Manufacturer Due Dates to Realize Effective Coordination Among Supply Chain Parties in a Make-to-Order Context

Mitsuru KURODA \(^{1}\) and Masaharu KIDA \(^{2}\)

ABSTRACT

This paper presents a methodology for achieving effective coordination among supply chain parties in situations where the manufacturer makes various products based on orders received from an unspecified number of customers. The customers usually wish to obtain their products as early as possible or to set their due dates unilaterally. Naturally the manufacturer’s workload varies over time and sometimes greatly exceeds its production capacity when many customers’ orders coincide. It is clear that manufacturing costs can undergo extraordinary increases, raising product prices when the manufacturer changes its production capacity according to the customers’ demands. The sole acceptable solution for both the customers and the manufacturer is coordination among all parties through information sharing, which will lead them to decide on appropriate due dates based on the overall benefit. The present paper proposes the concept of ideal manufacturer due dates that are estimated by considering all ongoing customer orders and shop status predictions, while still essentially guaranteeing fulfillment. We also present a methodology for quantifying the losses a supply chain can suffer due to customers’ unilateral actions. Finally, a method is discussed in which customers are motivated to select due dates close to the ideal manufacturer due dates, taking into consideration product price increments that may result from choosing particular due dates.

Key words: supply chain cost, coordination, information sharing, due-date estimation, customer order, ideal manufacture due date, unilateral due date, production capacity, fulfillment, make-to-order

1. INTRODUCTION

Information sharing is regarded as a primary means for improving the performance of supply chains. This has been verified in practice and by many studies over the past two decades. An example of such studies is one that provides a model for quantifying the value of downstream or upstream local information in a supply chain \([1]\). Specifically, two different supply chain conditions are considered and the performance of the supply chain in the two cases is compared. One case represents the situation where the central planner of the supply chain is assumed to obtain local information and use it for decision-making. The other represents the opposite situation where local players in the supply chain make exclusive use of their local information. If the supply chain-wide performance of the first case is superior to that of the second, the difference in performance is considered to be the value of the shared information and coordination is understood to be beneficial.

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As studies of supply chain management have primarily been in relation to situations with repetitive production and sales, the local information to be shared usually exists a priori; for instance, data on the inventory status of upstream or downstream players in a supply chain is known by those players but is seldom shared. In these situations, the sharing of information refers to local information being used to realize coordination among the parties, that is, the central planner can gain access to local information. In contrast, some situations prevent the sharing of the information needed because the information itself is known to the central planner and to the other parties a priori. Creation of the information, in general, must precede its sharing. Therefore, the seemingly established approach of sharing information to improve supply chain-wide performance needs advanced investigation to make its practice more universal.

Consider a situation where a manufacturer receives successive orders from an indefinite number of customers and makes various products based on the customer orders. The customers usually wish to obtain their products as early as possible or to unilaterally dictate the due dates of their orders. If the manufacturer tries to meet its customers’ requirements by increasing production capacity, its manufacturing costs may increase significantly and product prices will rise. It is common for manufacturers’ shop workloads to vary considerably over time. Given this, what local infor-
information should be shared among the parties of the supply chain in order to realize effective coordination?

Clearly, several significant problems are involved. First, most customers do not set their due dates on a rational basis. Some dates are decided arbitrarily. If possible, such irrationality in the setting of due dates must be removed. Second, the due dates must be decided so as to satisfy the requirements of all customers, rather than a single customer or a subset of customers. Third, due dates must be set considering the manufacturer's present and expected future shop status. Fourth, the manufacturer must fulfill the orders, that is, deliver the products to the customers on time. A question also arises in this consideration; whether or not it is possible to set due dates with the properties mentioned above.

We assume that rational due dates can be estimated by the manufacturer in such a supply chain because it possesses, at a minimum, all information regarding customer orders. We are not aware of any manufacturers that make it a rule to decide upon rational due dates through coordination with its customers, but have confidence in the possibility of rational due dates being estimated in practice. The author and other researchers have been engaged in due-date estimation for a number of years and have presented methods for its implementation [2-6]. Specifically, it has been shown that due-dates estimated using the method we advise essentially guarantee order fulfillment. We refer to such estimated due dates as ideal manufacturer due dates (IMDDs) and the total concept regarding them as the IMDD.

