IEMS Vol. 9, No. 3, pp. 196-203, September 2010.

Component Commonality and Order Matching Rules in Make-to-Forecast Production

Katsumi Morikawa†, Yusuke Deguchi, Katsuhiko Takahashi, Daisuke Hirotani
Faculty of Engineering, Hiroshima University, 1-4-1, Higashi-Hiroshima 739-8527, JAPAN
E-mail: {mkatsumi, takahasi, dhiro}@hiroshima-u.ac.jp

Received, April 1, 2010; Revised, June 30, 2010; Accepted, July 30, 2010

Abstract. Make-to-forecast production is a way to realize high customization and fast responsiveness. This study firstly investigates the effect of introducing a common component in a make-to-forecast production environment. The common component can eliminate a modification step, which is a major cost component in make-to-forecast production. It is illustrated, however, that introducing a versatile component that merely covers several variants is unattractive, and thus adding values to the common component is inevitable in this environment. Secondly, an order-matching rule under the condition that two partially overlapped delivery lead time intervals exist is proposed. The rule considers the effect of matching orders to units that can cover both intervals. An alternative re-matching rule is also developed and examined. Numerical experiments clarify that the proposed rule generally realizes higher contribution ratio and lower percentages of orphans and rejected orders. The proposed re-matching rule increases the average contribution ratio at the expense of increased orphans and order rejections.

Keywords: Make-to-forecast, Common Component, Order Matching Rule, Tactical and Operational Decisions

1. INTRODUCTION

Satisfying a wider variety of customer demands in shorter delivery lead times without increasing costs is a common goal for manufacturers. The make-to-forecast production environment termed and introduced by Akinc and Meredith (2006) lies between the make-to-order and assemble-to-order production environments, and is aimed at providing higher customization than the assemble-to-order, and faster responsiveness than the make-to-order. In make-to-forecast production, products are manufactured through a production line composed of several stations, and each station attaches one component to each arriving unit. In general, there are several variants in each component, and thus the bill-of-assembly (BOA) is given to all units. The BOA specifies the set of variants of components to reflect the requested product specifications. Because of the competitive market, acceptable customer delivery lead times are considerably shorter than manufacturing lead times. In addition, Meredith and Akinc (2007) say that because of its large size and high cost, it is practically impossible to hold partially or fully completed units as inventories. The long manufacturing lead times inevitably lead to releasing units from the upstream station without confirmed customer orders. Nevertheless, to satisfy a wider variety of product specifications from customers, units are often differentiated at the beginning of their production process. The BOA is thus firstly generated by forecasting or anticipating future customer orders. Orders that arrive randomly are matched to these units at the middle of the line when the remaining processing time of the units is within the delivery lead time of the orders. The BOA of a unit is updated when an order is matched to the unit, and incompatible variants already attached are changed later at a cost.

From a tactical point of view, introducing a common component that can be a substitute for several variants may be attractive because it can eliminate an expensive modification step. However, developing and using such a common component incurs additional costs and thus the effectiveness of component commonality must be investigated through comprehensive examinations. From the operational point of view, the order matching rule is still an important research issue. Meredith and Akinc (2007) assume that the delivery lead time of all orders is basically defined by an interval. This paper proposes a matching rule by extending previous rules under the condition that the delivery lead times are defined by two partially overlapped intervals.

The paper is organized as follows. In Section 2, some related previous papers are briefly reviewed and

† : Corresponding Author

then the research objective is clarified. In Section 3, a make-to-forecast production system is introduced, and then the expected advantages and drawbacks in introducing a common component are discussed. A new order matching rule and an alternative re-matching rule are introduced in Section 4 assuming that the delivery lead times of orders can be grouped into two partially overlapped intervals. Results of numerical experiments are illustrated in Section 5. The research findings and future research issues are mentioned in Section 6.

2. LITERATURE REVIEW AND RESEARCH OBJECTIVE

Raturi *et al.* (1990) introduce three case studies from firms building heavy machinery. They indicate that these firms produce highly customized products, yet they deliver their products with lead times significantly shorter than the manufacturing lead times. Therefore, products start to be produced from the upstream station without confirmed customer orders. Incoming orders and units in the production line are matched in the line if the expected completion date of these units is earlier than the maximum delivery date of orders. This production environment is named "build-to-forecast" in their paper. The problem of customization-responsiveness is discussed by McCutcheon *et al.* (1994), and they present a framework for choosing appropriate tactics: alter process design, alter product design, manage demand, manage supply, use slack resources, and build to forecast.

