically, engineering chain optimization is trying to maximize the profitable operation of their manufacturing and distribution chain. This could include measures like maximizing gross margin return on inventory invested (balancing the cost of inventory at all points in the engineering chain with availability to the customer), minimizing total operating expenses (transportation, inventory, and manufacturing), or maximizing the gross profit of products distributed through the

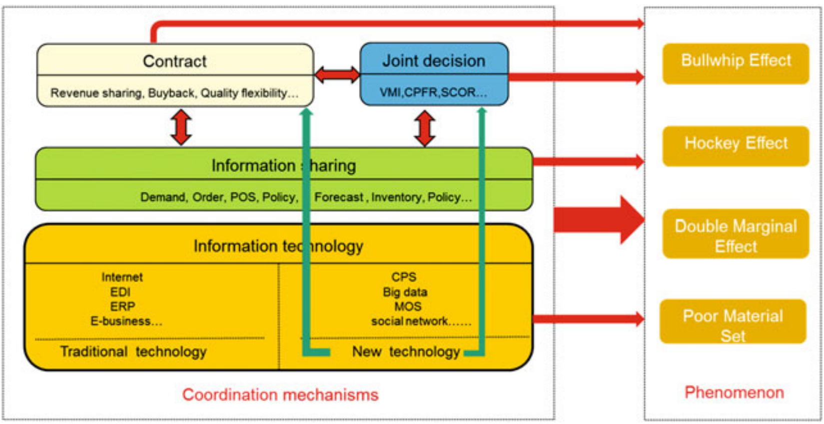

Fig. 1 The relationships of coordination mechanisms

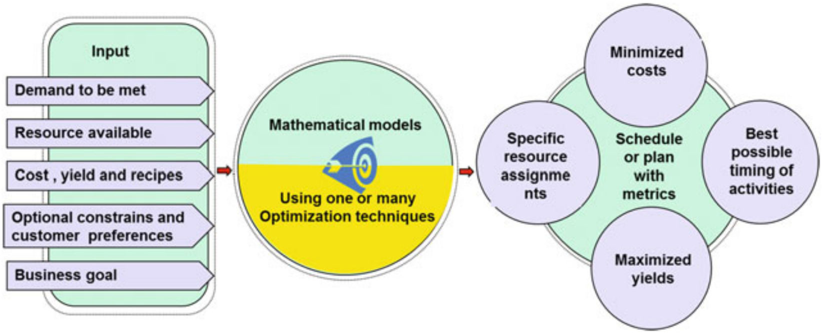

Fig. 2 The processor of modeling and optimization in EV chain

engineering chain. Engineering chain optimization involved the end-to-end process, which starts with the design of the product or service and ends with the time when it has been sold, consumed, and finally, discarded by the consumer; issues can be classified into two broad categories: configuration (design-oriented) issues that relate to the basic infrastructure on which the engineering chain executes and coordination (execution-oriented) issues that relate to the actual execution of the engineering chain.

The competitiveness and dynamic nature of today's marketplace are due to rapid advances in information technology, short product life cycles and the continuing trend in global outsourcing. Managing the resulting engineering chain networks effectively is a complex and challenging task which is imputable to a high level of uncertainty in engineering demand, conflict objectives, and vagueness of information, numerous decision variables, and constraints. System modeling is used in such cases to model the real system. These models can be mathematical models or simulation models. In order to capture the system complexity, mathematical models are rarely used to model engineering chain. Decisions are made at different levels in engineering chain. These decisions are needed to be supported by robust optimization techniques to enable decisions to evaluate the impact of their decisions prior to actually making them in the real environment.

Optimization techniques have shown a great potential to solve engineering chain problems that cause an immense challenge to decision makers. These challenges are imputable to a high level of uncertainty in supply demand, conflict objectives, lack of needed information, numerous decision variables, and inevitable constraints. Traditional techniques (e.g., linear programming, integer programming, and mixed-integer programming) have limited capabilities to handle the inherent interdependencies in current engineering chain networks. Optimization methodologies have to focus not only on improving a particular process performance but also on achieving a broader impact on engineering chain efficiency. Accordingly, metaheuristics were presented into engineering chain applications because of its global optimization capabilities in stochastic environments. On the other hand, statistical methods and metamodel-based methods can be incorporated with metaheuristics to provide more reliable solutions in a reasonable timeframe.

Manufacturing processes are also undergoing major challenges to achieve the Smart Factory vision such as to increase systematic processes, reuse, and improve understandability of complex structures. Most of the new factory concepts share attributes of smart networking (Dolgui and Proth 2010; Ivanov et al. 2013; Chick et al. 2014). That is why it becomes a timely and crucial topic to consider engineering chain as collaborative cyber-physical systems (Camarinha-Matos and Macedo 2010; Ivanov et al. 2014). Cyber-physical systems incorporate elements from both information and material subsystems which are integrated and decisions in them are cohesive (Zhuge 2011).

Some coordination mechanisms, such as quantity discount schedule and revenue-sharing schedule, are used to regulate the relationship among ``s members. The continuous evolving dynamic structure of the engineering chain poses many interesting challenges for effective system coordination. Very often, schedules are designed for the static environment such as a known market demand and a distribution function in the stochastic environment. These schedules can be defined as a static coordination mechanism. However, after the plan has been settled down, the environment is often disrupted by some unexpected events, such as machine breakdown, the raw material shortage, the SARS epidemic, and Hurricane Katrina. The disruptions have made companies aware of the need for active disruption management.

How to design adaptive coordination mechanisms is a problem, and some aspects can be considered as follows:

- Double check the traditional coordination mechanisms by further consideration of the more realistic business environment. For example, considering the influence of the widely used trade credit and its associated risk in realistic commerce.
- Realize the influences of a new relationship of customs and behaviors. For example, based on a review of the social network, consumption habits, and the ways of communication.
- Realize the influences of new ICT. For example, forecast demand directly using big data mining technology.
- Holistic coordination model for integrating currently commercial environment and novel manufacturing models.
- It must be noted that a typical engineering chain also deals with human systems, and hence, it is hard to coordinate engineering chain members may be visualized.
- There exist differences in the interest of engineering chain members as the members habitually work as an individual based on local perspective and opportunistic behavior results in a mismatch of supply and demand.

Today's markets call for elaborate competition schemes as a large variety of products is available to meet customer requirements. Mass customization has become an imperative for many manufacturers to survive in the growing competition characterized by heterogenic customer demands, accelerated new product development investments, and shortened product life cycles. Duray shows that the degree or type of customization depends on the point in the production cycle where the initial customer involvement is (Duray et al. 2000). They define four points in the production cycle, where each of the points is an expression of the degree of customization: design, fabrication, assembly, and use. The first three are quite easily recognized as commonly known, engineer-to-order (ETO), make-to-order (MTO), and assembly-to-order (ATO).

