Integration of product design and manufacturing through real-time due-date estimation and scheduling systems

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Received 3 January 2016

Abstract  
The present paper discusses the integration of product design and manufacturing by means of information sharing through due-date estimation and scheduling systems. The present author and other researchers have investigated a due-date estimation method in a make-to-order context. We analyzed and considered several manufacturing problems using the due-date estimation method. Among the problems researched were the following two: the first is the problem of optimizing the allocation of module inventories on semi-finished products and processed parts, and the second is the due-date estimation and production scheduling for customer orders with unfixed specification. In conducting our research, we realized that these problems are closely related with the integration of product design and manufacturing. In the present paper, we discuss the concrete examples found in these two problems and verify that the information sharing between the product design section and the manufacturing division is necessary in order to meet the increasingly strict requirements of customers and achieve more efficient manufacturing.

Key words: Integration, Product design, Manufacturing, Due-date estimation, Production scheduling, Due-date buffer, Shortening lead time, Module inventories, Unfixed specification, Information sharing

1. Introduction  
As a university freshman studying engineering, I remember a professor once said, “Manufacturers would be able to produce their products much more efficiently if the product designers could consider the situation of manufacturing where the products are being produced.” Although this was more than a half-century ago, I have never forgotten those words. However, I have had no chance to study this problem. Moreover, this seemed to be an ill-structured problem, in that the problem could not be analyzed by existing methods. Simon and Newell identified the concept of ill-structured problems and proposed the heuristic problem solving approach as a method by which to solve such problems (Simon and Newell, 1958).

Kuroda et al. (2002) investigated a method for solving a due-date estimation problem. In industrial practices, customers usually provide their desired due dates to manufacturers, who attempt to meet these due dates. Although this appears to suggest that estimating due dates for customers is meaningless, it is a worthy view from a stand point of scientific thinking. The practices mentioned above increase production costs because the manufacturers are forced to process the customer orders inefficiently. If manufactures could estimate their desired due dates on a rational basis and customers accept the recommended due dates, the production cost would be reduced and, as a result, average due dates might be earlier.

The method developed for due-date estimation was applied to various manufacturing problems and situations. Here, let me introduce two applications that strongly related to the objective of the present study. One is the module allocation problem (Kuroda and Mihira, 2008). The modules are defined as the semi-finished products or the processed parts that are used to produce multiple kinds of final products.

A manufacturer produces various kinds of final products based on the orders from customers, and customer demand is volatile. In other words, the volume and the arrival situation of customer orders are very changeable. Sometimes, orders for a certain kind of products cease for a long time. Then, after some unpredictable period, the
orders for that kind of products suddenly recover without notices.

In the environment of such volatile demand, module production is a very advantageous methodology, because it enables earlier due dates and efficient manufacturing. However, the sophisticated module inventory management is needed. This is the module allocation problem, which requires making decisions on standardizing semi-finished products and processed parts as well as maintaining the optimal inventory levels of them. The problem is clearly related to both the product design section and the manufacturing division.

Another application is due-date estimation for customer orders with unfixed specification (Kuroda, 2010). Customers often release their orders to manufacturers before their specifications are fixed in order to make the due dates earlier. However, in this situation, manufactures should accept the customer orders after confirming that the unfixed specifications are related only to the particular components of the product. The conditions are called “specification independence between components.”

In such cases, the customer order with unfixed specification is processed using the due-date estimation method, assuming an existent component which is resemble to the undecided component as the dummy component and the data on the operations required for the component are used. The due dates for customer orders with unfixed specification are obtained by adding due-date buffers to the estimated temporary completion time for the orders.

In order to guarantee that the due dates are met, the dates needing to be clarified for the undecided specification which are obtained by manufacturing division using the due-date estimation method are informed to the customers and product design section. Such a process enables cooperation between the product design section and the manufacturing division.

In Section 2, 3 and 4, the due-date estimation, the module allocation problem and the due-date estimation for customer orders with unfixed specification will be described in greater detail. In Section 5, the collaboration between the product design section and manufacturing division is discussed and it is clarified that the realization becomes possible through the information sharing under the situation in which real-time due-date estimation systems are executed.

2. Due-date estimation in a make-to-order context

2.1 New production scheduling

Due-date estimation was not a terminology widely known among researchers before the end of the last century. At that time, the advanced planning and scheduling (APS) package was developed and had a significant impact on production scheduling research. Advanced planning and scheduling is well explained by the following passage.

