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A Recursive Revised First Fit Algorithm for Cutting Stock Problem

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ABSTRACT

Cutting Stock Problem (CSP) is one of the kind of Bin Packing Problem (BPP). CSP contains different sized stock categories, which is a more general problem than BPP. Therefore, there are many applications using CSP. First Fit method is one of the heuristic methods for 1 dimensional BPP. In this paper, a new revised algorithm for First Fit method is proposed. First Fit method takes an approach to assign products to the good fitting bin, which sometimes causes bad yield rate at the final assignment. Therefore, it has a weakness that the yield rate becomes bad in the end. On the other hand, it has a good characteristics that problem can be calculated in a short time as it is a very simple method. The proposed method conquers this defect by taking recursive method in choosing stock size utilizing the characteristics of short computational time. This newly proposed method is applied to CSP for timber precutting and good results are obtained.

Keywords: cutting stock problem, bin packing problem, first fit algorithm.

1. INTRODUCTION

Cutting Stock Problem (CSP) is considered to be an extended problem of Bin Packing Problem (BPP) in which there are multiple stock lengths. In this paper, one-dimensional BPP is treated. One-dimensional BPP is a very simple combinational problem but it is NP-hard problem and there is no algorithm which can pursue optimal solution within polynomial time. So far, following researches were made on this. Integer Programming of BPP to be solved by utilizing Linear Programming Relaxation method is developed (Gilmore *et al*., 1961), but this method takes a lot of time to solve the problem. Concerning heuristic methods, there are First Fit (FF) method, Best Fit method and Minimum Bin Slack (MBS) method (Gupta *et al*., 1999; Fleszar *et al*., 2002), but few of them handle the problem which has different sized bins. As for meta-heuristic algorithm, there are many researches made on combinatorial optimization problem. For example, Lin *et al*. proposed a hybrid Genetic Algorithm (GA) for logistics network design (Lin *et al*., 2007), and Velayudhan *et al*. discussed about Ant Colony Optimization Problem applied to Traveling Salesman Problem (Velayudhan *et al*., 2007). The researches in which GA is applied to one-dimensional BPP are made by Falkenauer (1999) and Yakawa *et al*. (2005). H shaped steel in the steel maker has the similar cutting stock problems and many researches are made on this. But in allocating products to long beams, press schedule and roll exchange pattern are the big issues. Therefore constraints of these problems are quite different from the general CSP.

We have proposed a revised GA model (Toyoda

Table 1. Notation

Symbol	Description
m	number of stock sizes (categories).
n	number of products.
t, s	stock size number ($1 \leq t, s \leq m$)
i	product number ($1 \leq i \leq n$).
$k, k^{(t)}$	material number, material number in size t
$b_t, b_{\max}, b_{\min}$	stock length of category t. maximum and minimum stock length.
l_i	length of product i
I, I_k	set of products, set of products assigned to material k
I_{res}, L_{res}	set of residual unassigned products and their total length
$I^{(t)}_{res}, L^{(t)}_{res}$	set of residual unassigned products and their total length when the assignment to the material of size t is executed.
B, B_t	set of used materials, set of used materials of size t.
y, y_k	yield rate, yield rate of material k
$P = \{P(i)\}, Q = \{Q(i)\}$	products list in a length descending order
$M = \{M(t)\}$	material list which is taken from each category one by one and sorted by length decreasing order.
A, A_k	assignment result, assignment result to material k.

et al., 2007) and revised First Fit Decreasing (RFFD) method (Toyoda *et al*., 2008) before. We obtained high yield rates by proposing extended elitism method in the former one and we obtained good results by foreseeing the final result at the final stage in the latter one. But we could not foresee all the cases in the previous RFFD method. In this paper, we revise RFFD method to foresee all the cases in the final stage and aim to increase yield rates by developing the Recursive RFFD (R-RFFD) method.

The rest of the paper is organized as follows. In section 2, CSP is defined. RFFD is stated in section 3. R-RFFD is developed in section 4. Numerical example is exhibited in section 5, which is followed by the conclusion of section 6.