The problem that we encounter is how the IMDD is shared between the customers and the manufacturer. In other words, how can the value of IMDDs be quantified like the value of shared information in many past supply chain management studies? As noted above, the value of information is quantified by comparing the supply chain-wide performance of two cases: one where local information is shared among parties in a supply chain and the other where local information is utilized only by local players. In the present paper, IMDDs are the information to be shared between each customer and the manufacturer. Specifically, a parallel to the "sharing local information" case is IMDDs estimated by the manufacturer and used through the supply chain. The opposite condition is where manufacturers generally try to abide by their customers' unilaterally set due dates, including those that are irrational. We compare the performance of these two cases. In the comparison, the results will have negative values because the expense of the latter case is larger than that of the former case, as it seems difficult to compare values for measures such as profit or sales in this analysis. The obtained values will be regarded as additional supply chain costs in the present paper.

In contemplating such a model, how should irrational due dates be made to reflect customers' arbitrary decision-making? In the field of management science, for instance, models seldom deal with such irrational human behavior. Furthermore, almost all decision-making models are built based on rational thinking. It is inevitable, however that models considering irrational human behavior will be developed to investigate information sharing theories as described above. Therefore, we propose modeling customer behavior as a group, not as individuals. That is, suppose that all customers select their due dates as if sampling variables of an IMDD-related distribution function. It seems reasonable to think that the sampled variables represent unilateral customers' due dates (UCDDs), some of which are based on irrational customer behavior. The distribution function's parameters are used as measures showing the degree of irrationality of customers' decisions and influence on the estimation of supply chain-wide performance. Furthermore, IMDDs are related to the particular values of the parameters. As described above, the present paper investigates quantification of the disadvantages that result from irrational decisions made by all parties in a supply chain, not only customers, but the manufacturer as well, with the goal of eventually eliminating wasted expenses.

Finally, a method is discussed in which customers are motivated to select their due dates close to IMDDs through linking the selected due dates with prices estimated for their products based on the additional supply chain cost, which reflects the disadvantages caused by irrational decisions.

2. LITERATURE REVIEW

There have been a number of studies describing the due dates related to the simulation of the manufacturing shops as being discussed in the present paper. In this section, we divide these studies into three research dealings: (1) due-date assignment rules, (2) due-date management, and (3) due-date estimation algorithms, and show the features of each category citing the primal studies.

2.1 Due-date Assignment Rules
Conway, Maxwell and Miller [7] considered four due-date assignment rules and evaluated their effectiveness through a series of simulations of the dynamic job shop under several scheduling heuristics in the well-known textbook on scheduling published in 1967. The due-date assignment rules tested in the simulation experiments were the total work content (TWK), the number of operations (NOP), the constant allowance due date (CON) and the random allowance due date (RDM). The simulation results revealed that the TWK rule generally performed better in comparison to other rules concerning the due-date performance, especially the
ratio of tardy job numbers. In addition, the performance was revealed to differ greatly depending on the scheduling heuristics used.

Many researchers have based their work on the approach of Conway, Maxwell and Miller. These researchers have contributed to the expansion of the due-date assignment rules and have improved due-date performance through the use of various proposed assignment rules. For example, Eilon and Chowdhury [8] proposed two rules: the delay in queue (DIQ) rule and the jobs in queue (JIQ) rule. The former uses the average job waiting time in addition to the total work content, and the latter uses the total number of jobs waiting to be processed on machines along the job’s route as the information for due-date assignment. Their simulation results suggested that the JIQ rule was sensitive to current shop congestion and provided superior performance. Vig and Dooley [9] presented new due-date assignment rules, which utilized shop congestion information. These rules are called dynamic due-date assignment rules because the due-date assignment for a job was performed by obtaining the flow time estimates based on a sampling of recently completed jobs. The computational results showed that the proposed rules yielded more accurate and precise flow time estimates compared to TWK and NOP rules.

2.2 Due-date Management

In the 1990’s, a new trend, namely, the interactive approach between the customers and the manufacturers with respect to due-date decisions and/or pricing, began to be observed in the literature regarding due-date assignment. Tsubone, Matsura and Kanda [10] presented a model for interactive due-date management in order to reflect the reality of actual job shop control. It is common practice that the production capacity is modified according to the congestion level of the work shop and the customer requirement of earlier due dates. In addition, the customers’ desired due dates are sometimes changeable through negotiation between customers and manufacturers. In Tsubone et al.’s model, approximate and detailed due-date estimation are performed. The former uses an equation, which is the product of the total processing time and a coefficient. The coefficient is predetermined based on the historical data of the shop under consideration. In the case that the estimated due date is larger than the customer’s desired due-date, the detailed due-date estimation is performed by simulative scheduling using the FCFS dispatching rule. When the scheduling results are unsatisfactory, alternative schedules are generated under various production capacity levels. If necessary, negotiation with the customer is performed. The decision of capacity levels and negotiation with customers are performed based on human judgment.