“One of the salient functions of APS is the ability to estimate the possibility of earlier due dates immediately upon receipt of customer’s orders and to fulfill the requests with respect to not only due-dates, but also to specifications, prices, volumes, etc. for the case in which the customers place the final orders to the manufacturer. To secure customer orders, manufacturers are increasingly required to respond very quickly, often while on the telephone with the customer, and provide satisfactory replies to any inquiries, particularly those regarding due dates,” (quoted from the article by Kuroda et al. (2002)).

Before the appearance of the APS package, numerous researchers of production scheduling had tried to obtain better priority rules for dispatching jobs, which correspond to the customer orders in the present paper, under the several types of due dates, through executing a series of computer simulations. These researchers statistically analyzed computational results and evaluated the goodness of their priority rules in terms of such evaluation measures as the average due-date tardiness and the occurring rate of due-date tardiness. As a result, the relationship between priority rules and the evaluation measures have been clarified and the combined use of plural priority rules which bring better results, has been realized (for instance, the book by Baker (1974), the articles by Eilon and Choudhury (1976) and by Vig and Dooley (1991)). However, no satisfactory methods, namely, methods that usually provide an average due-date tardiness of zero were obtained.

The APS package presented new production scheduling problems. Upon solving these problems, the due date of each customer order is treated as a variable, and the customer order must be scheduled so as to be finished before or on the decided due date. In addition, the due date must be decided as early as possible in order to shorten the production lead time.
2.2 Algorithm for due-date estimation using due-date buffers

The decision on due-dates for the newly arrived customer orders is referred to as due-date estimation. Now, let us consider the solution of the abovementioned new scheduling problems developed by the author and others (Kuroda et al., 2002). The key solution concept is the use of time buffers on estimating due-dates. These time buffers are referred to as due-date buffers. A due-date buffer of specified size is assigned to each customer order upon arrival and this size gradually decreases as the customer order is being processed.

Individual due-date buffers indicate the largest tardiness of operations allowed to occur in the near future for the corresponding customer order. In contrast, the role of accumulated due-date buffers tends to be overlooked. The accumulated due-date buffer works as the resource to maintain the flexibility of overall production schedule.

The individual due-date buffers are reduced in such a way that the buffers for the newly arrived customer orders decrease significantly soon after arrival, decrease gradually after the processing has begun, and then decrease only slightly. As a result, the production schedule for a customer order is flexibly constructed and is finally fixed so as to be finished. Therefore, the work of due-date buffer changes depending on the current size which the individual customer order possesses.

The algorithm for due-date estimation is executed through a maximum of three stages. Here, let us describe the outline.

Stage 1 Due-date estimation is performed every time an order arrives. Temporary due-dates are assigned to the newly arrived customer orders, and they are scheduled using a backward simulation with all ongoing customer orders. When executing the backward simulation, a higher priority is given to customer orders having earlier operation start time at each facility, without discriminating the ongoing customer orders and the newly arrived customer orders. Then, all customer orders are scheduled using a forward simulation. At this time, the priority of the sequence processed at each facility is decided based on the backward simulation results. If all due dates of the ongoing orders are satisfied by the updated schedule, the schedule is accepted and the due-dates of the newly arrived customer orders are given by the following formula:

\[ D_i = ET_i^{(1)} + DB \]  

(1)

where \( D_i \) is the due-date of the newly arrived customer order \( i \), \( ET_i^{(1)} \) is the estimated completion time of the order \( i \), and \( DB \) is a predetermined size of the due-date buffer.

Stage 2 If all due dates of the ongoing orders are not satisfied by the updated schedule, the ongoing customer orders and the newly arrived customer orders are again scheduled together using a forward simulation. However, in this case, the higher priority is placed on all ongoing customer orders, which gives them the priority of being processed earlier compared with the newly arrived customer orders at all facilities. If all due dates of the ongoing orders are satisfied by the updated schedule, the schedule is accepted and the due-dates of the newly arrived customer orders are given by the following formula:

\[ D_i = ET_i^{(2)} + DB \]  

(2)

where \( D_i \) is the due-date of the newly arrived customer order \( i \) and \( ET_i^{(2)} \) is the estimated completion time of the order \( i \), obtained through the Stage 2 simulation.