2. DEFINITION OF CUTTING STOCK PROBLEM

First of all, notation is exhibited in Table 1. Suppose there are ample stocks of m kinds of length $b_t (t = 1, \ldots, m)$. We are to cut all of the products i ($i = 1, \ldots, n$) form the stock. We denote c_t as a cost to use material of size t. Then, 1 dimensional multiple stock length CSP is defined as follows.

$$J = \sum_{t=1}^{m} \sum_{k^{(t)} \in B_t} c_t \rightarrow \min \tag{1}$$

$$\text{Subject to} \sum_{i \in I_{k^{(t)}}} l_i \leq b_t,\ \forall k^{(t)} \in B_t\ (t = 1, \ldots, m) \tag{2}$$

$$\bigcup_{t=1}^{m} \bigcup_{k^{(t)} \in B_t} I_{k^{(t)}} = I \tag{3}$$

$$I_{k_1} \cap I_{k_2} = \phi,\ \forall k_1, k_2 \in B, k_1 \neq k_2 \tag{4}$$

If the cost is replaced with the volume of used materials, the objective function (1) is expressed as follows.

$$J = \sum_{t=1}^{m} \sum_{k^{(t)} \in B_t} b_t \rightarrow \min \tag{5}$$

As the yield rate is shown as Eq. (6) and when the total length of products is given, then the objective function (5) is equivalent to maximizing the yield rate.

$$y = \sum_{i \in I} l_i \Big/ \sum_{t=1}^{m} \sum_{k^{(t)} \in B_t} b_t \tag{6}$$

3. REVISING THE REVISED FIRST FIT ALGRITHM

3.1 First Fit Algorithm in BPP

First Fit method used in general BPP is to put product to the space where it is searched at first. First Fit Decreasing (FFD) method is to sort the products in the decreasing way and put a product to the space. It has a better result than the method which puts products at random (http://www.cs.arizona.edu/icon/oddsends/bpack/bpack.htm). Now, set the bin capacity as stock length and the item sizes as product order lengths, BPP as CSP which handles single stock length. FFD algorithm from the viewpoint of bin in which product is assigned to material k (that is called bin-oriented FFD) becomes as follows.

<*Algorithm-1*: Bin-oriented FFD>

Set product list by the order of length as $P = \{P(1), \ldots, P(n)\}$ which are to be cut from the stock. Set length of product i as l_i, the stock length as b, a material in the stock as k and products set which is assigned to

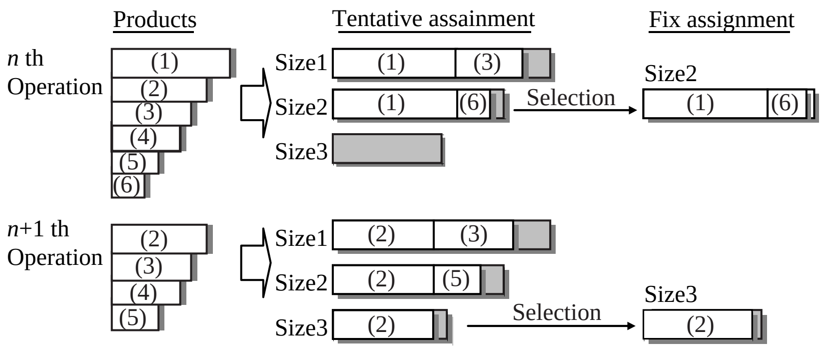

Fig. 1. A Revised First Fit Decreasing method for the problem which has multiple stock lengths

material k as I_k. Set $i = 1$.

Step 1. Add $P(i)$ to I_k if $\sum_{j \in I_k} l_j + l_{P(i)} \le b$

Step 2. If $i = n$, conclude the procedure, else, set $i \leftarrow i + 1$ and go to Step 1.

3.2 A Revised FFD Algorithm for Multiple Stock Lengths and Its Defect

Utilizing the relation that CSP has multiple stock sizes to select, we proposed the following Revised FFD (RFFD) algorithm and performed high yield rate (Toyoda *et al*., 2008).

After sorting the products in the decreasing order, iterate the following operations until all products are assigned to materials (Fig. 1).

(1) Assign the products to a material in each stock size by Algorithm-1;
(2) Select the assignment based upon a criterion which makes the best fit combination of material and products.

FFD method is an algorithm to make good fit assignment at each point and it does not make a total optimization. Therefore there often arise cases that the yield rates are bad at the final stage. To overcome this weakness, the first product in the unassigned product list that is the longest one must be assigned to the possible assignable material in process (1). If it is not assigned and left alone, effective assignment becomes hard (Fleszar *et al*., 2002). For example, in the n-th operation in Fig. 1, assignment to Size 3 is not executed because the length of Size 3 is shorter than that of Product 1.

Moreover, we have devised to improve the yield rates utilizing the condition that we handle multiple stock sizes. In improving the yield rate, the following selection criteria were set (Toyoda *et al*., 2008).

Criterion-1 (Yield Rate Criterion): Select the assignment which makes the highest yield rate.

Criterion-2 (Used volume Criterion): Select the assignment in which the total length of necessary materials is minimum for the rest products to be cut.