Akinc and Meredith (2006) discuss the capacity planning issue in the "make-to-forecast" production environment, and a Markov analysis approach is proposed. If the production capacity is insufficient for the average order arrival rate, then some incoming orders will be rejected. On the other hand, the surplus capacity will create a finished unit without a customer, which is termed an "orphan" in their paper. The production process considered is a giant, rigid assembly line and therefore it is practically impossible to stop, speed up or slow down the line. They indicate the relationship between the capacity and the number of orphans and rejected orders under a given demand level. Effect of delivery lead times, variations in the demand pattern, and the variability in the order arrivals are also examined. Meredith and Akinc (2007) propose several order matching rules in the situation that the delivery lead time of all orders is basically defined by an interval. Their analysis indicates that applying locally optimal assignment rules is beneficial. More than ten scenarios are also introduced in the numerical experiments to investigate the performance of the proposed matching rules under several different manufacturing conditions. Akinc and Meredith (2009) consider a special situation where there is an orphan, and they formulate a stochastic dynamic programming model to represent the managerial dilemma: modify the orphan for a new order or hold it for a possibly profitable future order. Optimal policies and their specific properties are illustrated.

This study is highly motivated by the study of Meredith and Akinc (2007). In their basic scenario, all orders arrive with a maximum delivery date of 10 weeks, while the manufacturing lead time is 20 weeks. They say that order specific delivery times can be incorporated into their matching rules. However, we think that a manufacturing environment facing two partially overlapped due date intervals requires further study. How to utilize and manage the overlapped zone is an interesting research issue.

In addition, from the tactical point of view, it is also interesting to survey the effect of introducing a common component in make-to-forecast production. We assume that in a station, one specific component, or variant, is selected from the set of variants based on its BOA and attached to the unit. The common component introduced in this study is a versatile component that can be attached to the unit no matter which variant is specified in the BOA. Therefore, the common component can surely eliminate the costly modification step for the component even if no order is matched to the unit at the time of attaching the component.

The common component has another important viewpoint. It is generally right and proper that a manufacturer should satisfy all of the requested specifications from a customer. However, it is not always profitable to do so. One important managerial decision of the manufacturer is to decide the product design considering clear milestones and differentiation strategies, and then to negotiate with customers with their value-added specifications. For example, if there are generally two motor variants, $v1$ and $v2$, and competitors also prepare these two variants, then the degree of cost reduction in addition to the responsiveness is the primary concern for the manufacturers. If a manufacturer develops a new motor $v3$ that can be used as a substitute for $v1$ and $v2$, and that can provide additional features such as lower energy consumption, higher expandability, space-saving, and so on, using $v3$ will also reduce the length and the variability of delivery time because of the elimination of possible later modification operations. Then a customer who originally requests $v1$ or $v2$ may be willing to pay additional money, say 10% of the original price of $v1$ or $v2$, for motor $v3$. Although it is not so easy to develop such a common component that follows the above scenario, it is absolutely important to examine such a strategy to survive in a severely competitive environment. Although component commonality is discussed in many papers (e.g., Van Mieghem (2004), Desai *et al*. (2001), Thonemann and Brandeau (2000)), the focus of this study is to indicate the importance of developing the value-added common component in make-to-forecast production.

3. MAKE-TO-FORECAST PRODUCTION

3.1 Production Environment

The make-to-forecast production environment considered in this study follows the study of Meredith and Akinc (2007). The production line is composed of 20 stations, and each station has one unit of partially assembled product. One variant is attached to the unit in a station based on the BOA, and each station requires one week for the assembly operation. Therefore, the manufacturing lead time of products is 20 weeks. The arrival of customer orders follows a Poisson process with mean arrival rate of 1.1458, and every order demands a single product within 10 weeks. (This delivery lead time condition will be changed in section 4.) Let i be the station number (i = 1, ⋯, 20), and l be an order. Station 1 is the most upstream station, and station 20 is the most downstream station. Component i is attached at station i, and there are several variants for component i. An order l involves the set of desired variants to be attached at each station. An incoming order requests variant j of component i with probability $P_i(j)$ regardless of other component requests.