Stage 3 If all due dates of the ongoing orders are not satisfied by the updated schedule, the ongoing customer orders and the newly arrived customer orders are scheduled together using a forward simulation, for a third time. In this case, a much higher priority is placed on all ongoing customer orders so as to avoid preemption of the newly arrived customer orders, even if they are being processed at a facility when an ongoing customer order arrives at the facility. Whether or not all of due dates of the ongoing orders are satisfied by the updated schedule, the schedule is accepted and the due-dates of the newly arrived customer orders are given by the following formula:

\[ D_i = ET_i^{(3)} + DB \]  

(3)

where \( D_i \) is the due-date of the newly arrived customer order \( i \) and \( ET_i^{(3)} \) is the estimated completion time of the order \( i \), obtained through the Stage 3 simulation.
2.3 Remarks on the due-date estimation algorithm

2.3.1 Effect of due-date buffers on the average lead time

As mentioned earlier, due-date buffers provide flexibility to the overall schedule. Hence, the average lead time, i.e., the average of the differences between completion times and due-date estimation executing times for all customer orders, must be reduced. The computational results indicate that the above mentioned ability of due-date buffers is conditionally correct. Table 1 was created using the data shown in Table 2 of Kuroda et al. (2002). The effect of due-date buffer on the average lead time is shown for three shop types, namely, job shop (JSR: 100%), flow shop (JSR: 0%) and intermediate shop (JSR: 50%), where the initial size of the due-date buffer is changed from 6 to 14.

Table 1 Effect of due-date buffer on average lead time

| Job shop ratio (JSR)* | 0%    | 50%    | 100%   |
|-----------------------|-------|--------|--------|
| Initial size of       | 6     | 63.57  | 78.30  | 91.02  |
| due-date buffer       | 10    | 61.47  | 72.75  | 81.06  |
|                       | 14    | 61.13  | 70.31  | 75.77  |

*Job shop ratio = (1 - number of customer orders with the identical routine / total number of customer orders) × 100%

The average lead time is drastically reduced as the initial due-date buffer increases in the case of job shop (JSR: 100%), but not in the flow shop (JSR: 0%). These results appear to be due to the ease of obtaining better overall schedules in the case of flow shop, which is called herein scheduling simplicity. This is supported by the fact that the effect of due-date buffers is recognized in the case of an intermediate shop (JSR = 50%), in which the scheduling flexibility is needed for obtaining better schedules.

2.3.2 Avoidance of due-date tardiness

The proposed due-date estimation algorithm does not guarantee the elimination of due-date tardiness. However due-date tardiness was not observed in most cases concerning not only the sample problems but also more complicated and larger problems. Even when due-date tardiness occurs, the tardiness time is very small, so as to be negligible in practice. In most cases, due-date tardiness is prevented and the average lead time for customer orders is reduced because of scheduling flexibility.
3. Solution of module allocation problem
3.1 Meaning of modules in manufacturing

Starr (1965) first presented the concept of modular production and discussed its use in the design and manufacturing of parts. At present, modular production is widely used, especially in the automobile industry. In the article by Kuroda and Mihira (2008), modules are defined as standard semi-finished products and processed parts that are used to produce various final products or higher-level semi-finished products with the intention of increasing operational efficiency. Kuroda and Mihira (2008) investigated the effect of due-date estimation in the case of holding module inventories under volatile demand, considering the cost generated by holding module inventories. Here, volatile demand means that the order pattern of particular products are not guaranteed to remain constant in the future. Therefore, the preferable level of an individual module inventory changes in a dynamic fashion as time passes.

3.2 Preparedness for modeling

Product structure supplies important data related to a customer order. When one or more common modules are included in two different product structures, a relation between these products exists. In the article by Kuroda and Mihira (2008), a graph representing such physical relations is referred to as a comprehensive product structure. For instance, the relation between two different product structures shown in Figure 1 is represented by the graph shown in Figure 2.

For the case in which more than one graph is obtained for a module allocation problem, the structures are independent from the standpoint of modules. However, if the nodes of these graphs are manufactured in identical facilities, they are not independent. In this case, more than two comprehensive product structures are considered in analyzing the problem.