A study considering the trade-off between the due-date decisions and pricing is described by Moodie [11] and Moodie and Bobrowski [12]. Here, equal partnership between two parties, the customer and the manufacturer, is assumed and the two parties independently provide trade-off curves, which respectively represent the acceptable region of net price and due date for the job, that is, the customer order under negotiation. Any combination of price and due date within the feasible region decided using both of the trade-off curves represent agreement between the two parties and one of the points that maximize their mutual benefit is selected as the most likely point of agreement. The due-date estimation is performed using various methods including simulation-based ones with the due-date assignment rules. They also consider the market scenario consisting of seven dimensions, each of which describes the situation of the customers and the manufacturer. It is reported that the JIQ rule is superior for busy scenarios, where a high number of jobs are in process, and the TWK rule is preferred for less busy scenarios, where a low number of jobs are in process [12].

2.3 Due-date Estimation Algorithms

In recent years, Kuroda et al. [2, 3] provided a new due-date estimation algorithm, which guarantees zero tardiness of customer orders with very high probability. Conventional due-date assignment methods using simulation consider the past and present shop status but let the future schedule for customer orders take the course of nature. Specifically, a part of ongoing customer orders are completed after the due dates when many customer orders arrive unexpectedly. In order to avoid the occurrence of tardy customer orders, it is necessary to absorb the influence of newly arrived customer orders on ongoing customer orders. In general, the following two measures can be adopted. The first is modification of the production capacity, and the second is assignment of later but possibly earlier due dates to newly arrived customer orders. The due-date estimation algorithms of Kuroda et al. [2-6] were developed with the objective of building a model based on the latter measures. The algorithms consist of three stages, which are described as follows:

Stage 1 Due-date estimation is performed every time a customer order arrives Temporary due-dates are assigned to the newly arrived customer orders, and they are scheduled using backward simulation together with the ongoing customer orders possess of fixed due dates. At this time, the priority for the processing sequence at each facility is decided based on the result of the backward simulation. Both the newly arrived customer orders and the ongoing customer orders are rescheduled using forward simulation with the priority on using each facility [13]. If all due-dates of the ongoing customer orders are satisfied by the updated schedules as the results of simulation, the schedule is accepted and the due-dates of the newly arrived customer orders are obtained by adding due-date buffers of a predetermined size to the estimated completion times of the newly arrived customer orders.
STAGE 2 If all of the due-dates of the ongoing orders are not satisfied by the updated schedule, the ongoing and the newly arrived orders are rescheduled together using forward simulation, as in Stage 1. However, in this case, higher priority is placed on the ongoing customer orders, which gives them the priority of being processed earlier compared to the newly arrived customer orders at all facilities. If all due-dates of the ongoing customer orders are satisfied by the updated schedules, the schedule is accepted and the due dates of newly arrived customer orders are obtained by adding due-date buffers of a predetermined size to the estimated completion times of the newly arrived customer orders.

STAGE 3 If all of the due dates of the ongoing orders are not satisfied by the updated schedule, the ongoing customer orders and newly arrived customer orders are scheduled together using forward simulation for a third time, placing a much higher priority on the ongoing customer orders, which does not allow preemption of the newly arrived customer orders if they are being processed at a facility when an ongoing customer order arrives at the facility. The schedule is accepted regardless whether all the due dates of the ongoing customer orders are satisfied by the updated schedule and the due dates of newly arrived customer orders are obtained by adding due-date buffers of a predetermined size to the estimated completion times of newly arrived customer orders.

As suggested above, the size of the due-date buffers assigned to all customer orders decreases toward zero according to the progress of processing customer orders. However, the operations in Stages 2 and 3 prevent the buffer sizes from being negative. Therefore, the elimination of tardy customer orders is guaranteed as long as all due dates of ongoing customer orders are satisfied in Stage 3 at the latest.

3. IDEAL MANUFACTURER DUE DATE AND UNILATERAL CUSTOMERS’ DUE DATES

In Section 1, we defined the IMDDs as the due dates obtained using the due-date estimation algorithm presented by Kuroda et al. They are shown by the following equation:

\[ D^*_i = ET_i + DB, \quad \text{for all } i \]  

where \( D^*_i \) is the due date of customer order \( i \), \( ET_i \) is the estimated completion time and \( DB \) is a common predetermined size of due-date buffers. \( DB \) can be changed according to customer order \( i \) but is fixed to a certain size for all orders. \( ET \) differs on the basis of the content on customer order \( i \) and changes reflecting the shop status at the time when the due-date estimation is performed. Therefore, there is no room for intentions of manufacturer which are arbitrary. The manufacturer can select the common size of due-date buffers to improve the overall production schedule but can not improve the schedules for particular customers as long as the common buffer size is used. These due dates are ideal for the manufacturer in the sense that the due dates for all customers are essentially fulfilled. It is possible to differ the size of the due-date buffer with customer orders intentionally [3] but such usage of the due-date buffer is not considered in the present paper.