The procedure of Criterion-2 is executed as shown in Fig. 2. Criterion-2 is an objective of Eq. (5) itself if it is executed to all products during assignment. We can not however make a prospect for all the assignment procedure. It can only be executed at the stage when the prospect of assignment can be made for the rest of procedure at the final stage. Set $I_{res}^{(t)}$ as the unassigned residual products when the residual products I_{res} has been assigned to a material $k^{(t)}$ of size t and set $L_{res}^{(t)}$ as the total length of $I_{res}^{(t)}$. Criterion-2 is taken at the final stage when the following condition is satisfied.

$$\min_{i=1,\dots,m} L_{res}^{(t)} = \min_{i=1,\dots,m} \{L_{res} - \sum_{i \in I_{k^{(t)}}} l_i\} \le b_{\max} \tag{7}$$

Define $b^{(t)}$ as follows:

$$b^{(t)} = \begin{cases} 0 & L_{res}^{(t)} = 0 \\ \min_{s=1,\dots,m} \{b_s \mid l_{res}^{(t)} \le b_s\} & 0 < L_{res}^{(t)} \le b_{\max} \\ b_{\min} \times 2 & b_{\max} < L_{res}^{(t)} \le \max\{b_{\max}, b_{\min} \times 2\} \\ b_{\min} + b_{\min+1} & \max\{b_{\max}, b_{\min} \times 2\} < L_{res}^{(t)} \le \max\{b_{\max}, b_{\min} + b_{\min+1}\} \\ L_{res}^{(t)} & L_{res}^{(t)} > \max\{b_{\max}, b_{\min} + b_{\min+1}\} \end{cases} \tag{8}$$

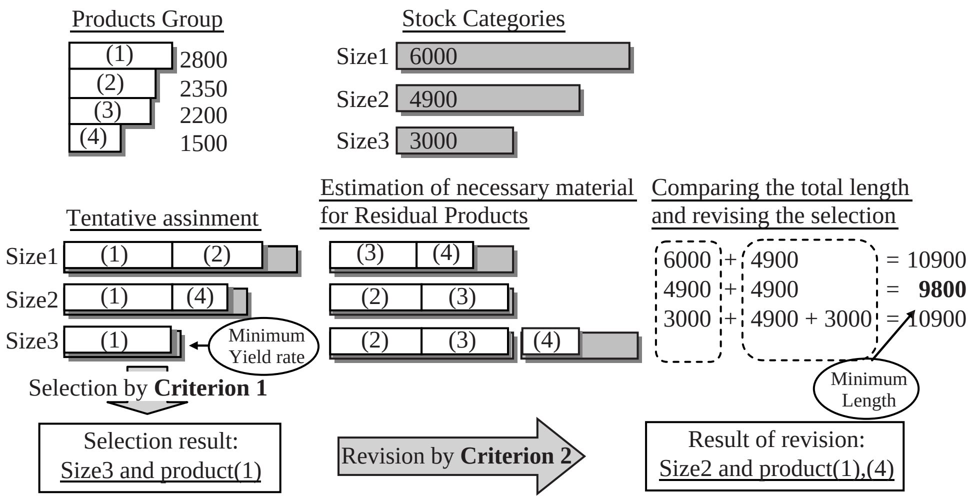

Fig. 2. The procedure of Criterion-2

where

$$b_{\max} = \max_{s=1,\ldots,m} b_s,\ b_{\min} = \min_{s=1,\ldots,m} b_s,$$

$$b_{\min+1} = \min_{s=1,\ldots,m} \{b_s \mid b_s > b_{\min}\}$$

Here, $b^{(t)}$ means that it is a total length of necessary materials for the rest of the products to be cut. Especially, the rest of the products can be cut form the material of size t when $0 \le L_{res}^{(t)} \le b_{\max}$. When $b_{\max} < L_{res}^{(t)}$, we can not make all of the prospect of the necessary materials. But when $L_{res}^{(t)}$ is less than ($b_{\min} \times 2$) or ($b_{\min} + b_{\min+1}$), assignments probably conclude after the next and the second next operations.

The above one is our past proposal. We have obtained better results than before and calculation results show that Criterion-2 is especially effective in improving yield rate. But it has a following defect. We choose the best assignments by executing Criterion-1, but Criterion-2 can not work well unless the assignment concludes within the two times calculations for the Criterion-2 to work.

3.3 A Revised RFFD Algorithm

For simplicity, the following condition is supposed.

$$b_{\max} \le 2b_{\min} \tag{9}$$

If Eq. (7) holds at the final stage of assignment, the following equation holds.

$$L_{res} \le \sum_{i \in I_k(t)} l_i + b_{\max} \le b_{\max} + b_{\max} \tag{10}$$

This means that the residual products I_{res} are all assignable to two materials of maximum length and material length required is less than $2b_{\max}$. From Eq. (9), $2b_{\max} \le 4b_{\min}$. Therefore we only have to seek materials less than or equal 3.