3.3 Definition of module allocation problem

We hereinafter discuss the case in which only one comprehensive product structure exists, because the module allocation problem remains valid even though the discussion is limited to this case. The comprehensive product structure represents the relationship between the group of final products under consideration and those components, each of which directly or indirectly constitutes a final product, and a module allocation problem is defined for the comprehensive product structure.
When the due-date estimation is subject to volatile customer demand, the module inventories are effective in decreasing lead times and estimating earlier due dates. However, the strategy of holding module inventories incurs unnecessary investment, inventory carrying cost, and obsolescence cost. Therefore, a Pareto-optimization approach was applied to treat the problem, where the average lead time and the total investment for module inventories are used as the performance criteria for solutions of the problem.

The individual module inventory levels are used as variables of the Pareto-optimization problem. The individual module inventory levels are controlled using a $\text{Max-Min}$ reordering policy. In other words, individual module inventory levels are controlled so as to be maintained in the range from $\text{Min}$ level to $\text{Max}$ level assigned for the particular module. However, in order to reduce the number of parameters, a special case of the $\text{Max-Min}$ reordering policy is considered, where $\text{Min}$ is set to be equal to $\text{Max}$. In other words, when the module inventory level is smaller than $\text{Max}$, a production order of the quantity ($\text{Max}$—the current level) is released to recover to $\text{Max}$ level. Then, the total investment for module inventories is estimated using the following equation:

$$TI = \sum_{k=1}^{K} \alpha_k \text{Max}(k), \quad (5)$$

where $TI$ is the total investment for module inventories, $\text{Max}(k)$ is the maximum level for module $k$, $K$ is the total number of module types under the current situation and $\alpha_k$ is the coefficient for converting the maximum inventory level for module $k$ into the amount of module investment. Moreover, $\alpha_k$ also provides an indication of the quantity variation from zero to the maximum level $\text{Max}(k)$ in the average.

Next, the module allocation problem is defined more precisely and can be described as a problem of obtaining the Pareto-optimal inventory levels for module $k$ ($k = 1, 2, \ldots, K$), considering two performance criteria, namely, the average lead time and the total investment for module inventories.

3.4 Solution method of module allocation problem

The problem is solved by alternately repeating the simulation process and the Pareto-optimization process. The simulation process is essentially the same as the due-date estimation and scheduling described above, except utilizing module inventories and maintaining the module inventory levels under the condition of newly given $\text{Max}(k)$, where $k = 1, 2, \ldots, K$.

In contrast, the Pareto-optimization process is entirely new. In the simulation process, $\text{Max}(k)$, where $k = 1, 2, \ldots, K$ are treated as parameters, while they are treated as variables in this process. Using a genetic algorithm (GA; it is suited to Pareto-optimization, because improvement of the solutions is repeated through maintaining numerous solutions), we attempt the Pareto-optimizing of $\text{Max}(k)$, where $k = 1, 2, \ldots, K$, considering both the average lead time which is obtained as a result of the simulation process, and total module investment computed with formula (5). Pareto-optimization is achieved by repeating these two processes until finally ceasing the computation. Figure 3 shows the procedure for the Pareto-optimizing module allocation problem.
The simulation process is modified so as to perform “make to stock” production in order to maintain the specified level of module inventories. Figure 4 shows how the “make to stock” strategy is performed in a “make to order” production context. BOM in the figure stands for “Bill of Material,” which refers a dataset of product structures, production processes and operation times. The “make to stock” policy is performed to increase the level of module inventories when the corresponding facilities have surplus capacities.

![Diagram](image)

Fig. 4 Scheme for performing the “make to stock” production strategy in the “make to order” production context (quoted from Kuroda and Mihira (2008))

3.5 Numerical experiments

3.5.1 Example problems

Figure 5 shows the comprehensive product structure, which represents the constitutional relationship among 10 products, 12 semi-finished products and 11 processed parts. At present, semi-finished product 2 through 9 and processed parts 1 and 4 through 11 are maintained as modules and usually produced based on the “make to stock” production strategy. Modules of semi-finished products are hereinafter called upper-level modules and modules of processed parts are hereinafter called lower-level modules. Example problems are defined as obtaining Pareto-optimal solutions for $\text{Max}(k)$, for all $k$, i.e., for eight upper-level modules and nine lower-level modules, subject to the below-described constraints.

The constraints characterizing the problems are the volatile customer demand as be shown in Table 3. In the table, two patterns of the demand, denoted, patterns I and II, are prepared for the numerical experiments. In Table 4, two different cases of inventory investment coefficients are shown. Case I represents the situation in which the difference of coefficients between two levels is not large, and case II represents the situation in which the difference of coefficients between two levels is large. Other constrains are numerous parameters related to the BOM described above. In the present paper, the product structures of 10 final products are composed of two semi-finished products each, and 12 semi-finished products are composed of two processed parts each.