As described in Section 1, a model representing unilateral customers’ due dates (UCDDs) has not been built so far. Therefore, we propose a probabilistic model that represents due dates set as the result of customers’ arbitrary decision-making. That is, suppose that all customers select their due dates as if sampling variables of a distribution function related to the IMDDs. Specifically, they are shown by the following equation:

\[ D_i^r = [D_i^p - \alpha(D_i^p - AT_i)/2, \]
\[ D_i^p + \alpha(D_i^p - AT_i)/2], \quad \text{for all } i \]  

where \( D_i^r \) is the unilateral customer due date of customer order \( i \), and \( AT_i \) is the arrival time of customer order \( i \), which is assumed to be equal to the time when due-date estimation is performed. \([L, U]\) is a sampled variable from a uniform distribution, of which the lower limit is \( L \) and the upper limit is \( U \). The range of uniform distribution is shown by parameter \( \alpha \), where \( \alpha \) is a non-negative real value, which is not larger than 1.0. When \( \alpha \) is equal to zero, \( D_i^r \) coincides with \( D_i^p \). Parameter \( \alpha \) represents the extent to which customer requirements are random. It is referred to as customers’ requirement randomness coefficient hereinafter.

Equation (2) is simplified to the following equation:

\[ D_i^r = [D_i^p - \alpha PT_i^{m}/2, \]
\[ D_i^p + \alpha PT_i^{m}/2], \quad \text{for all } i \]  

where \( PT_i^{m} \) is the ideal production lead time estimated by the manufacturer. It is supposed that the customers’ unilateral due dates will be represented more realistically when we use two parameters \( \alpha \) and \( \alpha^l \) in order to differentiate the lower limit and the upper limit of the uniform distribution. Specifically, the Equation (3) is rewritten as follows:

\[ D_i^r = [D_i^p - \alpha^l(PT_i^{m}/2), \]
\[ D_i^p + \alpha^l(PT_i^{m}/2)], \quad \text{for all } i \]  

In general, the lower limit parameter \( \alpha^l \) will be larger than upper limit parameter \( \alpha^u \), because customers desire earlier due dates without considering exceptions.
4. SUPPLY CHAIN-WIDE PERFORMANCE

4.1 Model of Overall Production Scheduling

As described in Section 1, the supply chain-wide performance differs based on the decision behavior of customers and the manufacturer. However, the measurable performances as the result of numerous decisions made in an entire supply chain are only observed at the manufacturer, especially, at its shop floors. Specifically, customer-order tardiness takes place in the planning level but does not end. It must be cleared by overtime and/or outsourcing on the shop floors. In other words, the result of all decisions, whether rational or irrational ones, is integrated into the performance of shop floors under the control of a manufacturer.

Therefore, we consider two levels of production scheduling; one is referred as planning-level scheduling, which has been discussed for estimating the due dates of customer orders, and the other is referred as shop-floor scheduling, which is needed for observing the performance of a supply chain being studied. Note that planning-level scheduling is middle to long ranged, and shop-floor-level scheduling is short ranged.

An overall scheduling model as depicted in Fig. 1 is considered. The relationship between the two scheduling models is described as follows: A certain early portion of the planning-level schedule, for example, a period corresponding to one or two days of the schedule, from the planning-level scheduling model is transferred to the shop floor scheduling model, and a short-range production schedule is updated everyday. On this occasion, the overtime for particular facilities is planned if necessary.

The customer orders completed in overtime are regarded as having been fulfilled if the day corresponds to its due date. Every time the operations for the day are finished, the head part of the schedule is made for planning-level scheduling, so as to reflect the result of the operations performed in the day. This is auxiliary scheduling, which is inevitable to the overall scheduling model and referred to as adjustment scheduling.

4.2 Performance Measures

Five performance measures are examined regarding the overall scheduling model. Two of them are examined with respect to the results of planning-level scheduling: the number of occurrences of tardy customer orders on the planning level and the average production lead time.

A tardy customer order occurs if determined completion time \( ET_i \) of customer order \( i \) becomes later than due date \( D_i \), on planning level. Production lead time \( PT_i \), of customer order \( i \) is the time length obtained by reducing arrival time \( AT_i \) from completion time \( ET_i \).