When assigning I_{res} to a material of size t, if total residual products length $L_{res}^{(t)}$ is not more than $b_{\max}$, a minimum length material no less than $L_{res}^{(t)}$ should be assigned. On the other hand, if $L_{res}^{(t)}$ is more than $b_{\max}$, additional assignment is executed for $I_{res}^{(t)}$. If it is assigned to a material of size s, assignment is concluded after assigning residual products to the third material of which length is minimum no less than $L_{res}^{(t)}$. Therefore, $b^{(t)}$ is expressed as follows, where $b^{(t)}$ is a minimum total length required to assign all the products after assigning I_{res} to a material of size t.

$$b^{(t)} = \begin{cases} \min\limits_{j=1,\ldots,m} \{b_j \mid L_{res}^{(t)} \le b_j\} & L_{res}^{(t)} \le b_{\max} \\ \operatorname*{mim}\limits_{s=1,\ldots,m} \{b_s + \min\limits_{j=1,\ldots,m} \{b_j \mid L_{res}^{(t)} \le b_j\}\} & L_{res}^{(t)} > b_{\max} \end{cases} \tag{11}$$

Therefore, calculating $b^{(t)}$ by Eq. (11), we only have to select the stock category which satisfies Eq. (12) at the final stage that Eq. (7) holds for I_{res}.

$$t_{\min} = \{t \mid \min_{t=1,\ldots,m} (b_t + b^{(t)})\} \tag{12}$$

If there is no condition expressed as Eq. (9), assignment does not necessarily converge within 3 times execution. But repeating assignment and fixing stock category s_1, s_2, … according to Criterion-1, total necessary material length $b^{(t)}$ can be estimated. In this case, latter part of Eq. (11) is replaced as follows.

$$b^{(t)} = b_{s_1} + b_{s_2} + \ldots + b_{s_{r-1}} + \min_{s_r=1,\ldots,m} [b_{s_r} + \min_{j+1,\ldots,m} \{b_j \mid L_{res}^{(s_r)} \le b_j\}] \tag{13}$$

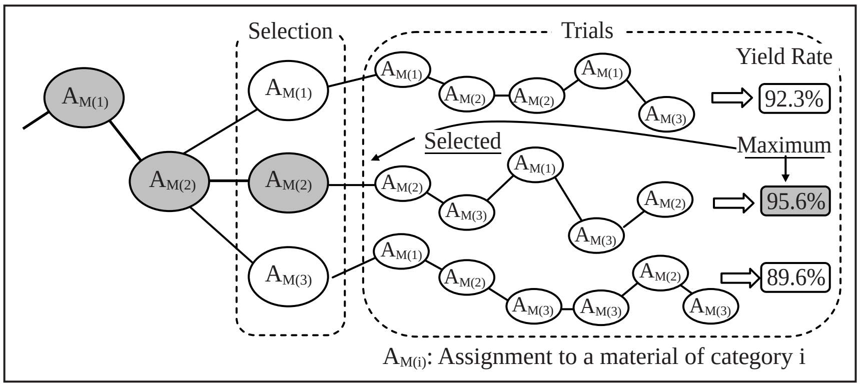

Fig. 3. Algorithm-3: Recursive RFFD

where r is an additional assigning times. Thus, we can conquer the vagueness of necessary material length. Now, we summarize the algorithm for simplicity under the condition of Eq. (9).

<*Algorithm-2*: RFFD >

Set product list by the order of length as $P = \{P(1), P(2), \ldots\}$, material list which is taken from each category one by one as $M = \{M(1), \ldots, M(m)\}$, assignment to $M(t)$ as $A_{M(t)}$, total assignment as A and selected assignment on the way as A_{sel}. Set product list by the order of length as $P_{res}^{(t)}$ in which products group assigned to $M(t)$ is deleted from P.

Step 1. For each $M(t)$ $(t = 1, \ldots, m)$,
If $l_{P(1)} \le b_{M(t)}$, execute assignment using Algorithm-1 and obtain assignment result $A_{M(t)}$.
If $l_{P(1)} > b_{M(t)}$, do not execute assignment.
Step 2. Apply Selection Criterion-1 to $A_{M(t)}$ and set selected assignment as A_{sel}.
Step 3. Examine whether selection criterion should be exchanged or not by Eq. (7). If it is not exchanged, go to Step 6.
Step 4. If $L_{res}^{(t)} > b_{\max}$, execute assignment to each $M(s)$ $(s = 1, \ldots, m)$ by Algorithm-1 for each product list $P_{res}^{(t)}$, Calculate total minimum material length from Eq. (11).
Step 5. Reset A_{sel} of Step 2 and obtain A_{sel} by applying Selection Criterion-2.
Step 6. Add A_{sel} to A.
Step 7. Delete products assigned in A_{sel} from P. If P is not empty, go to Step 1. Else, conclude the procedure.