In summary, engineering chain management in new business environment is complicated and has its own special characters mainly reflected in two aspects. One is the random information from customer orders and the complex relations among engineering chain cooperators, which can cause many complicated contradictions in strategic or operational level and bring dynamic or stochastic characteristics to it; the other is the outstanding relations of collaborative benefits and risks in this complicated environment. Therefore, we must probe the ways to respond to these characteristics and analyses, the coordination mechanisms, and optimization approaches in new business environment.

Coordination is essential for successful engineering chain management; we make a conjoint research of information sharing, operational research and behavior research to adaptive coordination mechanism, and the details are worded in Sect. 2 . As for modeling and optimization, review papers (Da Silveira et al. 2001; Fogliatto et al. 2012) defined four steps that described activities in generating and processing MC orders, namely (1) building the product catalog, (2) configuring customer orders, (3) transferring orders to manufacturing, and (4) manufacturing customized orders. We focus on step (3) to engineering chain optimization, transferring orders to manufacturing, which is specific to the manufacturer who fulfills the orders based on available production resources: materials and production capacity under the ATO engineering chain environment in Sect. 3.

2 Trust-Embedded Coordination in Information Sharing

2.1 Introduction

Information sharing is one of the most important coordination mechanisms in engineering chain (see Fig. 1). In industries, many firms follow electronic data interchange (EDI) system to place orders. Based on the received orders, their upper streamers determine their optimal capacities (Premkumar et al. 1994). Because the orders are costless, non-verifiable, and cancelable before shipping, they are commonly referred to soft-orders (Taylor and Plambeck 2007). Therefore, EDI based non-binding soft-orders primarily do not involve complex contracts. Since a downstream retailer has an incentive to over-order products for abundant supply, fully relying on the soft-orders usually leads to great capacity risks. Sometimes, an upstream supplier deems all soft-orders to be meaningless (Cai et al. 2013). Based on the above analysis, a critical question of information sharing by soft-orders is how much information to be credibly transmitted and what is the optimal decision under information asymmetric circumstance.

Information asymmetry in a supplier—retailer relationship is well studied; strategic information transmission and contract designing are helpful to align the pecuniary incentives of engineering chain partners and ensure credible information sharing (e.g., Cachon and Lariviere 2001; Özer et al. 2011). In industries, many firms share nonbinding unverified information via soft-orders. For example, Nike has started soft-order service via an EDI system for nearly 15 years. At the first year when the service was started, the service helped Nike to reduce its stock by 14% (Nike Inc. 1999). It is also reported that more than 41% of Asia Pacific firms have adopted EDI systems to transmit their soft-orders since 2008. Motivated by the practices, some behavior studies (e.g., Özer et al. 2011; Ebrahim-Khanjari et al. 2012) establish the role of trust in information sharing via soft-orders without complex contracts and verify that trust is the primary factor for credible information transmission. Since "trust is a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another" (Rousseau et al. 1998), it is also affected by instant behaviors in current transactions. In order to mathematically present the influence of instant behaviors to trust, we suggest a trust evaluation model. The proposed model is helpful to analyze the value of trust in the information sharing process and how trust affects engineering chain decisions.

We focus on a two-tier engineering chain consisted of a supplier and a retailer. Both the supplier and retailer do forecast independently before transaction. At the beginning of their transaction, the retailer places soft-orders and the supplier decides his capacity afterward. Because both supplier and retailer's forecasted demands are their private information, it is risky for both sides to make decisions under the highly information asymmetric circumstance. For example, the retailer does not know how much the supplier trusts when she places orders because the supplier's forecasted demand is unknown to her. Simultaneously, the supplier also faces potential loss stemming from the retailer's artificial soft-orders since he does not know the retailer's private forecast. Therefore, we provide a trust-embedded coordination to mitigate their risks and improve engineering chain performances. The coordination process consists of two stages: at the first stage, the retailer and supplier negotiate a cost-sharing rule; at the second stage, the retailer makes ordering decision and the supplier makes capacity decisions sequentially. We are interested in: what is the role of trust takes in their transaction? How does the negotiation power of the supplier/retailer affect the engineering chain decisions and performances? Whether the proposed trust-embedded coordination works effectively or not?

2.2 Modeling Trust

The existing psychology theories have proven that trust is affected by multiple factors. Some factors can be evaluated before a transaction, e.g., reputation, historical transaction, and peer recommendations from trustees; emotions, experience, and cognition from the trustors. The evaluations of these factors are pre-known and unchanging in a transaction, so that these factors can be named as predetermined factors. However, some instant behaviors in transactions can affect trust (Rousseau et al. 1998). Thus, some trust-affecting factors (i.e., instant behaviors) can only be evaluated in the current transaction. Thus, we name the factors that work in the current transaction as instant factors. For convenience, we denote all the predetermined factors by R and all instant factors by Δ. Moreover, because trust is a kind of psychological state, its distributions are often evaluated by regression approaches (Laeequddin et al. 2012). Thus, we consider trust T as a randomly distributed variable with cumulative density function (c.d.f) $F(t)$ and probability density function (p.d.f.) $f(t)$. According to the above analysis, trust T is formulated as:

$$T \sim f(\mathrm{t/R}, \Delta) \quad \text{where} \quad 0 \leq t \leq 1 \tag{1}$$

Equation (1) suggests a general model to quantify trust, where R denotes predetermined factors and Δ denotes instant factors. Since R and Δ might contain different items in different situations, the proposed trust model is general and applicable to different engineering chain problems. For example, a decision maker might analyze information in some complex situations, e.g., multiple partners, multiple engineering chain tiers, or complex transaction processes. The decision maker can classify all trust-affecting factors of his/her problem into two groups, the predetermined factors R and the instant factors Δ. Based on this classification, his/her trust level can be evaluated by Eq. (1). Therefore, our proposed trust evaluation model is general and could be used in the complex situations.

In the target problem of this paper, the predetermined trust-affecting factors include reputation and historical transactions of the retailer, experience and psychology state of the supplier, peer recommendation from the third side, and so on. When a transaction begins, the retailer places a soft-order. After that, the supplier calculates the information mismatch level by comparing his private forecasting demand with the retailer's soft-order. Because information mismatch harms trust level l (Kosfeld et al. 2005; Sriram 2005), the supplier updates his trust based on information mismatch. We let μ_S be the supplier's forecasted demand and μ_{RS} be the retailer ordered quantity; thus, the information mismatch can be denoted by $\Delta = \frac{|\mu_{RS} - \mu_S|}{\mu_s}$. Therefore, when $\Delta = 0$, we have $T \sim f(\mathrm{t}|\mathrm{R}, 0)$, which means the supplier's trust only depends on the predetermined factor R. Thus, the supplier's trust when $\Delta = 0$ can be named as "initial trust." As suggested by Özer et al. (2011), we have trust level T ranged within [0,1]. The fact of $T = 0$ suggests that the supplier fully distrusts the retailer's soft-order, while the fact of $T = 1$ indicates the supplier fully trusts the retailer's soft-order.