Three measures are examined with respect to the results of shop-floor scheduling: the number of occurrences of tardy customer orders on shop-floor level, the total required operation time after the due date and the total overtime. Tardy customer orders on shop floor level occurs if realized completion time \( ET' \) of customer order \( i \) becomes later than due date \( D' \), which is defined as the completion time of normal operation shift of the day, including the maximum overtime. The "sum of operation times after the due date" required for a tardy customer order is shown in Fig. 2 and the cumulative value for all tardy customer orders is called the total required time after the due date. Naturally, the total required operation time after due date should be minimized, and if possible, should be zero. In the overall scheduling model, the total required operation time after the due date is assumed to be clarified using night shifts and/or outsourcing.

The supply chain cost is obtained by transforming the sum of total overtime and the total required operation time after the due date into a monetary measure. It is composed of ordinary overtime cost and other extra labor cost. The supply chain cost is expected to increase according to the increase of customers' requirement randomness coefficient that reflects the extent of irrational behaviors of the supply chain parties. We, then, obtain the undesirable increment of supply chain cost caused probably by irrational behaviors, which is the difference between the supply chain

![Fig. 1: Overall Production Scheduling Model](image)

![Fig. 2: Required Operation Time after the Due Date for a Tardy Customer Order](image)
costs for two cases; one is the case using IMDDs and the other is the case using UCDDs. Naturally, the latter costs are expected to be larger than the former costs. The undesirable increment of supply chain cost will increase the customer payment to the manufacturer and, as a result, make end-users of the product bear the expense for irrational decision-making. Therefore, the undesirable increment of supply chain cost is called the additional supply chain cost in the present paper. It is regarded as the supply chain-wide performance that shows the value of information sharing.

5. NUMERICAL EXPERIMENTS

5.1 Design of Numerical Experiments
In the preceding section, the outline of a methodology for obtaining the value of shared information was suggested. Next, we will explain a set of numerical experiments, which are performed to observe those performance measures including the additional supply chain costs. At the end of explanation, the methodology will be clarified.

Essentially, the numerical experiments are divided into two subsets. The first subset is the numerical experiments regarding the IMDDs. A series of customer orders is designed to arrive randomly at a manufacturer, where planning-level scheduling is performed using the scheduling-based due-date estimation algorithm described in Section 2.3. Through the planning-level scheduling performed to process a predetermined number of customer orders, ideal manufacturer ideal due dates for all customer orders are successively estimated and at the same time, a production schedule on the planning level is made as to fulfill all estimated due dates, where the time and facility used for every operation for all customer orders processed are planned. On a parallel with planning-level scheduling, shop-floor scheduling is performed and, as a result, a shop-floor schedule is obtained on daily basis. All performance measures except the additional supply chain cost are observed from the obtained schedules on both the planning and shop-floor levels.

The second subset of numerical experiments is those regarding the UCDDs. The same series of customer orders arrives at the manufacturer in the same fashion, where the due date of each customer order has already been determined using Equation (2), in contrast to the previous case, and the scheduling based on backward/forward hybrid simulation [10] is performed so as to minimize due-date tardiness, where the occurrence of due-date tardiness is not avoidable because it is a general property inherited from using simulation without feedback loops. As the result of simulation, a production schedule is made for the predetermined number of customer orders. On a parallel with planning-level scheduling, shop-floor scheduling is performed in a manner identical to that of the previous case and, as a result, a shop-floor schedule is obtained on a daily basis. Similarly, performance measures are observed.

We reiterate that Equation (2) is presented on the premise that it will be used as a probabilistic model representing due dates set as the result of customers’ arbitrary decision-making. Specifically, UCDDs are decided by sampling a variable from a uniform distribution specified for the customer order. Therefore, n random numbers are needed if n customer orders are planned for a series of numerical experiments. Thus, a series of numerical experiments is finished and other series of numerical experiments are repeated using different series of random numbers for the set of arriving customer orders in order to eliminate the influence of random numbers on the computational results. The performance measures in the case of using UCDDs are evaluated by obtaining the average of computational results observed respectively.

We can now obtain the value of the additional supply chain cost by obtaining the difference between the sums of the cost concerning the total required operation time after the due date and the overtime cost for the cases of using IMDDs and of using UCDDs under a certain value of randomness coefficient \( \alpha \). Naturally, it is necessary that the latter subset of numerical experiments is repeatedly performed while changing parameter \( \alpha \), in order to examine the effect of randomness of UCDDs on the additional supply chain costs.