<*Selection Criterion-1* >

Set $A_{sel} = \{A_{M(t)} \mid \max_{t=1,\ldots,m} y_{M(t)}\}$ for $A_{M(t)}$.

<*Selection Criterion-2* >

Set $A_{sel} = \{A_{M(t)} \mid \max_{t=1,\ldots,m} (b_t + b^{(t)})\}$ for $A_{M(t)}$.

Here, $y_{M(t)}$ is a yield rate of material $M(t)$ and we call it "material yield rate" distinguished from total yield rate of Eq. (6).

4. PROPOSAL OF RECURSIVE RFFD

In the case that there is no condition expressed as Eq. (9), repeating assignment method is stated before (Eq.13). Extending this method, we try to execute this method from the first stage of assignment. In selecting assignment, RFFD is executed and based on this result, selection is executed. We name this method as Recursive RFFD method (Fig. 3).

<*Algorithm-3*: Recursive RFFD >

Set product list by the order of length as $P = \{P(1), P(2), \ldots\}$, material list which is taken from each stock one by one as $M = \{M(1), \ldots, M(m)\}$, assignment to $M(t)$ as $A_{M(t)}$, total assignment as A and selected assignment on the way as A_{sel}. Set product list by the order of length as $P_{res}^{(t)}$ in which products group assigned to $M(t)$ is deleted from P, and set assigned result by RFFD as $A_{res}^{(t)}$.

Step 1. Assign P to each material $M(t)$ $(t = 1, \ldots, m)$ using Algorithm-1 and obtain assignment result $A_{M(t)}$.
Step 2. Repeat the following assignment for $t = 1, \ldots, m$.
Step 2-1. Produce product list $P_{res}^{(t)}$ by removing products assigned to $M(t)$ from P. If $P_{res}^{(t)}$ is empty, go to Step 2-3.
Step 2-2. Apply Algorithm-2 to $P_{res}^{(t)}$, and obtain assignment result $A_{res}^{(t)}$.
Step 2-3. From assignment result $A + A_{M(t)} + A_{res}^{(t)}$, calculate yield rate.
Step 3. Apply Selection Criterion-3 below to each result of $A + A_{M(t)} + A_{res}^{(t)}$, and select $A_{M(t)}$ as A_{sel}. Add A_{sel} to the total assignment result A.
Step 4. Delete products assigned in A_{sel} from P. If P is not empty, go to Step 1. Else, conclude the procedure.

<*Selection Criterion-3*>

Following judgments are executed until t is uniquely determined for $A_{M(t)}$ ($t = 1, \ldots, m$). If it is not determined, select the one which is firstly fit.

Judgment-A: Set $A_{sel} = \{A_{M(t)} \mid \max_{t=1,\ldots,m} y^{(t)}\}$.

Judgment-B: Set $A_{sel} = \{A_{M(t)} \mid \max_{t=1,\ldots,m} y_{M(t)}\}$.

Judgment-C: Set $A_{sel} = \{A_{M(t)} \mid \max_{t=1,\ldots,m} (\max_{i \in I_{M(t)}} l_i)\}$.

Where $y^{(t)}$ is a final yield rate when P is assigned to $M(t)$ and residual part $P_{res}^{(t)}$ is assigned by Algorithm-2.

From the definition of $y^{(t)}$, if we select the assignment $A_{M(t)}$, then we can get final yield rate which would be equal to or more than this yield rate $y^{(t)}$. This means that this yield rate is said to be a guaranteed minimum yield rate. Judgment-A of Selection Criterion-3 expects to increase this guaranteed yield rate by selecting the maximum yield rate on RFFD trials. Thus, reaching total optimization can be expected by forecasting the final result instead of taking optimum in each stage. But there may be many cases that A_{sel} is not determined uniquely only by Judgment-A because $y^{(t)}$ is the discrete value by the sum of the length of the material used. Therefore, additional Judgments are executed until it is selected uniquely. Judgment-B means that it reserves assignment of higher yield rate. Judgment-C intends to lighten the future step burden by taking assignment for the longest product, because the length of the assignable longest product may differ by the stock length in step 1.