As there is no confirmed order when releasing a unit into station 1, two rules, i.e., mixed and standard rules, are proposed by Meredith and Akinc (2007). The mixed rule generates a BOA based on the probability of each variant, $P_i(j)$, randomly. On the other hand, the standard rule generates a specific BOA that incurs the smallest expected modification cost for each component. The modification cost will be explained later.

Orders that have arrived within a week are matched to free units at stations 11 to 20 at the end of each week. A free or unmatched unit is a unit without a matched order. Apparently, one free unit cannot be matched to two or more orders, and therefore, there is a possibility that there are no free units at these stations while there is still one or more arrived orders. In such a case, these unmatched orders are rejected, and removed from the queue of arrived orders. On the other hand, there is also a possibility that at the end of a week, all units at stations 11 to 20 are free and no orders have been received within this week. In this case, the finished unit at station 20 becomes an orphan, and this orphan will be disposed of at cost. Meredith and Akinc (2007) indicate that in principle, the percentages of rejected orders and orphans are defined by the relative difference between the production capacity and the rate of order arrivals.

It is also necessary to explain one additional situation. Let us consider the situation that at the end of a week, station 20 has a free unit while another station between 11 and 19 has a matched unit. In this case, it is possible to avoid the occurrence of an orphan by changing the order assignment from the matched unit to the free unit. The original matched unit then becomes a free unit. This re-matching is reasonable under the condition that the actual modification operation of a unit will be conducted after the unit leaves station 20, and the lead time of this modification is negligible. The effective re-matching decisions will reduce the number of orphans without increasing modification costs so much.

When an order l is matched to a unit at station i, the variants already attached to the unit, and the desired variants specified in l, are compared. If there is a mismatch between them, the mismatched variant attached will be replaced with the desired variant as described above. The cost of modification from variant h attached at station i to j does not depend on h and is given by $0.5C_i(j)$, where $C_i(j)$ means the monetary value of variant j of component i. Variant values and their probabilities of demand shown in Meredith and Akinc (2007) were used in the numerical experiment in section 5.

A free unit is assembled based on its BOA, and if an order is matched to the unit, then the BOA is replaced with the specifications of the order and the remaining assembly operations are conducted based on the matched order.

3.2 Performance Measures

Based on the proposal of Meredith and Akinc (2007) this study also considers three measures. The first is the net contribution and the maximum contribution. Let M_l be the sum of the monetary value of components specified in an order l. Then the maximum contribution of order l is given by $R \cdot M_l$, where R is the contribution percentage and R = 30% was used in the numerical experiments in section 5. The net contribution is given by $R \cdot M_l - E_l$, where E_l stands for the total modification cost required to satisfy the specifications of order l. Averaged values over all shipped units are used when evaluating these measures.

The second measure is the percentage of orphans, and the third is the percentage of rejected orders.

3.3 Introducing Component Commonality

To cope with various product specifications under severe lead time competition, several realistic methods are pointed out by Meredith and Akinc (2007). One common strategy is to redesign the product to shorten the production lead time. Other strategies include the introduction of modular design for easy modification, and building expensive variants that cover a wider range of specifications. They indicate that these methods are beneficial, but their effectiveness is limited.

As stated before, introducing a common component is a method to eliminate costly modification operations. However, under the production environment described above, introducing a common component seems not as attractive in terms of the contribution values. For example, let us assume that there are two components $v1$ and $v2$, and the monetary value of $v1$ is less than that of $v2$. A component cv is a common component of variants $v1$ and $v2$, and cv is more expensive than the dedicated components (Van Mieghem, 2004). It is natural that a customer requesting variant $v1$ (or $v2$) does not want to pay much more even if he or she knows that the manufacturer attached cv instead of $v1$ (or $v2$). Therefore, even if the manufacturer produces all products using the expensive common component cv, the merit of component commonality is only the complete elimination of possible later modification operations. Thus the expected saving will be wiped out by the increased cost of using cv for all products.