In this context, market demand is formulated as $D = \mu_0 + \varepsilon$, where μ is a positive constant denoting average market demand and ε describes demand fluctuation. They both know that ε is a random variable with c.d.f. $\Gamma(\varepsilon)$ and p.d.f. $\tau(\varepsilon)$. In the engineering chain we studied, both the retailer and supplier forecast the value of μ_0 individually. Because the retailer is more close to consumers and professional on marketing, we assume the retailer can precisely forecast the distribution of market demand. Although the retailer's forecasted demand is μ_R, she places a soft-order μ_{RS} to the supplier. After receiving the retailer's soft-order μ_{RS}, the supplier updates his demand evaluation based on ordered quantity μ_{RS} and his own forecasted demand quantity μ_S. As suggested by Clemen and Winkler (1999), we assume that the supplier combines two demands of μ_{RS} and μ_S using a simple weighted average approach. Therefore, the supplier believes that the average market demand is:

$$\mu = T\mu_{RS} + (1-T)\mu_S, \quad \text{where} \quad T \sim f(t|R, \Delta) \tag{2}$$

Since μ is a random variable, we let $G(t)$ and $g(t)$ denote its c.d.f. and p.d.f., respectively. Because $T \in [0, 1]$, we have $\min(\mu_{RS}, \mu_S) \leq E(\mu) \leq \max(\mu_{RS}, \mu_S)$ based on Eq. (2), which indicates that the supplier insists that average demand is within his own forecasted demand and the retailer's soft-order. Although the retailer does not know the value of μ_S, she can employ the concept of Bayes' rule to evaluate it. We assume that she evaluates μ_S to be μ'_S. Therefore, the retailer believes her trustworthiness T' to be:

$$T' \sim f(t'|R, \Delta') \quad \text{where} \quad t' \in [0, 1], \; \Delta' = \frac{|\mu_{RS} - \mu'_S|}{\mu'_S} \tag{3}$$

Let μ'_S denote the retailer's evaluation on μ_S, the retailer's evaluation of μ is written as:

$$\mu' = T'\mu_{RS} + (1-T')\mu'_S \tag{4}$$

Since T' is a random variable, μ' is also a random variable.

2.3 Profit Functions

Because of advantages in information collection and customer demand forecasting, retailers in engineering chain most probably know the real demand information. Similarly, to some existing studies (e.g., Cachon and Lariviere 2001; Özer and Wei 2006), we assume that the retailer knows the demand information since she is more close to market. We also assume that the wholesale price p_S , retail price p_R, production cost c, and capacity preparation cost c_k for each product are known.

Both the supplier and retailer have their individual forecasts and communicate with soft-orders; their transaction follows such a sequence: (1) both the retailer and supplier forecast the average market demand and the retailer evaluates the supplier's forecasted demand; (2) the retailer places a soft-order to the supplier; (3) the supplier evaluates the market demand based on the retailer's soft-order and his private forecast. After that, he determines his optimal production capacity. The decision process is illustrated in Fig. 3.

Different from the decision process given by Özer et al. (2011), we do not only analyze the supplier's optimal determinations but also solve the retailer's optimal decision in this paper. As shown in Fig. 1, the engineering chain decisions are made following a Stackelberg game, where the retailer is the leader and the supplier is the follower. In the game, the retailer decides her ordered quantity at first and the supplier determines his optimal capacity based on the retailer's decision.

1. The retailer's decision.

Let Q denote the supplier's capacity, the retailer's profit is:

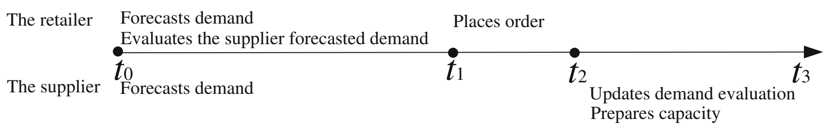

Fig. 3 Sequence of events in decentralized pattern

$$\Pi_R = \underset{\varepsilon}{E}[(p_R - p_S)\min(Q,\ \mu_R) + \varepsilon)] \tag{5}$$

Because the retailer evaluates μ_S to be μ'_S (Eq. 4), the supplier's expected profit in retailer's belief is:

$$\Pi'_S = \underset{\varepsilon}{E}[(p_S - c)\min(Q,\ \mu'_S + \varepsilon) - c_k Q] \tag{6}$$

Note that formula $\mu'_S + \varepsilon$ is random, we assume its c.d.f. and p.d.f. to be $G'(t')$ and $g'(t')$, respectively. Let μ^*_{RS} and Q'^* be the optimal solutions of $\max(\Pi_R)$ and $\max(\Pi'_S)$, respectively. We can solve the retailer's decision Q'^* by Eq. (6). Then, we introduce Q'^* into Eq. (5) and compute the retailer's decision μ^*_{RS} (Corollary 1).

Corollary 1 For $\forall \mu_R$, we have

$$\mu^*_{RS} = \arg\max_{\mu_{RS}} Q'^*,\ Q'^* = G'^{-1}\left(\frac{p_S - c - c_k}{p_S - c}\right) + E(\mu')$$

Proof. Because the retailer and supplier make decisions sequentially, we solve the supplier's decision at first. For a given μ_{RS}, we have $\mu' = T'\mu_{RS} + (1 - T')\mu'_S$, where $T' \sim f(t'|R, \Delta')$ (Eq. 3). We introduce μ' into Eq. (6) and have:

$$\frac{d\Pi'_S}{dQ} = (p_S - c)[1 - G'(Q - E(\mu'))] - c_k$$
$$\frac{d^2\Pi'_S}{dQdQ} = -(p_S - c)g'(Q - E(\mu')) < 0$$

Therefore, according to Eq. (1), we have the supplier's optimal solution as follows:

$$Q'^* = \arg\max_{Q} \Pi'_S = G^{-1}\left(\frac{p_S - c - c_k}{p_S - c}\right) + E(\mu')$$

Because $\prod_R$ strictly increases with Q, we have the retailer's decision on optimal soft-order:

$$\mu_{RS}^{*} = \arg\max_{\mu_{RS}} \Pi_R = \arg\max_{\mu_{RS}} Q'^{*}.$$

In Corollary 1, Q'^{*} is the retailer's evaluation about the supplier's capacity when she orders μ_{RS}^{*}. Therefore, the retailer's maximum expected profit is $\prod_R'^{*}(Q'^{*})$.

2. The supplier's decision.
After receiving the retailer's soft-order μ_{RS}, the supplier evaluated market demand is $\mu(\mu_{RS})$ by Eq. (2). We have the supplier's profit function:

$$\begin{aligned} \Pi_S &= \underset{\varepsilon}{E}[(p_S - c)\min(Q, \mu(\mu_{RS}) + \varepsilon) - c_k Q] \\ &\Rightarrow Q^{*} = \arg\max_{Q} \Pi_S = E[T\mu_{RS} + (1-T)\mu_S] + G^{-1}\left(\frac{p_S - c - c_k}{p_S - c}\right) \end{aligned} \tag{7}$$

Introducing μ_{RS}^{*} into Eq. (7), we have the supplier's optimal capacity decision:

$$Q^{*} = E[T\mu_{RS}^{*} + (1-T)\mu_S + G^{-1}\left(\frac{p_S - c - c_k}{p_S - c}\right)$$

The solutions of μ_{RS}^{*} and Q^{*} indicate that both the retailer and supplier's optimal decisions are directly linked with μ_S'.