In RFFD of Algorithm-2, assigning material of $l_{P(1)} > b_{M(t)}$ is prohibited; therefore the longest product is surely assigned. On the other hand, this restriction is not inserted in Step 1 in Algorithm-3, and for this case, product $P(i)$ which satisfies $\max_i \{l_{P(i)} \le b_{M(t)}\}$ is assigned to the stock of category t. In the assignment of Step 2-2, it uses Algorithm-2. This means that we take the method to widen the chance in Step 1 and to obtain better yield rate to secure in Step 2-2.

5. APPLYING TO HOUSING TIMBER PRECUTTING PROBLEM

Our proposal method is applied to the horizontal timbers of 10 typical wooden houses constructed by post & beam construction system. These precutting are executed based on the several stock lengths (3 m – 6 m) in each grade, shape and species (Appendix Table 1). For a general sized house, 150-200 pieces horizontal timbers are precut which are categorized into 15-20 lots considering the characteristics of each stock. The objective is to maximize the yield rates.

A width for sawing waste is required in precutting the materials. In this case, the width is set to 5 mm.

Table 1. Execution environment

Hardware	Type of Machine	IBM Think Pad G41
	CPU	Intel Pentium 3GHz
	Memory	512 Mbyte
Software	OS	Windows XP
	Programming Language	MS Excel VBA, MS Excel 2002

5.1 Comparison with Other Methods

For comparison, we pick up Japan Patent No. 3565262 (Murata, 2001) and a genetic algorithm (GA) using Extended Elitism Method which we proposed and applied to precut CSP (Toyoda *et al*., 2007). The results of RFFD we have proposed before are also added. An algorithm of the Patent is as follows:

<*An Algorithm of the Patent*>

Step 1. Calculate the sum of length of all products.

Step 2. List up the combinations of materials of which the total length surpasses the above length calculated.

Step 3. By judging the combinations' length in the ascending order, search the minimum length combination of materials in which all products can be assigned.

Step 4. In addition, investigate the combination in order to minimize the total materials' length.

5.2 Experimental Results

Execution environment is exhibited in Table 1. Comparison of assignment results of 10 houses are exhibited in Table 2. In Table 2, "Prod.s" is products, "R-RFFD" is Recursive RFFD, "n-RFFD" means revised RFFD and "o-RFFD" means RFFD before revision. "GA" means Extended Elitism GA and "Patent" means Patent Algorithm. Maximum yield rate after 50 times repetition is taken in GA and it is an optimal solution for House 2.

Execution time is written in "(sec)", and they were all within seconds for R-RFFD and RFFD. GA took about 50 minutes for one house including 50 times repetition. Calculation time for Patent Algorithm is assumed to be several minutes. R-RFFD and RFFD calculation times are by far the shorter one compared with other methods. Moreover, the results of R-RFFD have nearly the same level with those of GA. Rapid calculation is one of the characteristics of RFFD. R-RFFD is to obtain better results by the repeating algorithm utilizing the characteristics of fast RFFD calculation time. R-RFFD itself has a rapid calculation characteristic, therefore the proposed method is a very practical and an effective algorithm.

There is little difference between new RFFD and old RFFD. This is because materials to use in most cases

Table 2. Comparison of the assignment results (by house)

	Number of		Yield rate							
Houses	Lots	Prod.s	R-RFFD (%)	(sec)	N-RFFD (%)	(sec)	O-RFFD (%)	(sec)	GA (%)	Patent (%)
1	16	201	94.12	(1.0)	93.73	(0.9)	93.73	(0.9)	94.16	93.37
2	18	199	95.02	(1.0	94.54	(0.7)	94.45	(0.8)	95.21	94.60
3	17	136	94.03	(0.8)	93.72	(0.7)	93.72	(0.7)	94.09	92.76
4	20	295	94.52	(1.3)	94.21	(1.0)	94.21	(1.1)	94.67	93.36
5	19	257	93.99	(1.2)	93.60	(0.9)	93.60	(0.9)	94.13	93.30
6	19	181	93.32	(1.0)	93.17	(0.8)	93.15	(0.8)	93.46	92.64
7	16	162	93.10	(0.8)	92.67	(0.7)	92.65	(0.7)	93.10	92.30
8	18	220	93.95	(1.1)	93.78	(0.8)	93.78	(0.8)	94.09	93.32
9	15	214	94.33	(1.0)	94.08	(0.7)	94.08	(0.7)	94.43	93.29
10	19	190	94.79	(1.1)	94.62	(0.9)	94.62	(0.9)	94.85	94.09

are within 2 for the assignment which bears $t_{\min}$ of Eq. (12) in the final stage.