A more profitable approach is to satisfy the customer's demand by using requested variants that are cheaper than the common component, and accepting the unavoidable modification cost. For example, if the BOA is generated by the standard rule, $v2$ is always selected in this case. If the matched order requests $v1$, then the modification cost from $v2$ to $v1$ is one-half of $v1$. In general, some customers will specify $v2$ and these profitable orders incur no modification cost. A similar examination can be made under the mixed-rule-based BOA.

Although the merit of introducing commonality involves risk-pooling (Van Mieghem, 2004), manufacturing cost reduction (Desai *et al*., 2001), and complexity cost reduction (Thonemann and Brandeau, 2000), the above discussion illustrates the importance of developing a value-added common component instead of one that merely covers several variants in make-to-forecast production. If a customer recognizes the added value of the common component, and implicitly agrees to pay additionally a fixed percentage α of the value of the originally desired variant, then there is a possibility that the common component can become a profitable component for the manufacturer. The monetary value of the common component and a reasonable value of α are important factors when deciding whether a common component has to develop or not.

In this study we assume that a customer desires a variant j of component i, but implicitly accepts to pay additional money for using the common component, then the value of this order l, M_l, described in 3.2 is modified as follows:

$$M_l \leftarrow M_l + \alpha \cdot C_i(j),$$

where the value of M_l on the right-hand side is the original value under variant j. When calculating the net contribution, the difference of the monetary value of the common component and variant j, and the modification cost, must be subtracted from the maximum contribution.

4. ORDER MATCHING UNDER TWO PARTIALLY OVERLAPPED LEAD TIMES

4.1 Additional Assumptions

In the previous section, we assume that the delivery lead time of all orders is given as an interval of one week to 10 weeks. However, some customers may want to receive products with another interval. Although Meredith and Akinc (2007) consider a JIT environment in their experiment, there is no proposal on how to expand the matching rules under the condition of complicated delivery time restrictions. In this section, therefore, we consider a situation where there are two delivery intervals: from 1 to 10 weeks (interval A), and from 6 to 15 weeks (interval B). Units at stations 11 to 20 are matching candidates for orders with interval A. Stations 6 to 15 contain eligible units for orders with interval B. To simplify the description, zones A and B are introduced as shown in Figure 1. Zone A, for example, contains stations 11 to 20, and is responsible for orders with interval A. The same condition is assumed in another part of the production environment explained in section 3.

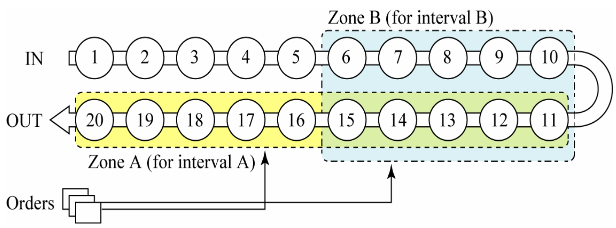

Figure 1. Two zones defined by delivery lead time intervals.

4.2 Order Matching and Re-matching Rules

4.2.1 Order matching rules

Based on Meredith and Akinc (2007), this study proposes the following rule that uses several matching rules depending on the matching conditions in zones A and B.

Order matching for zone A: Zone A contains the final station of the line, i.e., station 20, and an additional re-matching cost will be incurred if the unit at station 20 is unmatched. Therefore, orders with interval A are assigned from the downstream station first.

Order matching for zone B: Two rules are used in this zone based on the following matching conditions:
- If all units at stations 16 to 20 are already matched, then it is expected that the occurrence of re-matching is low. Therefore, allocate orders that maximize the net contribution at that time.
- If there is at least one unmatched unit at stations 16 to 20, then assign orders from the downstream station.

The above method focuses the order matching condition at stations 11 to 15, the overlapped stations between zones A and B. If orders are assigned from the downstream stations for zone B, then there is a possibility that an order with interval A arrives but all units in zone A are already matched. If one or more orders with interval B are assigned to units at stations 6 to 10 (upstream stations), then we can assign more orders with interval A to units at stations 11 to 15. On the other hand, if the maximization of total net contribution is applied to zone B, then under the condition of lower arrival of orders with interval A, re-matching operations will be needed. This unfavorable condition will be avoided by assigning orders from the downstream station. The proposed method changes rules depending on the matching condition, and tries to realize lower frequency of re-matching operations, order rejections, and achieve higher net contribution.

In this paper, the following two alternative matching rules are also introduced to investigate the performance of the proposed rule described above.