![Diagram](image)

Fig. 5 The comprehensive product structure for the example problems (quoted from Kuroda and Mihira (2008))
3.5.2 Computational results

Pareto-optimization was performed subject to four combinations of primal constraints: case I—pattern I, case I—pattern II, case II—pattern I and case II—pattern II and four numerical experiments were denoted by I—I, I—II, II—I and II—II. The computational results illustrate how the Pareto-optimization was successfully performed. As an example, we present the computational result of numerical experiment I—II.

Table 5 Pareto optimization example (quoted from Kuroda and Mihira (2008); partially modified)  

| Solution no. | Upper-level modules | Lower-level modules | Module inventory investment | Average lead time |
|--------------|---------------------|---------------------|-----------------------------|-------------------|
|              | Semi-finished product number | Processed part number |                             |                   |
|              | 2 3 4 5 6 7 8 9 | 1 4 5 6 7 8 9 10 11 |                             |                   |
| 1            | 8 0 6 1 0 4 2 2 | 5 2 0 0 2 2 7 0 0 | 64                          | 386.00            |
| 2            | 8 0 6 1 0 4 3 2 | 5 2 0 0 9 2 2 0 0 | 68                          | 381.42            |
| 3            | 7 0 6 1 0 7 2 2 | 5 2 1 2 2 2 7 0 0 | 71                          | 376.76            |
| 4            | 8 0 6 1 0 7 3 2 | 6 2 1 5 1 2 2 0 2 | 73                          | 366.89            |
| 5            | 10 0 1 5 0 0 0 9 | 1 4 3 1 1 2 2 5 0 | 75                          | 327.60            |
| 6            | 8 6 5 4 2 3 4 1 | 4 3 3 0 0 8 0 1 0 | 85                          | 322.07            |
| 7            | 6 2 5 10 4 8 4 0 | 5 1 0 0 0 1 3 1 0 | 89                          | 307.31            |
| 8            | 8 6 5 4 0 8 5 1 | 3 9 0 0 2 1 3 1 0 | 93                          | 305.16            |
| 9            | 10 9 1 4 3 8 0 4 | 4 0 1 2 1 1 2 7 0 | 96                          | 298.28            |

Solutions from 10 to 20 are not shown in order to save pages.

| numerical experiment | I—II |
|----------------------|------|
| Solution no.         |      |
| 21                   | 8 9 4 10 6 8 8 8 | 4 1 5 2 0 6 2 0 0 | 142 | 247.00 |
| 22                   | 10 9 7 10 3 8 7 8 | 1 0 4 5 1 1 2 7 0 | 145 | 244.00 |
| 23                   | 8 6 5 10 10 10 4 10 | 2 8 5 6 0 8 2 0 0 | 157 | 243.98 |
| 24                   | 8 10 3 10 10 7 7 10 | 5 2 1 2 4 6 7 3 0 | 160 | 242.01 |
| 25                   | 10 9 9 10 10 8 7 8 | 4 6 5 2 1 1 2 7 0 | 170 | 235.09 |

Table 5 shows 25 non-dominated solutions obtained through 50 generations planned in advance. These solutions are not inferior to other solutions with respect to two criteria: module inventory investment and average lead time. The number in the left-hand column represents the sequence of non-dominated solutions decided based on the ascending order of module inventory investment. At the same time, the sequence coincides with the descending order of the average lead time. This means that 25 solutions are non-dominated. In other words, Pareto-optimization is achieved. In numerical experiment II—I, 34 non-dominated solutions were obtained. The total number of non-dominated solutions is not planned beforehand but is obtained as a result.

The right-hand side of the sequence of non-dominated solutions shows the final variable values of each solution obtained as a result of the Pareto-optimization process, i.e., the parameters $Max(k)$ for controlling the module inventory in the simulation process. As mentioned above, the module inventory investment is computed using equation (5) and the average lead time is obtained through a simulation process using the parameters $Max(k)$ for all $k$. 