Table 1 summarizes the scale of scheduling problems treated herein and the associated parameters used in the numerical experiment. The primary premises are as follows:

(a) The same product structure as shown in Fig. 2 is assumed for all customer orders (P level, S level).
(b) The processing times for operations are determined by sampling from a uniform distribution and, as a result, the workload differs with customer orders (P level, S level).
(c) The average processing times are planned to be identical for all operations (P level, S level).
(d) A one to one correspondence relation exists between an operation and a facility or station; the particular operation can be operated only at the corresponding facility or station (P level, S level).
(e) Arrival intervals to manufacturer are sampled from variables of an exponential distribution (P level).
(f) When an operation can not be finished in the regular shift time, an overtime operation at the corresponding facility is planned as long as the operation is finished in the maximum over time (S level).
(g) If the required operation time after the due date can not be clarified until the end of overtime, the remaining operations are assumed to be processed in night shift and/or by outsourcing (S level).
(h) Identical buffer ratio is used for all customer orders in a series of numerical experiments (P level).
(i) Identical customers’ requirement randomness coefficient is used for all customer orders in a series of numerical experiments (P level).
Table 1: Scale of scheduling problems and associated parameters

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Numbers of customer orders</td>
<td>100</td>
</tr>
<tr>
<td>Initial number of customer orders in the shop</td>
<td>7</td>
</tr>
<tr>
<td>Number of stations</td>
<td>6</td>
</tr>
<tr>
<td>Machining stations</td>
<td>5</td>
</tr>
<tr>
<td>Assembly station</td>
<td>1</td>
</tr>
<tr>
<td>Number of combined parts</td>
<td>2</td>
</tr>
<tr>
<td>Number of operations per customer order</td>
<td>11</td>
</tr>
<tr>
<td>Processing times (time units)*</td>
<td></td>
</tr>
<tr>
<td>Machining processes**</td>
<td>[1, 9]</td>
</tr>
<tr>
<td>Assembly process**</td>
<td>[2, 18]</td>
</tr>
<tr>
<td>Average utilizations (%)</td>
<td>80</td>
</tr>
<tr>
<td>Job-shop ratios (%)***</td>
<td>0, 50, 100</td>
</tr>
<tr>
<td>Buffer ratios (%) ****</td>
<td>0, 10, 20, 30, 40</td>
</tr>
<tr>
<td>Customer-requirement randomness coefficients α (%)****</td>
<td>0, 10, 20, 30, 40, 50</td>
</tr>
<tr>
<td>Seeds of random numbers used to decide UCDDs</td>
<td>10 cases</td>
</tr>
<tr>
<td>Operation hours per shift</td>
<td>8 hours</td>
</tr>
<tr>
<td>Maximum overtime per shift</td>
<td>2 hours</td>
</tr>
</tbody>
</table>

* One time unit corresponds to 0.1 hour.
** Processing times are sampled from variables of a uniform distribution and converted into integers.
*** Job-shop ratio = (1 – number of customer orders with the identical routine/total number of customer orders) × 100
**** Buffer ratio is the ratio of the buffer size to the sum of operation times for a customer order.
***** Equation (2) is assumed to decide UCDDs.

P level and S level in the parenthesis at the end of above sentences signify whether the premises are set up for both or either of them.

2. Experimental Results
Tables 2 and 3 summarize the experimental results respectively for a flow shop and a typical job shop. These tables show the values of the performance measures described in Section 4.2. The primary findings are as follows:

1. The number of occurrences of tardy customer orders using the UCDD becomes larger than when using the IMDD for both of the planning and shop-floor levels, as was predicted. They increase as the randomness coefficient becomes larger; in the case of the UCDD for the shop-floor level but not for the planning level.

2. The total required operation time after the due date when using the UCDD is extremely large compared to when using the IMDD, except for the case of a zero percent randomness coefficient.

3. With respect to lead time, differences are seldom observed between two cases, except when using the IMDD under job shop and zero buffer ratio. In other words, the property that larger due-date buffers reduce lead times in the case of the job shop is reconfirmed in this computational result (see [2, 3]).

4. With respect to total overtime, no noticeable differences are observed between two cases, although the total overtime when using the UCDD is larger than using the IMDD. Note that the maximum overtime per facility is limited to two hours in this experiment, so the difference would increase if the maximum overtime is relaxed.

5. Although the model of zero randomness coefficients when using the UCDD appears to resemble the model for the IMDD, differences are observed regarding the performance measures, which are caused by the differential properties of their scheduling algorithms. The algorithm when using the IMDD is simulation with a control function and without control when using the UCDD. Naturally, data on customer orders are common to both numerical computations.