Rule 1 (From downstream station): All orders are matched to eligible units that satisfy their due date from the downstream station first regardless of net contribution.

Rule 2 (Maximize contribution): Orders with interval A are matched to units from the downstream station. On the other hand, orders with interval B are matched to maximize the net contribution.

The former (rule 1) is a direct extension of the unit priority FCFS (first come, first served) rule described in Meredith and Akinc (2007), and can be considered as a baseline rule because of its simplicity. As the former rule does not consider the contribution, the latter rule investigates the importance of contribution maximization for zone B. The net contribution maximization is the most profitable method in Meredith and Akinc (2007).

4.2.2 Order re-matching rules

A re-matching operation is activated to avoid the occurrence of an orphan, and this operation incurs additional cost as described before. Meredith and Akinc (2007) concentrate on minimizing the monetary loss at that time when selecting a matched unit for the candidate of re-matching. Their proposal is reasonable but it may be also important to consider the effect of current re-matching in later periods. More specifically, if the unit at station 19 is selected as a candidate for re-matching, the chance that another re-matching is needed at the end of the next week is not so small. To avoid such successive re-matching operations, therefore, this study focuses on the matched unit at the most upstream station, and for which the delivery due date includes the week which follows. It is expected that this re-matching method will reduce the number of total and successive re-matching operations.

Based on the above discussions, this study investigates the effect of re-matching rules on the three performance measures by applying the following rules:

Loss minimization rule: Select a matched unit that minimizes monetary loss at the time of decision.

Re-matching minimization rule: Select a matched unit at the most upstream station and for which delivery due date includes the week which follows (proposed rule).

5. NUMERICAL EXPERIMENTS

5.1 Examination of Component Commonality

The performance of using a common component was evaluated by comparing the net contribution value obtained under the standard BOA approach and conditions described in section 3. We assumed that at station 15 there are currently two component variants, and introducing a common component for these variants is under consideration. There are two cases in this scenario: an order was already assigned to the unit at station 15, or not. In the former case, the desired variant was attached. On the other hand, in the latter case, the common component was attached to the unit. The matching rule adopted was a simplistic FCFS rule named HR-1 in Meredith and Akinc (2007). Orders which arrived earlier were matched to the oldest free unit. Re-matching operations are never invoked in this rule.

The monetary values of two variants available at this station were 10 and 18. Therefore, the value of the common component was varied from 19 to 22, and four different values of α, i.e., 0, 0.1, 0.2, and 0.25 were investigated. The simulation length was 52052 weeks and the results of first 52 weeks were discarded.

Figure 2 shows the summary of results in terms of the average net contribution, and the average contribution ratio. The standard BOA produced the net contribution of 41.073, and the contribution ratio of 0.297. From the figure, we can find that even if the value of the common component was 19, the introduction of the common component incurred a negative effect on the net contribution if the value of α was less than 0.1. If the manufacturer estimates the value of the common component to be 21, it is mandatory that this component adds values from its original variants by at least 25%. If the sales group does not agree with this value, then the standard BOA based planning is preferable.

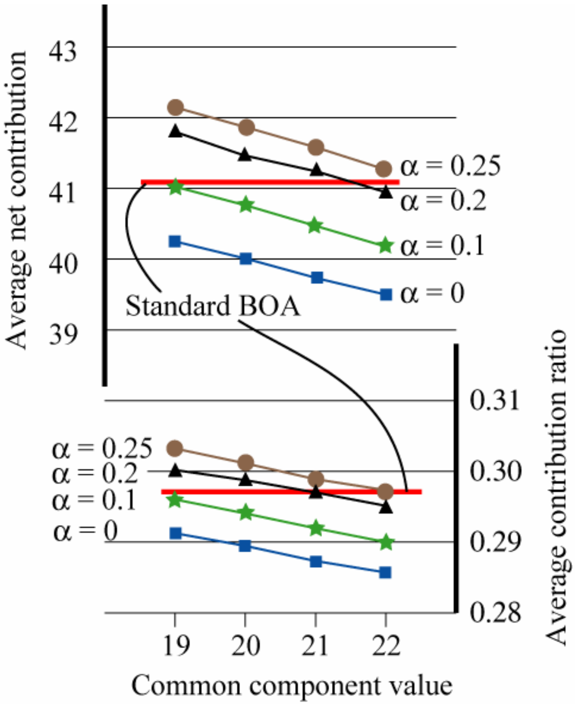

Figure 2. Average net contribution and contribution ratio under different values of common component.