Table 3 Two patterns of customer demand (quoted from Kuroda and Mihira (2008))  

| Product | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Total |
|---------|---|---|---|---|---|---|---|---|---|----|-------|
| Pattern I | 0.1 | 0.05 | 0.2 | 0.1 | 0.05 | 0.1 | 0.2 | 0.05 | 0.1 | 0.05 | 1.00 |
| Pattern II | 0.3 | 0.1 | 0.05 | 0.05 | 0.1 | 0.05 | 0.1 | 0.05 | 0.1 | 0.1 | 1.00 |

Table 4 Two cases with different inventory investment coefficients (quoted from Kuroda and Mihira (2008))

| Case | Upper-level modules | Lower-level modules |
|------|---------------------|---------------------|
| I    | 2                   | 1                   |
| II   | 10                  | 1                   |
4. Due-date estimation for customer orders with unfixed specification

4.1 Customer situation for placing orders with unfixed specification

Thus far, due-date estimation and production scheduling have been researched on the premise that all data are given. In practice, however, in make-to-order production, data are often missing even when customers place orders to manufacturers. As an example, consider a customer who is constructing a large warehouse for storing various heavy articles and is planning to handle the articles using several forklifts. At present, the customer has not yet placed orders for forklifts with the maker. The size, weight and shape of articles are approximately determined but the heights of the shelves used to store articles are not decided. The customer wants to use the warehouse soon after it has been constructed. Therefore, the customer decides to place orders to a forklift maker, despite the specification on the fork holder having not yet been fixed.

The forklift maker accepts the order because all specifications of other components, the body, the driver’s seat, the engine, the wheel and so on, of the forklift are fixed and the influence of an unfixed specification about the fork holder to other components is limited and manageable. The product structure of a forklift is so simple that the abovementioned example can be used to illustrate the situation with customers placing orders with unfixed specification. This problem is herein described in a general manner.

4.2 Specification independence between components

Kuroda (2010) presented a general method by which to treat real-world problems. Figure 6 shows a product structure composed of two types of components whose specifications are decided or undecided. We assume that no components are standardized but are produced when the production order is placed. A triangle in the figure represents a product family, that is, a product or a parent component and their child components.

Two assumptions are necessary for discussing a product family. The first assumption is the specification independence between child components in a family. Other child components are assumed to be decided even if some child components are undecided.

This assumption permits the situation in which none of the sub-component of a component are decided. The second assumption is the specification independence of a parent components from the specification of its child components. In other words, it is assumed that a parent component can be decided even if most of its child components are undecided. If this assumption does not hold, a product structure cannot exist when one of the components is undecided (quoted from Kuroda (2010); partially modified).

4.3 Response to customer orders with unfixed specification

In order to meet the customer demands, it is necessary for the manufacturer to assign to the customer the latest date at which the specifications can be fixed in and to show the due date of the customer order with unfixed specification. The customer is satisfied with the information supplied by the manufacturer if the two dates are acceptable to the customer. The latest date at which the specification can be fixed is called the specification clarifying date. For the case that plural components are not decided, the latest dates of fixing the respective specification are announced to the customer.
customer. One such date is referred to as the specification clarifying date for component \( ij \), where \( i \) is the identification number of the order and \( j \) is the identification number of the component for order \( i \). The latest date at which the specifications can be fixed is obtained as the result of scheduling for the due-date estimation of customer order \( i \). Until the specifications are fixed, a dummy component which replaces undecided component \( j \) is temporarily used.

4.4 Modification of the ordinal due-date estimation method for treating customer orders with unfixed specification

(1) Use of dummy components replacing undecided components

As described in section 4.3, dummy components are used in place of undecided components. The dummy components are selected from the components which were manufactured in the past and that are the most similar to the potential desired components.

The start time of manufacturing the selected dummy components in the production schedule is useful in deciding the component specification clarifying dates. In addition, the dummy components are useful in realizing a realistic work load. If the work load of undecided components are neglected until the component clarifying dates arrive, the work load is estimated to be much lower than it actually is, resulting in due-date tardiness.

(2) Use of the longer due-date buffer for the customer orders with unfixed specification

Thus far, the size of the due-date buffer has not been discriminated on the basis of the condition of customer orders because the buffers have been thought of as a means of providing flexibility to the overall production schedule. However, accepting the customer orders with unfixed specification implies two types of customer orders; ordinal customer orders and customer orders with unfixed specification. In this situation, a method that uses the characteristics of due-date buffers seems appropriate.

When a large size of due-date buffer and small size of due-date buffer are used in a mixed manner, the average lead time of customer orders with smaller buffers is shorter compared with that of customer orders with larger buffers. Such a result is explained by the priority rule used in the due-date estimation algorithm.