Engineering chain ineffectiveness resulting from information asymmetric is a classic and well-documented problem in information sharing studies, and it is proved that both the supplier and retailer face potential losses when they make decisions in a decentralized pattern. Therefore, we are interested in designing a trust-embedded coordination mechanism to mitigate both the partners' risks of loss and show how much the engineering chain can benefit from the coordination.

Due to the poor engineering chain performance resulting from double marginalization, many contracts are proposed to coordinate the engineering chain performances, e.g., quantity discount contract, buy-back contract, and wholesale price contract (Cachon 2003). Different from the contracts above, we consider the supplier's trust in building a cost-sharing contract.

In the contract we proposed, both the retailer and supplier negotiate a cost-sharing rule right after their forecasts/evaluations are made. The engineering chain decisions are made following a two-stage decision process (Fig. 4). At Stage 1, both the supplier and retailer negotiate a cost-sharing rule under the information asymmetric circumstance. Once they reach an agreement on shared cost of per ordered product after the negotiation, the order is regarded as "bounded." That is, when the retailer places a soft-order and pays the negotiated shared cost, the supplier guarantees the order to be fully satisfied. Note that if they cannot successfully negotiate a cost-sharing rule, then the retailer's order will not be guaranteed by the supplier, and the order is regarded as "unbounded." At Stage 2, the retailer determines her ordered quantity and the supplier decides his optimal capacity.

Stage 1. Negotiation on shared cost.

Let m be the shared cost for each ordered product in the cost-sharing contract and let $\tilde{\Pi}_R = \underset{\varepsilon}{E}[(p_R - p_S)\min(Q, \mu_R + \varepsilon)]$ where $Q \geq \mu_{RS}$, then we have the retailer's expected profit in binding pattern as $\tilde{\Pi}_R - \mu_{RS}m$. Note that the retailer shares cost to bind her order only if the profit in binding pattern is no less than that in unbinding pattern,

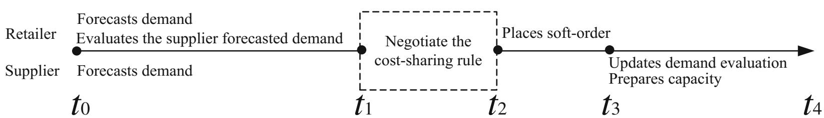

Fig. 4 Sequence of events in the coordination pattern

i.e., $\tilde{\Pi}_R^* - \mu_{RS} m \geq \Pi_R^*$. We name the constraint as "retailer's binding constraint," which can be transformed as:

$$m \leq \frac{\tilde{\Pi}_R^* - \Pi_R^*}{\mu_{RS}} \tag{8}$$

When the retailer's soft-order is bounded, the supplier's capacity is no less than the retailer's order. Thus, let $\tilde{\Pi}_S = \underset{\varepsilon}{E}[(p_S - c)\min(Q, \mu + \varepsilon) - c_k Q]$ where $Q \geq \mu_{RS}$, we have the supplier's profit in binding pattern $\tilde{\Pi}_S + \mu_{RS} m$. Simultaneously, the supplier will agree to bind retailer's soft-order only if his expected profit from binding is no less than that in unbinding pattern. For a given ordered quantity μ_{RS}, the supplier's maximum profit in unbinding pattern is calculated by $\Pi_S^* = \Pi_S[Q^*(\mu_{RS})]$ (Eq. 7). Thus, we have $\tilde{\Pi}_S^* + \mu_{RS} m \geq \Pi_S^*$. We name the constraint as "supplier's binding constraint," which can be transformed as:

$$m \geq \frac{\tilde{\Pi}_S^* - \Pi_S^*}{\mu_{RS}} \tag{9}$$

Equations (8–9) give the retailer and supplier's requirements on binding the retailer's soft-orders. Therefore, there exist two negotiation results.

Negotiation result 1: soft-order is not bounded.

Based on Eqs. (8) and (9), we have $m \in \varphi$ if $\tilde{\Pi}_S^* - \Pi_S^* > \Pi_R^* - \tilde{\Pi}_R^*$. Therefore, the soft-order is not bounded under this situation, and both the supplier and retailer make decisions in unbinding pattern.

Negotiation result 2: soft-order is bounded.

When $\tilde{\Pi}_S^* - \Pi_S^* \leq {\Pi_R}^* - {\tilde{\Pi}_R}^*$, the supplier and retailer are able to negotiate a value of shared cost m, where $m \in \left[\frac{\tilde{\Pi}_S^* - \Pi_S^*}{\mu_{RS}}, \frac{\Pi_R^* - \tilde{\Pi}_R^*}{\mu_{RS}}\right]$. Because both the supplier and retailer have their own private demand forecasts, the cost-sharing rule is negotiated depending on their negotiation power in the engineering chain. As suggested by Blodgett that the negotiation power is proportionally linked with profit-sharing, we denote w, where

$w \in (0, 1)$, as the supplier's negotiation power and $1 - w$ as the retailer negotiation power, respectively. Let $m_S = \frac{\tilde{\Pi}_S^* - \Pi_S^*}{\mu_{RS}}$ and $m_R = \frac{\tilde{\Pi}_R^* - \Pi_R^*}{\mu_{RS}}$, the negotiated shared cost $m^*(\mu_{RS})$ for each bounded product in the first stage is written as $m^*(\mu_{RS}) = m_S + w(m_R - m_S)$. Under the extreme situation that the retailer dominates the engineering chain (i.e., $w \to 1$), we have $m^*(\mu_{RS}) \to m_R$; otherwise, if the supplier dominates the engineering chain, we have $m^*(\mu_{RS}) \to m_S$.

Stage 2. Order and capacity decisions.

In this stage, the retailer and supplier make decisions sequentially based on the negotiation results at Stage 1.

Under negotiation result 1, the retailer and supplier make decisions in unbinding pattern. Thus, their optimal solutions can be obtained based on Corollary 1:

$$\begin{aligned}\{\mu_{RS}^*, Q^*\} = \Bigg\{ &\arg\max_{\mu_{RS}} \left[G'\left(\frac{p_S - c - c_k}{p_S - c}\right) + E(\mu')\right], E[\mu_S T(\mu_{RS}^*) + \mu_{RS}^* - \mu_{RS}^* T(\mu_{RS}^*)] \\ &+ G^{-1}\left(\frac{p_S - c - c_k}{p_S - c}\right)\Bigg\}\end{aligned} \tag{10}$$

However, under the negotiation result 2, the retailer has her order bounded by sharing a cost $m^*(\mu_{RS})$ for per unit of ordered products. Thus, the supplier takes the retailer ordered quantity as lower bound of his capacity.