Finally, we obtain the labor cost increment for overtime and the total required operation time after the due date. The difference of the labor cost increments depending on use of the IMDD or the UCDD is regarded as the additional supply chain costs. Tables 4 and 5 show the costs regarding all combinations of five buffer ratios and six randomness coefficients, divided into the cases of flow shop and typical job shop (job-shop ratio: 50%). A part of them is also shown in the bottom
of Tables 2 and 3 so as to emphasize that the additional supply chain costs corresponds with zero in the case of using the IMDD. Fig. 3 shows the change in the additional supply chain cost according to the increase in the customers’ requirements\(-\)randomness coefficient for the flow shop case, and Fig. 4 shows that for the typical job shop case. The additional supply chain costs should be shown with any monetary unit but they are represented by the relative cost because it is enough to designate the relation between the costs and two parameters. These figures reveal the following:

(6) The additional supply chain cost in the case of the flow shop tends to become larger compared to that in the case of the job shop. This difference is thought to be caused by the functional distinction between the two manufacturing processes, that is, the job shop is supposed to be more flexible to the variations in the workload to facilities, while, the flow shop is supposed to lack flexibility.

(7) The effect of the due\(-\)date buffer on reducing the supply chain cost is noticeable in the case of the flow shop, but not in the case of the job shop. However, the effect of the customers’ requirement coefficient on reducing the cost is remarkable in both cases of the flow shop and the job shop.

(8) Figures 3 and 4 show that a large part of the additional supply chain cost can be drastically eliminated by decreasing the customers’ requirement randomness coefficient. In relation to the model used in this numerical experiment, the effect seems sufficiently satisfactory if the customers’ requirement randomness can be reduced to about 20\%. Though the level to be reduced is not generally described, this numerical experiment suggests that even a relatively small reduction in customers’ irrational behavior will have a great effect in practice.
Table 4: Additional supply chain cost (flow shop)

<table>
<thead>
<tr>
<th>Buffer ratio</th>
<th>Customers' requirement randomness coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
</tr>
<tr>
<td>0%</td>
<td>39.50</td>
</tr>
<tr>
<td>10%</td>
<td>23.60</td>
</tr>
<tr>
<td>20%</td>
<td>20.86</td>
</tr>
<tr>
<td>30%</td>
<td>21.64</td>
</tr>
<tr>
<td>40%</td>
<td>30.71</td>
</tr>
</tbody>
</table>

Table 5: Additional supply chain cost (typical job shop)

<table>
<thead>
<tr>
<th>Buffer ratio</th>
<th>Customers' requirement randomness coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
</tr>
<tr>
<td>0%</td>
<td>56.36</td>
</tr>
<tr>
<td>10%</td>
<td>62.57</td>
</tr>
<tr>
<td>20%</td>
<td>14.64</td>
</tr>
<tr>
<td>30%</td>
<td>6.50</td>
</tr>
<tr>
<td>40%</td>
<td>2.57</td>
</tr>
</tbody>
</table>

Additional SC relative cost

Due-data buffer ratio

Fig. 3: Additional supply chain cost for the flow shop
6. DISCUSSIONS

The IMDDs should undoubtedly be regarded as a guideline for deciding the final due dates. As the number of customers that want due dates closer to the IMDDs increases, the additional supply chain cost greatly decreases. The problem lies in how to realize this situation. As described in Section 2.2, Moodie et al. [11, 12] proposed the concept of using two trade-off curves provided by the customer and the manufacturer, which respectively represent the desired relationships between the due date and the product price. The two trade-off curves are assumed to be obtained independently and not to be available to their counterpart in advance.

A proposal based on the results of this research is that the manufacturer provides a trade-off curve, which represents the relationship between the due date and the additional charge, with each customer. The additional charge refers to the cost that the customer should bear when the customer selects due dates different from its IMDD. This charge must be a function of x, where x is the difference from its IMDD. The additional charge will be zero or trivial when the selected due date is near its IMDD and will increase rapidly as the absolute value of the difference becomes larger. Such a function will motivate customers to select due dates closer to their IMDDs.

The problem lies in how to set up the function to be sufficiently rational to be accepted by customers. The due-date estimation algorithm described in the present paper is thought to provide a potential solution to this problem. The influences of various due dates, including the ideal customer due date, on the production schedule can be evaluated through a series of simulation of planning-level scheduling using the due-date estimation algorithm. As a result of the simulated scheduling, earlier due dates exceeding some range peculiar to the customer, in which the IMDD is the center point, will incur the tardiness of some ongoing customer orders. Such tardiness will translate into a monetary amount. Thus, a function of the additional charge for the particular customer order can be obtained. The customer must accept a due-date even if an additional charge is required, as long as the customer is convinced of the process of evaluation and the related data. That is, coordination through information sharing will be realized.