5.2 Performance of Order Matching and Re-matching Rules

The alternative two matching rules (Rules 1 and 2) and the proposed rule described in section 4 (named Rule 3 in this experiment) were evaluated under the two re-matching rules also introduced in Section 4. The simulation length of one run was 520 weeks, and the average values over 1000 replications were obtained. Under two re-matching rules, nine different ratios of orders with intervals A and B were considered as follows: (A : B) = {(1 : 9), (2 : 8), (3 : 7), (4 : 6), (5 : 5), (6 : 4), (7 : 3), (8 : 2), (9 : 1)}. The mixed rule was used to generate the BOA.

Figure 3 illustrates the summary of simulation results under the loss minimization rule for re-matching. The top graph indicates the average contribution ratio, the middle graph shows the average percentage of orphans produced, and the bottom graph displays the average percentage of rejected orders under 9 different ratios of orders with intervals A and B denoted by (A : B) on the horizontal axis. Figure 4 shows analogous results under the proposed re-matching rule, i.e., re-matching minimization rule.

In Figure 3, Rule 1 (from the downstream station) was less sensitive to the change of order ratio, while Rules 2 and 3 were sensitive to the ratio, especially when the ratio of orders with interval B increased. The reason for this result can be partially explained by the increase in the number of re-matching operations shown in Table 1. For increased ratios of interval B, Rule 2 marked highest values, and Rule 3 roughly reduced the average value by half. Because of its matching mechanism, Rule 1 never invokes re-matching operations.

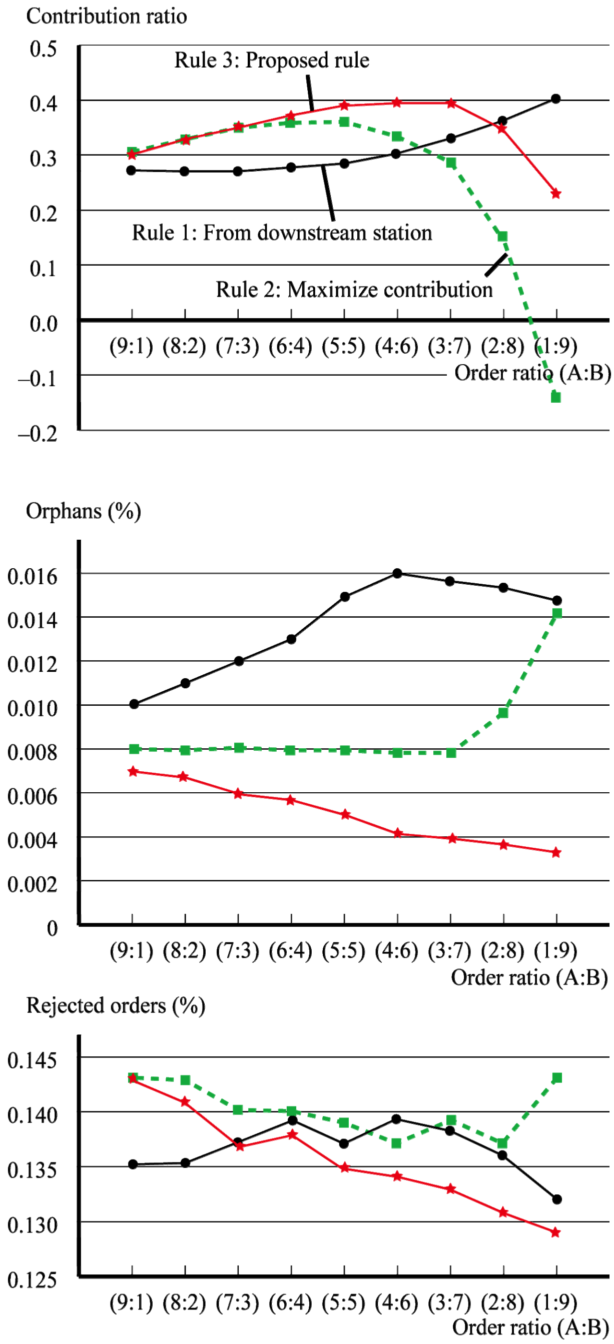

Figure 3. Performance of three matching rules under loss minimization rule.