1. The retailer's decision.
   Let $\Pi'_S = \underset{\varepsilon}{E}[(p_S - c)\min(Q, \mu'_S + \varepsilon) - c_k Q]$, then the supplier's expected profit from the retailer's belief is $\Pi'_S + \mu_{RS} m^*(\mu_{RS})$. Therefore, the supplier's optimal reaction Q'^* from the retailer's belief can be written as:

$$\tilde{Q}'^*(\mu_{RS}) = \arg\max_Q [\Pi'_S + \mu_{RS} m^*(\mu_{RS})] = \arg\max_Q \Pi'_S$$

where $\Pi'_S = \underset{\varepsilon}{E}[(p_S - c)\min(Q, \mu'_S + \varepsilon) - c_k Q]$
s.t. $Q \geq \mu_{RS}$.

Corollary 2 For a given μ_{RS}, we have,

$$\tilde{Q}'^{*}(\mu_{RS}) = \max\left\{\mu_{RS}, E[T'\mu_{RS} + (1 - T')\mu'_S] + G'^{-1}\left(\frac{p_S - c - c_k}{p_S - c}\right)\right\}$$

Corollary 2 presents the supplier's reaction from the retailer's belief for a given value of μ_{RS}. Let $\tilde{\Pi}_R = \underset{\varepsilon}{E}[(p_R - p_S)\min(\tilde{Q}'^{*}(\mu_{RS}), \mu_R + \varepsilon)]$, the retailer's expected profit can be written as $\tilde{\Pi}_R - \mu_{RS} m(\mu_{RS})$. Therefore, the retailer's optimal ordered quantity $\tilde{\mu}^{*}_{RS}$ can be calculated by Eq. (11):

$$\tilde{\mu}^{*}_{RS} = \arg\max_{\mu_{RS}}[\tilde{\Pi}_R - \mu_{RS} m(\mu_{RS})] \tag{11}$$

where $\tilde{\Pi}_R = \underset{\varepsilon}{E}[(p_R - p_S)\min(\tilde{Q}'^{*}(\mu_{RS}), \mu_R + \varepsilon)]$.

(2) The supplier's decision.
After receiving the retailer's order $\tilde{\mu}^{*}_{RS}$, the supplier updates his forecasted demand to be $\mu(\tilde{\mu}^{*}_{RS})$ according to Eq. (2). The supplier's expected profit becomes $\tilde{\Pi}_S + m^{*}\tilde{\mu}^{*}_{RS}$, and his optimal capacity $\tilde{Q}^{*}$ can be written as:

$$\tilde{Q}^{*} = \arg\max_{Q}(\tilde{\Pi}_S + m^{*}\tilde{\mu}^{*}_{RS}) = \arg\max_{Q}\ \tilde{\Pi}_S$$

where $\tilde{\Pi}_S = \underset{\varepsilon}{E}[(p_S - c)\min(Q, \mu(\tilde{\mu}^{*}_{RS}) + \varepsilon) - c_k Q]$
s.t. $Q \geq \tilde{\mu}^{*}_{RS}$.

Corollary 3. For a given $\tilde{\mu}_{RS}^*$, we obtain

$$\tilde{Q}^*(\tilde{\mu}_{RS}^*) = \max\{\tilde{\mu}_{RS}^*, E[\tilde{\mu}_{RS}^* T(\tilde{\mu}_{RS}^*) + \mu_S(\tilde{\mu}_{RS}^*) - T(\tilde{\mu}_{RS}^*)\mu_S(\tilde{\mu}_{RS}^*)] + G^{-1}(\tfrac{p_S-c-c_k}{p_S-c})\}$$

Equation (11) and Corollary 3 present the engineering chain decisions when the soft-order is bounded. According to Eqs. (10–11) and Corollary 3, the equilibrium solution of retailer's soft-order, shared cost, and the supplier's capacity in coordination pattern are summarized as follows:

$$\begin{cases} \{\mu_{RS}^*, Q^*, \varphi\} & \text{if} \quad \tilde{\Pi}_S^* - \Pi_S^* > \Pi_R^* - \tilde{\Pi}_R^* \\ \{\tilde{\mu}_{RS}^*, \tilde{Q}^*(\tilde{\mu}_{RS}^*), m^*(\tilde{\mu}_{RS}^*)\} & \text{if} \quad \tilde{\Pi}_S^* - \Pi_S^* \leq \Pi_R^* - \tilde{\Pi}_R^* \end{cases} \tag{12}$$

Remarks: The retailer and supplier's decisions under the two-stage coordination process are calculated in Sect. 4.2. According to the retailer and supplier's binding conditions, it is obvious that both partners' expected profits in the proposed contract are no less than those in a decentralized pattern. Therefore, the two-stage coordination process is acceptable by both the retailer and the supplier.

The retailer makes decisions based on her belief of μ_S' since the supplier's forecasted demand μ_S is unknown to her. Simultaneously, the supplier makes decisions based on his evaluated market demand μ, while the real market demand is μ_R. Thus, the retailer and supplier do not know their real expected profits when they make their individual decisions. Since T, μ_S', and ε are random variables, an analytical study is prohibitively complicated. Therefore, we provide an experimental study to observe the roles that trust plays in decision making and examine the performance of our coordination contact.

2.4 Experimental Study

To find the effects of the trust on engineering chain decisions and the performance of the proposed trust-embedded cost-sharing coordination, we set up several scenarios in our experiment. The conclusions are as follows:

1. Evaluating Trust
   Observation 1. Many positive experiences are needed to gain trust, but a few negative experiences will lead to a big loss of trust.
   Observation 2. Trust-embedded coordination works since both the retailer and supplier value trust differently.
   Observation 3. The supplier's negotiation power does not necessarily mean profitability, i.e., a supplier's strong negotiation power might lead to a coordination failure.

The proposed trust-embedded coordination performs more efficiently when market demand volume is large. Since demand information distortion and demand volume fluctuations over time are common in industries, the proposed trust-embedded coordination is potentially helpful in practice.

3 ATP-Based Flexible Order Allocation Optimization in ATO Engineering Chain

3.1 Introduction

As a tool for enhancing the responsiveness of order promising and the reliability of order fulfillment, the available-to-promise (ATP) has increasingly attracted the attentions of the engineering chain managers and researchers. It directly links available resources, including both materials and production capacity, which affect the overall performance of an engineering chain.

In the traditional order fulfillment processes, the manufacturer makes order fulfillment plans after the arrival of new orders without consideration of resources availability. It might result in a high risk for the order fulfillments. In order to reduce the risk that some orders may not be fulfilled, companies have to keep large amounts of inventory. The rejections of some strategic customer orders or the high-profit orders may cause unbalanced usages of resources and ruin long-term interests. Therefore, it is important to ensure a high customer service level and maximize the profits by optimally allocating the key components and limited production capacity to the strategic customers or the high-profit orders.

