Trim Loss Minimization for Construction Reinforcement Steel with Oversupply Constraints

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***Abstract*—Construction work consumes a large amount of construction reinforcement steel and it demands this steel in various particular sizes according to structural designs. The steel have to be cut to the right sizes before uses. The cutting process creates a lot of trim loss and costly wastes. This research develops a new procedure for arranging cutting plans with minimum trim loss. The procedure is based on the optimization of one dimensional cutting stock problem. A set of efficient cutting patterns is generated first and then the cutting replications are determined from the optimization. The problem model has oversupply constraints which do not allow cutting any item more than the demanded pieces. Few remaining undersupplied items are lastly cut using the best fit decreasing algorithm. Therefore, the cutting plans created from this procedure will not make any oversupply which becomes waste and they will cut all pieces exactly as demanded. Test results indicated that this developed procedure could produce low trim-loss cutting plans. Also, the suitable number of efficient cutting patterns and the suitable allowable trim loss of the patterns could help result good cutting plans.**

***Index Terms*—cutting plan, trim loss, steel bar, reinforcement steel, minimization**

I. Introduction

Construction work uses various types of one-dimensional materials such as reinforcement steel bars, structural steels, pipes, timber etc. These construction materials come in a standard length (stock materials) and are cut into many different desired lengths. The cutting process creates a number of trim losses. Construction work of reinforced-concrete structures requires a lot of reinforcement steel bars. Their unit cost is quite high compared to the wage of workers. An efficient cutting plan which produces fewer trim losses is worth to make. The survey of the current practice indicated that steel workers were responsible for creating the cutting plan (the cutting patterns and the replication cutting times) whereas engineers prepared the demand list. They used their own intuition and experience to make the plan without any calculation tool. The percentage of waste from trim loss was very high.

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One Dimensional Cutting Stock Problem (1D-CSP) is to find a cutting plan that satisfies the demand list and give the minimum trim loss. The stock has only one standard length (*LS*) with unlimited quantities. The demand list is comprised of the *n* different demand lengths (L_i) (L_1, L_2, L_3, ..., L_n). Each of L_i is required with the certain number of B_i pieces (B_1, B_2, B_3, ..., B_n). All these demands must be fulfilled. The assortment of these demand items consists of many pieces (B_i) of various lengths (L_i). Problem characteristic of cutting construction steel bars is strongly heterogeneous and the suitable solution approach is the pattern-based approach. This approach is to create cutting-patterns first and repeatedly cut these patterns for a number of times until satisfy the demand list. Too many feasible cutting patterns are the issue of this solution approach.

Gilmore and Gomory [1]-[2] were the pioneers who proposed the solution methods using Linear Programming relaxation of Integer Programming and Delayed Pattern Generation Technique to overcome the difficulty. Vahrenkamp [3] proposed the Random Search method to create just a limit number of efficient cutting patterns to be used. He defined any cutting pattern as efficient if it gave trim loss smaller than the shortest demand length and the allowable trim loss.

Another issue of the pattern-based approach was the timing of creating the cutting patterns. Sequential Heuristic Procedure (SHP) [4] created one efficient pattern at a time and applied the pattern as many as possible. It then updated the remaining demand and created another efficient pattern to be cut. It repeated these steps until all demand items were satisfied. SHP gave inconsistent results heavily depending on the pattern created each time. Some methods preferred to prepare a set of patterns in one time beforehand. Salem et al. [5] used the algorithm from Pierce [6] to generate all the efficient feasible cutting patterns. Then, they used them for the optimization problem.

II. Cutting Plan of Construction Reinforcement Steel with Oversupply Constraints

This research aims to develop a new cutting-plan arrangement procedure for construction reinforcement

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steel and test it. Since the demand for construction reinforcement steel is usually comprised of various diameter sizes and lengths, the suitable cutting plan is the pattern-based approach. The demand of each diameter size is considered as a separate problem.