The average percentage of orphans was high when Rule 1 was applied. This reflects the characteristic of Rule 1; orders with interval B are firstly matched to the units at stations 11 to 15, and therefore the units at stations 6 to 10 have less opportunity to be matched to orders. This trend generally increases the possibility that the unmatched unit at station 20 cannot be re-matched to one of the orders at stations 11 to 15 because of the delivery lead time restriction. The average percentage of rejected orders indicated a relatively similar trend. However, the proposed rule (Rule 3) showed smaller percentages under higher arrival ratios of orders with interval B.

Table 1. The average number of re-matching operations in Rules 1, 2 and 3 under two re-matching rules.

Ratio (A:B)	Loss minimization rule			Re-matching minimization rule		
	1	2	3	1	2	3
(9:1)	0	3.14	2.15	0	1.93	0.48
(8:2)	0	8.03	5.19	0	4.96	1.13
(7:3)	0	16.12	9.07	0	9.71	2.03
(6:4)	0	28.01	15.41	0	16.79	3.43
(5:5)	0	45.39	22.34	0	26.00	5.77
(4:6)	0	73.18	35.25	0	39.01	9.13
(3:7)	0	113.14	55.73	0	57.92	14.07
(2:8)	0	198.82	93.24	0	89.52	24.12
(1:9)	0	360.37	180.55	0	149.65	44.51

Table 2. The average number of successive re-matching operations in rules 1, 2 and 3 under two re-matching rules.

Ratio (A:B)	Loss minimization rule			Re-matching minimization rule		
	1	2	3	1	2	3
(9:1)	0	0.005	0.004	0	0	0
(8:2)	0	0.043	0.017	0	0	0
(7:3)	0	0.128	0.012	0	0	0
(6:4)	0	0.337	0.019	0	0	0
(5:5)	0	0.689	0.015	0	0	0
(4:6)	0	1.339	0.024	0	0	0
(3:7)	0	2.471	0.022	0	0	0
(2:8)	0	5.187	0.010	0	0	0
(1:9)	0	12.144	0.013	0	0	0

The effect of the re-matching rule can be investigated by comparing graphs shown in Figure 3 and Figure 4. We can find that the proposed re-matching rule, i.e., re-matching minimization, improved the average contribution ratio at the expense of increased orphans and order rejections. This result also indicates the effect of re-matching operations on the contribution. The number of re-matching operations and the number of successive re-matching operations are summarized in Table 2. Table 1 and Table 2 state that the proposed re-matching rule reduced the number of re-matching operations, and completely eliminated successive re-matching operations.