From the current literatures (Xiong et al. 2003; Chen and Huang 2006; Yu-tao et al. 2008; Meyr 2009; Gao et al. 2012; Yang and Fung 2014) on available-to-promise and order fulfillment in engineering chain areas, although there have been some achievements in the research of ATP allocation and order fulfillment, the current literatures mainly focus on a single factory in MTS (make-to-stock) engineering chain. Very few papers consider the ATO and MTO engineering chain operation environment for a manufacturer who has multiple factories located in different areas. The study is also very limited on combining the ATP allocation model, which considers the customer priorities, and order fulfillment model, which is based on either batch orders or real-time orders. Based on the pre-allocation ATP of production capacity and components engineering capacity, we study an order fulfillment problem for a manufacturer with multiple factories in the ATO engineering chain. The order fulfillment models are established based on two kinds of order fulfillment mechanisms, i.e., the batch order fulfillment mechanism and the real-time order fulfillment mechanism. In the batch order fulfillment model, we propose a hybrid policy combining re-delivery and product substitution. In addition, the resource ATP (production capacity ATP and components engineering capacity ATP) searching rules are developed when the resource ATP is needed in the real-time order fulfillment model.

We focus on the optimization of the order fulfillment processes for a manufacturer with multiple production sites under the assemble-to-order (ATO) environment. Based on the constraints between the resources (production capacity and components) and customer demand priority level, a pre-allocated ATP model is established for the ATO engineering chain. Then, a batch fulfillment model (based on periodic operation) and a real-time fulfillment model (based on real-time operation) are presented by using the pre-allocated ATP results obtained from the pre-allocated ATP model.

3.2 ATP Pre-allocation Model

We consider a manufacturer, which has multiple factories and produces multiple products that are sold in multiple areas at different prices. Under the ATO engineering chain environment, the end products can be finished by simple assembling operations. And all factories can produce all kinds of products. However, due to the different cost on production equipment, labor, and other factors, the production cost and efficiency for the same product are different among factories.

In order to better achieve the manufacturer's development strategy and more profits, we classify the forecasting demand of next planned period into two levels according to historical sales data. An ATP pre-allocation model is built to allocate the component ATP and production capacity ATP for each demand level. Since that production is carried out only after orders arrive in the ATO engineering chain. To simplify the model, we assume that there is no initial stock of components and end products in the manufacturer at the beginning. Without loss of generality, we assume that the production lead time is assumed to be one period and the production preparation time and cost are negligible. And the components can be supplied at the beginning of each period.

The notations used in the ATP pre-allocation model are listed in Table 1.

In order to handle the difference between forecasting demand and actual demand in next period, we express the reserving rates of production capacity and components as cp and mp, respectively. The value of cp depends on the forecasting accuracy of demand quantity, while the

Table 1 Indices for ATP per-allocation model

Indices	Descriptions
f	Set of factories ($f \in F$)
m	Set of components ($m \in M$)
p	Set of products ($p \in P$)
t, τ	set of periods ($t \in T$, $\tau \in T$)
r	Set of demand levels ($r \in R$)
l	Set of selling areas ($l \in L$)

Table 2 Notations in the ATP pre-allocation model

Data	Descriptions
$Q_{\tau lrp}$	The total forecast demand quantity of product p coming from r demand level during period τ in selling area l
V_{lrp}	The unit profit of product p supplied to the r demand level in selling area l
$uscap_{fp}$	The consumed product capacity by factory f for making one unit of product p
$usmtrl_{pm}$	The consumed component m quantities for making one unit of product p
Cap_{tf}	The available product capacity in factory f during period t
$Matl_{tm}$	The greatest supplied quantities of component m during period t by vendor
$Cmsto_{fm}$	The inventory cost of component m in factory f each period per unit
$Cpsto_{fm}$	The inventory cost of product p in factory f each period per unit
$Ctran_{flp}$	The transportation cost of product p from factory f to selling area l per unit
Ie_{tfm}	The inventory of component m at the beginning of period t in factory f
It_{tfm}	The inventory of component m at the end of period t in factory f
Iep_{tfp}	The inventory of product p at the beginning of period t in factory f
Itp_{tfp}	The inventory of product p at the end of period t in factory f

value of mp depends on the forecasting accuracy level of demand for the variety of products. Then, some variables used in the ATP pre-allocation model are listed in Table 2.

Through the ATP pre-allocation model, the engineering plan, product capacity pre-allocation plan, component re-allocation plan, reserving product capacity plan, and reserving component plan can be obtained. The decision variables are shown in Table 3.

A mixed-integer programming model can be used to describe the re-allocated available-to-promise planning problem as follows:

$$\begin{aligned}\max\ Y^1 = &\sum_{t=1}^{T}\sum_{f=1}^{F}\sum_{l=1}^{L}\sum_{r=1}^{R}\sum_{\tau=t}^{T}\sum_{p=1}^{P}\left(Qatp_{tflr\tau p}\cdot V_{lrp}\right) - \sum_{t=1}^{T}\sum_{f=1}^{F}\sum_{m=1}^{M} Cmsto_{fm}\cdot\left(\frac{Ie_{tfm}+It_{tfm}}{2}\right)\\ &-\sum_{t=1}^{T}\sum_{f=1}^{F}\sum_{p=1}^{P} Cpsto_{fp}\cdot\left(\frac{Iep_{tfp}+Itp_{tfp}}{2}\right) - \sum_{t=1}^{T}\sum_{f=1}^{F}\sum_{l=1}^{L}\sum_{r=1}^{R}\sum_{\tau=t}^{T}\sum_{p=1}^{P}\left(Ctran_{flp}\cdot Qatp_{tflr\tau p}\right)\end{aligned} \tag{13}$$

Table 3 Decision variables in ATP pre-allocation model

Decision variable	Descriptions
QP_{tfp}	The quantities of product p produced by factory f during period t
$QatP_{tflr\tau p}$	The quantities of product p supplied by factory f for the demand in period τ from r demand level in selling area l during period t
$SD_{f\tau p}$	The quantities of product p supplied by factory f for the demand in period τ
$pre{-}Matp_{tfr\tau m}$	The pre-allocated quantities of component m supplied by factory f for demand happened in period τ from r demand level during period t
$pre{-}Catp_{tfr\tau}$	The pre-allocated quantities of production capacity supplied by factory f for the demand in period τ from r demand level during period t
$Pmatl_{tfm}$	The quantities of component m received by factory f at the beginning of period t
mf_{tfm}	The real reserved quantities of component m in factory f during period t
cf_{tf}	The real reserved quantities of production capacity in factory f during period t

The first term is the profit derived from the anticipated sales based on the forecasting demand. The second term represents the inventory holding cost incurred for unused components when the component usage is less than the available supply during each period. The third term shows the inventory holding cost incurred for unsold products during each period. The last term represents the transportation cost from each factory to the demanding area.