As described in Section 4.3, the highest priority is given to the customer order with the earliest planned operation starting time among the customer orders waiting at any facility in the shop, and the starting times are decided through a back-ward simulation. Naturally, the customer orders with the larger initial due-date buffer possesses the higher probabilities of being processed later regarding the first operation. As a result, manufacturing of the customer orders with a larger initial buffer will generally be delayed.

4.5 Consideration on the time for designing components constituting customer orders

In Kuroda (2010), the time required for designing components is not described. This does not mean that the time is not essential to the due-date estimation and production scheduling but it is only because the due-date estimation has been thought to be executed after the required design tasks are finished.

However, the present paper aims to discuss the relation between the product design section and manufacturing division, so it is advantageous to define the term clearly. Then, let us define the due-date estimation time as “the due-date estimation time for a customer order for which the design task has been completed.” Similarly, the phrase “latest date for fixing the specification” was used in Section 4.3. This should be also defined clearly. Its meaning must agree with the “time for deciding the component specifications considering the required design tasks.”

5. Possibility of integrating the product design and manufacturing

5.1 Effect of information sharing between a manufacturer and its customers

Kuroda and Kida (2010) analyzed the effect of utilizing the ideal manufacturer due date (IMDD) when the customers place their order. The IMDD is the due-dates obtained by the due-date estimation algorithm described earlier herein, and the due date requested by the customer is referred to as the customer due date (CDD). In the model used for the analysis, the CDD is generated by sampling data from a uniform distribution, the average value of which is the IMDD. The analysis is performed as follows: The overall production schedule is obtained by performing a series of backward simulations considering CDDs and forward simulations using the priority rule based on the results of the backward simulation. The overall production schedule is regarded as the middle- or long-range production schedule. The shop schedule covering the shop production for two days is prepared using the head part of the middle- or long-range production schedule and is updated every day. The normal work period for a day is set to eight hours, but
overtime work is always permitted in order to finish operations for some customer orders, due dates of which are midnight on the day or the next.

As expected, as the range of the uniform distribution for setting the CDDs of customer orders decreases, the total overtime work can be drastically reduced. In other words, the computational result suggests that setting CDD so as to approach the IMDD is desirable from the standpoint of reducing the manufacturing cost. This numerical example reveals the significance of information sharing between the manufacturer and the customers. The total overtime cost is regarded as the value of information (for the definition, see Chen (2003)), because this cost can be eliminated through the use of the IMDD.

In the following two sections, the desirable information sharing between the product design section and the manufacturing division will be discussed. Although the value of information is not computed, the analysis presented hereinafter is based on the research results shown in the articles by Kuroda and Mihira (2008) and by Kuroda (2010).

5.2 Optimal module inventory allocation

5.2.1 Developing modules

This problem is essentially concerned with product design and manufacturing. First, let us consider the situation in which a manufacturer does not hold module inventories. The manufacturer considers the acquisition of customers to be of primary importance, and, as much, short lead times are crucial. As the means of reducing the lead time, holding module inventories of semi-finished products and processed parts is thought to be inevitable. However, the manufacturer must determine which semi-finished product and processed parts should be held in inventory and the required level of module inventories.

This requires the assumption that the abovementioned due-date estimation and scheduling system has been implemented. Under this assumption, the task of product design section is clarified to be the selection of the semi-finished products that can be used for multiple final products. Design change of the semi-finished product that can be used as the modules will be discussed. Concerning the processed parts, similar tasks must be performed.

On the other hand, the manufacturing division must modify the current “make to order” production system so as to produce the standardized semi-finished products and processed parts based on the “make to stock” production strategy. In order to analyze the relation between the level of module inventories and the expected average lead time, Pareto-optimization of the problem described in Section 3 is recommended. This analysis is only possible if the due-date estimation and scheduling system has been installed and the system has been modified as described above.

For the case in which the modules are not being used at present, the total investment for module inventories can be estimated by the following equation:

\[ TI = \sum_{k=1}^{K} \alpha_k \text{Max}(k) + \sum_{k=1}^{K} C_k, \]

where \( TI \) is the total investment for module inventories, \( \text{Max}(k) \) is the maximum level for module \( k \), \( K \) is the total number of module types under consideration and \( \alpha_k \) is the coefficient for converting the maximum inventory level for module \( k \) into the amount of module investment for each year. Moreover, \( C_k \) is the development cost for module \( k \), where \( C_k \) must be converted into the depreciation amount for each year.