7. CONCLUSIONS

Information sharing has been regarded as a primary means for achieving coordination among the parties of a supply chain. However, some situations prevent information sharing because the information to be shared is unknown to the supply chain parties a
priori. That is, the creation of information to be shared must precede all other things. The present paper considered the situation where such creation of shared information is necessary to realize effective coordination in a supply chain. Specifically, a manufacturer receives successive orders from an indefinite number of customers and makes various products based on the customer orders. The customers usually wish to obtain their products as early as possible or to unilaterally dictate the due dates of their orders. If the manufacturer tries to meet its customers' requirements by increasing production capacity, its manufacturing costs may increase significantly and product prices will rise.

In this situation, the following significant problems are involved.

(1) Most customers do not set their due dates on a rational basis. Some dates are decided arbitrarily.
(2) The due dates must be decided so as to satisfy the requirements of all customers, rather than a single customer or a subset of customers.
(3) Due dates must be set considering the manufacturer's present and expected future shop status.
(4) The manufacturer must fulfill the orders, that is, deliver the products to the customers on time.

We assumed that rational due dates could be estimated by the manufacturer in such a supply chain because it possessed all information regarding customer orders, and proposed the use of a due-date estimation algorithm, of which properties seemed suitable to solve the problems mentioned above. If possible, such rational due dates were thought to be shared among the supply chain partners, that is, the manufacturer and customers. In the present paper, we called the estimated due dates "ideal manufacturer due dates" or IMDDs and the "related all concepts including the algorithm" the IMDD. In addition, we called the conventional due dates "unilateral customers' due dates" or UCDDs and the "unilateral due-date assignment" the UCDD.

The present paper adopted the "value of shared information" approach in order to realize the effective coordination among the supply chain parties. First, we tried to quantify the value of shared information, that is, the disadvantage of using UCDDs, assuming that IMDDs could be shared among a manufacturer and the customers. For this purpose, an overall scheduling model mainly composed of planning-level scheduling and shop floor-level scheduling was built. In the case of the IMDD, the planning-level schedule is updated through repeating the due-date estimation using the algorithm mentioned above, every time a customer order arrives, and the shop floor-level schedule is made, considering the head part of the updated planning-level schedule and the manufacturing shop status on a daily basis. However, in the case of the UCDD, the planning-level schedule is updated using simulation, where the due dates of customer orders are assumed to be unilaterally assigned and the shop floor-level schedule is made on a daily basis. UCDDs are obtained by sampling variables of the IMDD-related functions with coefficient \( \alpha \), which represents the randomness of customers' requirements.

Next, a set of numerical experiments were performed using the overall scheduling model, where the data for arriving customer orders were fixed and numerical experiments were performed under various conditions. The results of numerical experiments performed separately for the respective cases were obtained and several performance measures, that is, average planning-level lead time, number of tardy orders on the planning level, number of tardy orders on the shop floor level, total required operation time after the due date and total overtime both on the shop floor-level, were compared between the IMDD and the UCDD cases. As predicted, the former measures realized smaller values, under some conditions much smaller, than the latter ones.

We noticed two performance measures observed at the shop floor, that is, the overtime and the required operation time after the due date, because those times needed extra labor cost and as a result increased the manufacturing cost. The sum of those times was then transformed into a monetary measure and the difference of amounts in the two cases was finally obtained. We call the amount "the additional supply chain cost," because the amount often occurs through the irrational decision-making of the customers and manufacturer, increases the product prices to be paid by the customers and makes the end-users on the supply chain bear the higher prices of the products. In this sense, the additional supply chain cost is essentially the supply chain-wide performance.

In addition, we recognized that the additional supply chain cost rose sharply as the customers' requirement randomness coefficient \( \alpha \) increased. Undoubtedly, the additional supply chain cost will be reduced if more customers decide their due dates close to IMDDs. In order to realize ideal coordination among supply chain parties, it is also desirable for this information to be shared as well as IMDDs. Sometimes, customers desire much earlier due dates for certain reasons, such as wanting to quickly install a new facility to replace an old facility. In order to adapt situations such as these, it is desirable for the manufacturer to provide a trade-off curve, which represents the relationship between the due date and the additional charge, with each customer. The additional charge refers to the cost that customers should bear when selecting due dates different from IMDDs. A reasonable trade-off curve can be prepared using the relationship between the additional supply chain cost and the customer' requirement randomness.
coefficient $\alpha$, in addition to the IMDD particular to the customer.

REFERENCES