The constraints on the pre-allocation resource problem for the each demand level are given in the following. Constraints (14)–(15) represent the demand restrictions. For the manufacturer, the production capacity and the available component supply are limited. Constraint (14) shows that the demand will be met as much as possible. The production quantities in every factory during each period are represented in constraint (15). In ATP pre-allocated plans, to avoid the delayed distribution, the product will not be allocated to the previous demand; this is represented by constraint (16).

$$\sum_{t=1}^{\tau}\sum_{f=1}^{F} Qatp_{tflr\,\tau p} \leq Q_{\tau lrp}, \quad \forall \tau, l, r, p \tag{14}$$

$$QP_{tfp} = \sum_{l=1}^{L}\sum_{r=1}^{R}\sum_{\tau=t}^{T} Qatp_{tflr\,\tau p}, \quad \forall f, p, t \tag{15}$$

$$\sum_{t=2}^{T}\sum_{f=1}^{F}\sum_{l=1}^{L}\sum_{r=1}^{R}\sum_{\tau=1}^{t-1} Qatp_{tflr\,\tau p} = 0, \tag{16}$$

Constraints (17)–(19) provide the production capacity restriction. Due to the finite production capacity, constraint (17) shows that the production quantities of each factory cannot exceed the available supply quantities during each period. Constraint (18) represents the real reserved quantities of production capacity. Constraint (19) gives the pre-allocated production capacity policy for each factory during different periods, which will be used by the real-time order fulfillment model.

$$\sum_{p=1}^{P} (QP_{tfp} \cdot uscap_{fp}) \leq Cap_{tf} \cdot (1 - cp), \quad \forall t, f \tag{17}$$

$$cf_{tf} = Cap_{tf} - \sum_{p=1}^{P} (QP_{tfp} \cdot uscap_{fp}), \quad \forall t, f \tag{18}$$

$$\sum_{l=1}^{L}\sum_{p=1}^{P} (Qatp_{tflr\,\tau p} \cdot uscap_{fp}) = pre - Catp_{tfr\,\tau}, \quad \forall t, f, r, \tau \tag{19}$$

Constraints (20–23) represent the components' restrictions. Constraint (20) provides the procurement plan which can be used by the batch order fulfillment model and the real-time order fulfillment model. In constraint (20), the production component reserved rate *mp* is used to balance the forecasting inaccuracy on product variety or the demand fluctuations. Constraint (21) indicates that the procurement quantities for each type of components cannot exceed the available supply capacity during each period. Constraint (22) gives the real reserved quantities for each component type. The pre-allocated component ATP policy can be obtained by constraint (23).

$$\sum_{p=1}^{P} (QP_{tfp} \cdot usmtrl_{pm}) \leq (1 - mp) \cdot Pmatl_{tfm}, \ \forall t, f, m \tag{20}$$

$$\sum_{f=1}^{F} Pmatl_{tfm} \leq Mat_{tm}, \ \forall t, m \tag{21}$$

$$mf_{tfm} = Pmatl_{tfm} - \sum_{p=1}^{P} (QP_{tfp} \cdot usmtrl_{pm}), \ \forall t, f, m \tag{22}$$

$$\sum_{l=1}^{L} \sum_{p=1}^{P} (Qatp_{tflr\tau p} \cdot usmtrl_{pm}) = pre - Matp_{tfr\tau m}, \ \forall t, f, r, \tau, m \tag{23}$$

Constraints (24–28) give the inventory levels of each type of component at the beginning and end of each period.

$$Ie_{1fm} = Pmatl_{1fm}, \ \forall f, m \tag{24}$$

$$Ie_{tfm} = It_{(t-1)fm} + Pmatl_{tfm}, \ \forall t \geq 2, f, m \tag{25}$$

$$It_{tfm} = Ie_{tfm} - \sum_{p=1}^{P} (QP_{tfp} \cdot usmtrl_{pm}), \ \forall t, f, m \tag{26}$$

$$Iep_{1fp} = 0, \ \forall f, p \tag{27}$$

$$Iep_{tfp} = Itp_{(t-1)fp}, \ \forall t \geq 2, f, p \tag{28}$$

In addition, decision variables $Pmatl_{tfm}$, QP_{tfp}, and $Qatp_{tflr\tau p}$ are integers and greater than or equal to zero.

We assume that products have the same functions but with different performances. Some customers would accept the substitution products if they can obtain some compensation. When the resource ATP is in shortage, the manufacturer can choose re-delivery order fulfillment policy, product substitution order fulfillment policy, or high-demand-level-priority order fulfillment policy to better meet customers' demand. The re-delivery order fulfillment policy shows that the manufacturer is able to meet customers' orders by two deliveries with the condition that customers allow receiving the products by two deliveries for the order and the quantity of the first delivery must meet the customers' request. The product substitution order fulfillment policy indicates that the manufacturer can meet customers' demand by substituting products partly when specified products are not available. The high-demand-level-priority order fulfillment policy says that pre-allocated production component ATP and capacity ATP for the lower demand level can be switched to higher demand level. In terms of the responses to the customers' orders, there are two order fulfillment models: the batch order fulfillment model and the real-time order fulfillment model.

In the batch order fulfillment model, all orders gathered during the batch interval will be fulfilled, and fulfillment date and quantities for each order will be given. The batch order fulfillment model can be used to determine whether or not the order can be accepted by the manufacturer and whether or not we need to apply the re-delivery order fulfillment policy or the product substitution order fulfillment policy, and the detailed fulfilled plan.

To avoid the situation that the orders of the strategic customers or the high-profit orders are rejected due to limited resources, in the real-time order fulfillment model, the high-demand-level-priority order fulfillment policy is adopted. With this policy, the higher level demand can use the pre-allocated production component ATP and capacity ATP that are already assigned to the lower level demand when the resource is in shortage. This real-time order fulfillment model will search the production capacity ATP along the backward time dimension, the demand level dimension, and the selling areas dimension. And this model will search the production component ATP along both forward and backward time dimension, the demand level dimension, and the selling areas dimension when components are in shortage.

3.3 Experimental Study

The proposed models are verified and tested through an example of the MP4 electronics manufacturing industry. The manufacturer has two factories and produces four kinds of products that have the same functions with different performances in two selling areas. The performance sequence of the four products is, from low to high, P1, P2, P3, and P4. In this paper, according to the customers' importance, we divide the customers into two levels and each level has a different priority.

To summarize, we can conclude the batch mechanism is better than the real-time mechanism on the order fulfillment. However, in order to response quickly, more and more manufacturers operate based on real-time order fulfillment mechanism. In addition, before orders are fulfilled, it is helpful for the manufacturer to optimize the pre-allocated resource ATP plan. And, the manufacturer can reserve some resources according to the inaccuracy of demand forecasting.