Comparison of the assignment results by lot for House 1 and House 2 are exhibited in Table 3. The yield rate by house is averaged, but there was distinguished difference between R-RFFD and RFFD by lot. In Lot No. 1 and 8 of House 1 and Lot No. 1, 7, 14 and 15 of House 2, the difference of the each yield rate is more than 1%. Especially, in Lot No. 14 and 15 of House 2, these are about 2% and 3%, respectively. There was also a difference between R-RFFD and GA in Lot No. 8 of House 1 and Lot No. 7, 15 of House 2. Lot No. 8 of House 1 and Lot No. 7 of House 2 consist of rather short products and have many combination patterns, where the optimal solutions are hard to find. Much more cases should be examined hereafter.

5.3 Evaluation of the Proposed Methods to Improve Yield Rate

Following methods are devised to improve yield rate. Evaluation is executed.

(1) Adjustment at the final stage

In RFFD, we knew that the adjustment at the final stage is very effective to improve yield rate (Toyoda *et al*., 2008). But in R-RFFD, the trial assignments produce the same effect as the adjustment in RFFD, therefore we can assume that the final adjustment might be not so effective as RFFD.

(2) How to handle the longest product

In R-RFFD of Algorithm-3, the restriction that the longest product must be assigned is not applied in Step 1, but is applied in recursive step (Step 2) because Algorithm-2 is used in Step 2-2. When this restriction is applied to both Step 1 and Step 2-2 in Algorithm-3, we call it as “strict condition”, and when this restriction is not applied to both steps, we call it as “condition free”.

Examination results are exhibited in Table 4. Here “Baseline” is the result in which parameters are set in the same way as is done in the former section. “No ADJ.” is the case where final adjustment is not executed. “Strict Cond.” and “Cond. Free” means the case of strict condition and condition free for the longest product. The results of RFFD are also added for the reference. In the case of RFFD, “Baseline” is the result to which the restriction is applied.

Baseline results became better than others as a whole. The final adjustment in R-RFFD was not so effective as expected, but there were certain effect for improving yield rate. This means that the final adjustments on the trial runs derive the better selections. As for the handling of the longest product, the baseline of R-RFFD obtained better results than other conditions, even though the effectiveness was not so clear as RFFD. This is because selection option is widened by removing the restriction in Step1, and the restriction in Step 2 improves the yield rate of trial runs. Thus, each method proved to have an effect on improving yield rate.

6. CONCLUSION

We proposed a new heuristic algorithm for Multiple Stock Length CSP by revising First Fit algorithm. First Fit algorithm takes an approach to assign products to the good fitting stock, which sometimes causes bad yield rate at the final assignment. Therefore, it has a weakness that the yield rate becomes bad in the end. On the other hand, it has a good characteristics that problem can be calculated in a short time as it is a very simple method. The proposal method took recursive method in choosing stock lengths utilizing the characteristics of short computational time. Thus, reaching the total optimization could be expected by forecasting the final result instead of taking optimum in each stage. This newly proposed method was applied to CSP for timber precutting and good results were obtained with short calculation times.

Table 3. Comparison of the assignment results (by lot)

Houses	Num. of Stock			Yield rate				
	Lot	Prod.s	Sizes	R-RFFD (%)	N-RFFD (%)	O-RFFD (%)	GA (%)	Patent (%)
1	1	37	3	95.05	93.43	93.43	95.05	92.04
	2	18	3	96.26	96.26	96.26	96.26	96.26
	3	3	5	89.97	89.97	89.97	89.97	89.97
	4	17	6	95.90	95.60	95.60	95.90	95.75
	5	4	5	92.02	92.02	92.02	92.02	92.02
	6	11	5	96.36	94.36	94.36	94.36	94.36
	7	1	5	29.13	29.13	29.13	29.13	29.13
	8	36	5	97.93	96.89	96.89	98.36	97.51
	9	9	3	92.84	92.84	92.84	92.84	92.84
	10	6	5	95.56	95.56	95.56	95.56	95.56
	11	8	5	93.34	92.97	92.97	93.34	90.82
	12	3	5	94.94	94.94	94.94	94.94	93.89
	13	24	3	95.82	95.82	95.82	95.82	95.82
	14	16	2	92.94	92.94	92.94	92.94	90.87
	15	2	2	63.71	63.71	63.71	63.71	63.71
	16	6	2	90.48	90.48	90.48	90.48	90.48
		201		94.12	93.73	93.73	94.16	93.37
2	1	38	3	96.91	95.76	95.76	96.91	95.67
	2	13	3	96.34	96.34	96.34	96.34	96.34
	3	14	6	97.58	97.36	97.36	97.58	96.27
	4	5	5	98.82	92.82	92.82	92.82	92.82
	5	22	5	94.40	94.22	94.22	94.40	94.03
	6	2	5	92.02	92.02	92.02	92.02	92.02
	7	23	5	96.58	95.57	95.57	98.67	97.36
	8	1	3	25.00	25.00	25.00	25.00	25.00
	9	1	5	93.85	93.85	93.85	93.85	93.85
	10	4	6	95.69	95.69	95.69	95.69	95.69
	11	4	5	89.93	89.93	89.93	89.93	89.93
	12	3	5	96.22	96.22	96.22	96.22	96.22
	13	8	5	96.01	96.01	96.01	96.01	96.01
	14	11	5	98.81	96.92	94.65	98.81	96.92
	15	15	3	95.34	92.37	92.37	96.46	95.34
	16	3	5	98.31	98.31	98.31	98.31	98.31
	17	4	2	83.64	83.64	83.64	83.64	83.64
	18	28	2	92.76	92.76	92.76	92.76	92.76
		199		95.02	94.54	94.45	95.21	94.60