The computational results performed under the various plans on the standardization of semi-finished products and processed parts must be shared among the product design section, the manufacturing division and the top management. As a result, through a series of Pareto-optimization analyses, the manufacture will be able to obtain a clear understanding of which modules should be manufactured and held in stock.

5.2.2 Updating the module inventory levels

The Pareto-optimal module allocation is decided on the premise that customer demands are volatile, i.e., always changing, sometimes remarkably. Therefore, the Pareto-optimal module allocation must be revised on a regular basis. For cases in which demand for the particular modules for semi-finished products increases suddenly, reflecting new demands in the revised module allocation becomes infeasible. As a result, the difference between the revised level of module inventory \( \text{Max}(k) \) and the present level of module inventory \( \text{Max}^p(k) \) may be large. As the method for controlling the sudden increase of \( \text{Max}(k) \), involving the following term in total investment \( TI \) for the Pareto-optimization and avoiding the sudden change of module inventory levels will be suggested.

\[ M(\text{Max}(k)) = \sum_{k=1}^{K} \gamma_k \left( \text{Max}(k) - \text{Max}^p(k) \right)^2, \]
where \( \text{Max}^p(k), k = 1, 2, \ldots, K \) represents the module allocation, which was selected last time, \( \gamma_k \) is the non-negative coefficient for the resistance of changing the inventory level of module \( k \). Naturally, the resistance becomes stronger as coefficient \( \gamma_k \) increases. The manufacturing division is responsible for properly controlling the module inventories. The revised level of module inventories should be shared between the product design section and the manufacturing division, together with the reason for having selected the inventory levels for the exceptional case.

### 5.2.3 Avoiding the obsolescence of module inventories

Regarding the module development and inventory management, the obsolescence of modules is always considered. Module obsolescence occurs when the customer demand on a final product drops suddenly and continues to be low for a long period of time, so that these modules, if not used in other products, will likely become worthless. One way to avoid such situations is to understand why the customer demand for a particular final product decreases suddenly. Depending on the reason for such a decrease, increasing the level of the corresponding module inventories should be ceased as early as possible. Regarding this ability, the proposed module allocation function of the system is lacking such an ability. However, the manufacturing division should be responsible for the obsolescence of modules and should formally inquire as to the reason for such a change.

### 5.3 Due-date estimation for customer orders with unfixed specification

In Section 4.5, the due-date estimation time was interpreted to mean the due-date estimation time for a customer order, for which the required design tasks have been completed. In addition, the latest date for fixing the specification was interpreted as being the time for deciding the component specifications considering the required design tasks. These interpretations for these terms suggest that the customer oriented characteristics of the due-date estimation method will be modified so as to be also product designer oriented. Figure 7 (the upper figure) depicts the relationship among the specification clarifying date, the design end time for the undecided component and the start time of the operation for the decided component.

In Section 4.5, it is also clarified that the required design tasks are usually finished before the execution of the due-date estimation for the respective customer order. However, the design tasks are not always finished before the execution of due-date estimation. In this case, the design task end time for the customer order must be treated in a manner similar to that for an undecided component, and the product design section will be informed of the latest design task end time (see the lower figure in Figure 7).

![Fig. 7 Relationship among the specification clarifying time for the undecided component, the design task start time, the design task end time, and the operation start time for the decided component or the component with the finished design](image-url)
Thus, the latest product design end date or time is valuable information for the product design section. As a result of having this information, a manufacturer can better predict due dates and further shorten lead times.

6. Concluding remarks

In the present paper, the possibility of integrating product design and manufacturing was discussed. The following procedure was introduced for this purpose. Three papers for which the present author was sole author or one of the coauthors are reviewed in detail.

After a review of previous research, the realization of collaboration between the product design section and the manufacturing division through a proposed due-date estimation and scheduling system was discussed. This system was demonstrated to be able to identify problems that must be solved by product designers and manufacturers, as well as the information that is required in order to solve the identified problems. The importance of real-time information sharing between the product design section and the manufacturing division is confirmed through discussion.

Finally it should be stressed that the information sharing itself between the product design section and the manufacturing division may not be valued, but the situation of such sharing being performed naturally without effort must be really important. The present paper suggests that the proposed system has the high possibility of realizing the desirable situation.

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