4 Conclusions

To remain competitive, firms must reduce operating costs while continuously improving customer service by coordinating and optimizing the overall engineering chain performances in the new business environment. Currently, engineering chain management is complicated and has its own special characters mainly reflected in two aspects. One is the random information from customer orders and the complex relations among engineering chain cooperators; the other is the outstanding relations of collaborative benefits and risks in this complicated environment. Therefore, we must probe the ways to respond to these characteristics and analyses, the coordination mechanisms, and optimization approaches in new business environment. We made a conjoint research of information sharing, operational research and behavior research to adaptive coordination mechanism. As for modeling and optimization, we focus on transferring orders to manufacturing and manufacturing customized orders under the ATO engineering chain environment, which is specific to fulfill the orders based on available production resources: materials and production capacity. Some conclusions are drawn as follows:

Since decision makers' feeling on trust is seldom studied in operations management area, investigating trust in engineering chain information sharing is meaningful. We first formulate a trust evaluation model based on psychology and statistics theories. The proposed model analytically explains that many positive experiences are needed to gain trust, but a few negative experiences will lead to a big loss of trust. Because of information asymmetry, both the engineering chain partners value trust differently and the engineering chain performs ineffectively. A coordination contract with a two-stage decision process is thereby proposed to coordinate the engineering chain. At the first stage, the supplier and retailer negotiate the cost-sharing rule. At the second stage, the retailer decides whether or not to bind her soft-orders and her optimal ordered quantity, while the supplier determines his optimal capacity. In order to maximize the supplier's expected profit, we find that there exists a crucial threshold of the supplier's negotiation power in negotiation, and strategically, making use of negotiation power is helpful to avoid business failures.

According to the pre-allocated production capacity and components, two order fulfillment models are formulated based on the batch processing and real-time mechanisms. In both order fulfillment models, an ATP searching method along the time dimension, the demand priority level dimension, the product dimension, or the selling area dimension is proposed when production capacity and components are in shortage. Several numerical examples are used to illustrate the proposed models. The experimental results show that the order fulfillment model with pre-allocation ATP is better than that without ATP pre-allocation. As a global optimization model, the batch mechanism is better than the real-time mechanism on the order fulfillments. When resources are in shortage, it is better to adopt the ATP searching method in the order fulfillment processes.

References

Cachon, G. P. (2003). Supply chain coordination with contracts. *Handbooks in Operations Research and Management Science, 11,* 227–339.

Cachon, G. P., & Lariviere, M. A. (2001). Contracting to assure supply: How to share demand forecasts in a supply chain. *Management Science, 47*(5), 629–646.

Cai, S., Goh, M., de Souza, R., & Li, G. (2013). Knowledge sharing in collaborative supply chain: Twin effects of trust and power. *International Journal of Production Research, 51*(7), 2060–2076.

Camarinha-Matos, L. M., & Macedo, P. (2010). A conceptual model of value systems in collaborative networks. *Journal of Intelligent Manufacturing, 21*(3), 287–299.

Chen, C.-T., & Huang, S.-F. (2006). Order-fulfillment ability analysis in the supply-chain system with fuzzy operation times. *International Journal of Production Economics, 101*(1), 185–193.

Chick, S. E., Huchzermeier, A., & Netessine, S. (2014). Europe's solution factories. *Harvard Business Review, 92*(4), 111–115.

Clemen, R. T., & Winkler, R. L. (1999). Combining probability distributions from experts in risk analysis. *Risk Analysis, 19*(2), 187–203.

Da Silveira, G., Borenstein, D., & Fogliatto, F. S. (2001). Mass customization: Literature review and research directions. *International Journal of Production Economics, 72*(1), 1–13.

Dolgui, A., & Proth, J.-M. (2010). *Supply chain engineering: Useful methods and techniques*. London: Springer Science & Business Media.

Duray, R., Ward, P. T., Milligan, G. W., & Berry, W. L. (2000). Approaches to mass customization: Configurations and empirical validation. *Journal of Operations Management, 18*(6), 605–625.

Ebrahim-Khanjari, N., Hopp, W., & Iravani, S. M. (2012). Trust and information sharing in supply chain. *Production and Operations Management, 21*(3), 444–464.

Fogliatto, F. S., da Silveira, G. J., & Borenstein, D. (2012). The mass customization decade: An updated review of the literature. *International Journal of Production Economics, 138*(1), 14–25.

Gao, L., Xu, S. H., & Ball, M. O. (2012). Managing an available-to-promise assembly system with dynamic short-term pseudo-order forecast. *Management Science, 58*(4), 770–790.

Ivanov, D., Pavlov, A., & Sokolov, B. (2014). Optimal distribution (re) planning in a centralized multi-stage supply network under conditions of the ripple effect and structure dynamics. *European Journal of Operational Research, 237*(2), 758–770.

Ivanov, D., Sokolov, B., & Pavlov, A. (2013). Dual problem formulation and its application to optimal redesign of an integrated production—distribution network with structure dynamics and ripple effect considerations. *International Journal of Production Research, 51*(18), 5386–5403.

Kosfeld, M., Heinrichs, M., Zak, P. J., Fischbacher, U., & Fehr, E. (2005). Oxytocin increases trust in humans. *Nature, 435*(7042), 673–676.

Laeequddin, M., Sahay, B., Sahay, V., & Abdul Waheed, K. (2012). Trust building in supply chain partners relationship: An integrated conceptual model. *Journal of Management Development, 31*(6), 550–564.

Meyr, H. (2009). *Customer segmentation, allocation planning and order promising in make-to-stock production. Supply chain planning* (pp. 1–28). Heidelberg: Springer.

Nike Inc. (1999). Annual Report.

Özer, Ö., & Wei, W. (2006). Strategic commitments for an optimal capacity decision under asymmetric forecast information. *Management Science, 52*(8), 1238–1257.

Özer, Ö., Zheng, Y., & Chen, K.-Y. (2011). Trust in forecast information sharing. *Management Science, 57*(6), 1111–1137.

Premkumar, G., Ramamurthy, K., & Nilakanta, S. (1994). Implementation of electronic data interchange: An innovation diffusion perspective. *Journal of Management Information Systems, 11*(2), 157–186.

Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of Management Review, 23*(3), 393–404.

Sriram, M. (2005). Information asymmetry and trust: A framework for studying microfinance in India. *Vikalpa, 30*(4), 77.

Taylor, T. A., & Plambeck, E. L. (2007). Supply chain relationships and contracts: The impact of repeated interaction on capacity investment and procurement. *Management Science, 53*(10), 1577–1593.

Xiong, M., Tor, S. B., Khoo, L. P., & Chen, C.-H. (2003). A web-enhanced dynamic BOM-based available-to-promise system. *International Journal of Production Economics, 84*(2), 133–147.

Yang, W., & Fung, R. Y. (2014). An available-to-promise decision support system for a multi-site make-to-order production system. *International Journal of Production Research, 52*(14), 4253–4266.
Yu-tao, F., Sheng-chen, Y., & Yang, X. (2008). System for performing resource management and control and task scheduling in grid computing. In *International Symposium on Computer Science and Computational Technology, ISCSCT 2008.* IEEE.
Zhuge, H. (2011). Semantic linking through spaces for cyber-physical-socio intelligence: A methodology. *Artificial Intelligence, 175*(5), 988–1019.

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