Table 4. Comparison of the assignment results for each condition (by house)

	R-RFFD				RFFD		
Houses	Baseline (%)	No Adj. (%)	StrictCond. (%)	Cond.Free. (%)	Baseline (%)	No ADJ. (%)	Cond.Free. (%)
1	94.12	94.00	94.01	94.12	93.73	93.29	94.00
2	95.02	94.92	95.02	94.88	94.54	93.46	94.51
3	94.03	94.03	94.03	94.03	93.72	93.26	93.84
4	94.52	94.40	94.47	94.40	94.21	93.73	93.96
5	93.99	93.98	93.99	93.92	93.60	92.91	93.41
6	93.32	93.32	93.32	93.32	93.17	92.21	93.17
7	93.10	92.92	92.88	93.00	92.67	90.79	92.14
8	93.95	93.86	93.99	93.86	93.78	93.14	93.48
9	94.33	94.30	94.33	94.12	94.08	93.64	93.11
10	94.79	94.72	94.71	94.75	94.62	94.01	94.54

In Japanese typical wooden house, the volume of precut timbers is about 25 m^3, therefore 1% improvement of yield rate bears about 100 dollars cost reduction. If it is applied to much valuable materials like a steel, it would bear huge cost reduction. Our proposal algorithm is simple to understand and easy to implement, and provides good-quality solutions. The effectiveness of this method should be examined in various cases.

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Appendix Table 1. Sample of Timber Precutting Products of House 2

(length: mm)

Lot. No	Products: Shape	Species	Grade	Length	Stock Sizes
1	S10	323	292	3846.0	4000.0
				3846.0	3680.0
				3604.0	3000.0
				3555.0	
				3490.0	
				3437.0	
				3236.0	
				3137.0	
				2992.5	
				2844.0	
				2844.0	
				2694.0	
				2694.0	
				2694.0	
				2645.0	
				2294.0	
				2144.0	
				2096.5	
				2009.0	
				1934.0	
				1934.0	
				1859.0	
				1784.0	
				1784.0	
				1634.0	
				1542.0	
				1392.0	
				1219.6	
				1039.7	
				992.0	
				992.0	
				874.0	
				874.0	
				874.0	
				874.0	
				1050.0	
				1050.0	
				750.0	
Number of Products = 38					
2	S10	801	292	3604.0	4000.0
				3604.0	3680.0
				3604.0	3000.0
				3445.0	
				3445.0	
				1806.0	
				1024.0	
				1024.0	
				1024.0	
				1024.0	
				874.0	
				1169.0	
				750.0	
Number of Products = 13					
3	S24	328	294	3980.0	6000.0
				3862.0	4900.0
				3604.0	4500.0
				3604.0	4000.0
				3604.0	3700.0
				3517.0	3000.0
				3102.0	
				3070.0	
				2865.0	
				2725.0	
				2694.0	
				2497.0	
				2105.0	
				1902.0	
Number of Products = 14					
4	S21	328	293	3517.0	6000.0
				3102.0	4900.0
				2844.0	4500.0
				2694.0	4000.0
				2694.0	3000.0
Number of Products = 5					
5	S18	328	293	3862.0	6000.0
				3604.0	4900.0
				3517.0	4500.0
				2725.0	4000.0
				2694.0	3000.0
				2694.0	
				2694.0	
				2694.0	
				2694.0	
				2694.0	
				2694.0	
				2694.0	
				2694.0	
				2694.0	
				1242.0	
				1219.5	
				1024.0	
				1024.0	
				1024.0	
				874.0	
				874.0	
				874.0	
Number of Products = 22					
6	S15	328	293	2694.0	6000.0
				1815.0	4900.0
					4500.0
					4000.0
					3000.0
Number of Products = 2					