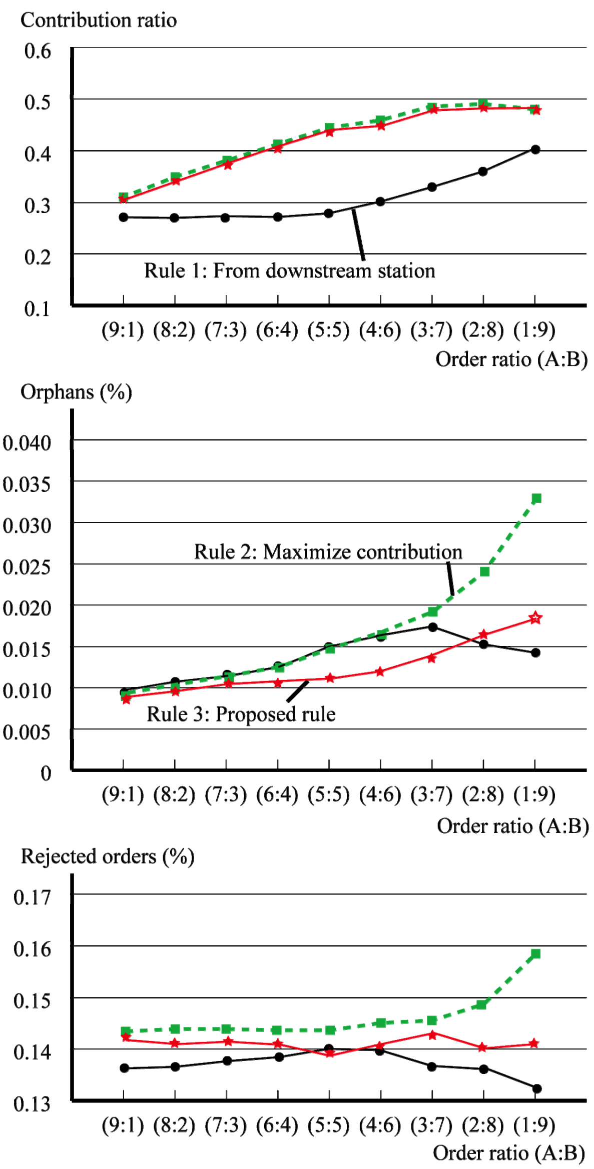

Figure 4. Performance of three matching rules under re-matching minimization rule.

From these results we can summarize the preferred combination of order matching and re-matching rules to be as follows:

1. If the minimization of orphans and rejected orders are more important than the contribution ratio, the proposed matching rule (Rule 3) with loss minimization rule for re-matching generally performs best.
2. If the maximization of contribution ratio has the highest priority, then the combination of proposed matching and re-matching rule (re-matching minimization rule) normally exhibits the most favorable performance.

6. CONCLUSION

This study has investigated tactical and operational issues in a make-to-forecast production environment. The manufacturing conditions of the make-to-forecast are firstly described and the importance of the introduction of a common component is discussed. Under the assumed cost structure, it is not so attractive to employ a common component. Therefore, when developing the common component, it is crucial to add significant value to it. This tactical decision must also reflect the differentiation strategies of the company. A new order matching rule under the condition of two partially overlapped delivery lead time intervals is then proposed. This rule pays attention to the stations covered by both intervals. An alternative re-matching rule is also developed. The proposed matching rule generally shows higher contribution ratio and lower percentages of orphans and rejected orders. The proposed re-matching rule increases the average contribution ratio at the expense of increased orphans and order rejections.

Examining the effect of component commonality from a broader viewpoint is an interesting research issue. Several practical restrictions, including the unavailability of modification and/or re-matching, will also need to be considered in future research.

ACKNOWLEDGMENT

This work was partially supported by funding from the Ministry of Education, Culture, Sports, Science and Technology, Japan (MEXT), Grant-in-Aid for Cyber Campus Project, "Development of Programs for Practical Human Resources and Competency Portfolio System", and Japan Society for the Promotion of Science, Grant-in-Aid for Scientific Research (Grant No. 21310 094); "Reference Modeling Development of Integrated Process for Product Strategy, Product Development, and Manufacturing Factory System."

The work by Yusuke Deguchi at the Hiroshima University Graduate School set off this study. Currently he works for a private company.

REFERENCES

Akinc, U. and Meredith, J. (2006), Choosing the appropriate capacity for a make-to-forecast production environment using a Markov analysis approach, *IIE Transactions*, **38**, 847-858.

Akinc, U. and Meredith, J. (2009), Modeling the manager's match-or-wait dilemma in a make-to-forecast production situation, *Omega*, **37**, 300-311.

Desai, P., Kekre, S., Radhakrishnan, S., and Srinivasan, K. (2001), Product differentiation and commonality in design: Balancing revenue and cost drivers, *Management Science*, **47**, 37-51.

McCutcheon, D. M., Raturi, A. S., and Meredith, J. R. (1994), The customization-responsiveness squeeze, *Sloan Management Review*, Winter, 89-99.

Meredith, J. and Akinc, U. (2007), Characterizing and structuring a new make-to-forecast production strategy, *Journal of Operations Management*, **25**, 623-642.

Raturi, A. S., Meredith, J. R., McCutcheon, D. M., and Camm, J. D. (1990), Coping with the build-to-forecast environment, *Journal of Operations Management*, **9**, 230-249.

Thonemann, U. W. and Brandeau, M. L. (2000), Optimal commonality in component design, *Operations Research*, **48**, 1-19.

Van Mieghem, J. A. (2004), Commonality strategies: Value drivers and equivalence with flexible capacity and inventory substitution, *Management Science*, **50**, 419-424.