A cutting pattern is a detail of cutting the standard length stock with different demand lengths and pieces where $P_j = [A_{1j}, A_{2j}, A_{3j}, \ldots, A_{nj}]$ and $\sum_i^n (L_i \times A_{ij}) \leq LS$. A_{ij} is number of pieces of L_i of a P_j. Any pattern will create a mount of trim loss equal to $T_j = LS - \sum_i^n (L_i \times A_{ij})$. For any typical demand list, there can be a lot of feasible cutting patterns but only some of them are considered to be efficient. Any efficient pattern is defined as the one which has trim loss shorter than or equal to allowable trim loss (T_w). The allowable trim loss can be specified as needed but it should be shorter than the shortest L_i ($T_w < Min(L_i)$). A set of different efficient patterns must be generated and used for the cutting plan. However, these efficient patterns do not guarantee the minimum total trim loss. The demand list must be exactly fulfilled. Any surplus or oversupplied pieces will be considered as waste. If any demand length is missing from the set of patterns, the demand list cannot be completely fulfilled. Therefore, the set must be comprised of various unique patterns and also the number of different efficient patterns (*nEffPat*) in the set should be adequate. This research proposes the algorithm called "Intensive Search" to create a set of various efficient cutting patterns. The algorithm uses the availability ratio (V_i) as a weighted random wheel to construct an efficient pattern. $V_i = (B_i / \sum_j A_{ij})$ is a ratio between the number of demand pieces of L_i and the sum of the number of appearances in the current set of patterns. The availability ratio can express the variety of L_i within the patterns already created. Any L_i with high V_i shows that this length presents less in the set of patterns created; therefore, it should get more probability to be selected to construct the current pattern. On the other hand, any L_i with low V_i means that this length has already existed frequently in the current set of patterns; therefore, it should get less probability to be selected. The result should get $\sum_j A_{ij}$ of all patterns in proportion to B_i. A set of efficient cutting patterns is created. All these patterns must be different.

The optimal solutions of the 1D-CSP model are the numbers of cutting times of efficient cutting patterns that give the minimum total trim loss. The Genetic Algorithm (GA) is used for the optimization. The important GA parameters are predefined as Population size = 100, Crossover rate = 0.5, Mutation rate = 0.2, and Maximum trials = 1,000,000. Decision variables are the number of cutting times (X_j) of any efficient cutting pattern (P_j), where $X_j \in \mathbb{N}$ and j = 1 to *nEffPat*. The problem model is constrained with the condition that prevents any oversupplied item because it becomes waste. However, the existing 1D-CSP models normally allow oversupplies items which add more wastes. The supplies that are cut from the set of patterns are $S_i = \sum_j (A_{ij} \times X_j)$ and $S_i <= B_i$. The undersupplied pieces of any demand length are calculated as $US_i = B_i - S_i$. These undersupplies must be minimized and will be later cut. The objective function is defined as the minimization of the sum of [$(TL_{pat})^2 + \sum_i (L_i \times US_i)^2$]. The first term is the square of the pattern trim loss which is: $TL_{pat} = \sum_j (T_j \times X_j)$. It is the conventional objective of this problem model type. The square product is used to magnify the scale of the value. The second term is the sum of squares of the undersupplied lengths. This term aims to restrict the amount of undersupplies to minimum.

Lastly, a small amount of the undersupplies remained from the previous step are then cut using Best Fit Decreasing (BFD) algorithm [7]. The BFD algorithm starts with sorting all undersupplied items in a descending order by length. Then, cut each item with the stock which gives the least remaining length. The results from cutting the undersupplies with BFD are the cutting patterns (Q_k), the trim loss of Q_k (T_k), and the numbers of cutting times of Q_k (Y_k). The sum of trim loss from BFD is $TL_{BFD} = \sum_k (T_k \times Y_k)$. The sum of the number of stocks used is $\sum_k Y_k$.

III. Test Results

The test problem was arranged from the construction project data. The standard length of stocks (*LS*) was given as 10 meters. The number of different demand lengths (n) is 15. The details of demand lengths were in Fig. 1. The total of demand lengths was 918.73 meters that was a reasonable job per lot. Also, Fig. 1 shows an example of the set of efficient cutting patterns which were generated by the Intensive Search Algorithm.

Important parameters of the solution procedure which are the number of efficient cutting patterns (*nEffPat*) and allowable trim loss of any efficient pattern (T_w) were separately tested into two test-sets. Each test-set used five groups. Each group was run repeatedly 30 runtimes with the total of 150 runtimes. Each group used different testing-parameter values whereas keeping the other parameter value constant. The first test-set specified value of *nEffPat* as 10, 20, 30, 40, and 50 in each group. The set of efficient cutting patterns used in each group was newly generated whereas T_w = 0.20 meter was kept constant. The second test-set for T_w values which are specified as 0.10, 0.20, 0.30, 0.40, and 0.50 meter. The set of efficient cutting patterns used in each group was newly generated whereas *nEffPat* = 30 was kept constant. All results were analyzed with various indexes such as total trim loss (*TL*), percentage of waste (*%waste*) based on the total demand lengths, total number of stocks used (*nLS*), and number of different efficient cutting-patterns used (*nDiffPat*). Given that $TL = TL_{pat} + TL_{BFD}$ – (Retails). Retails are the sum of leftovers which are considered as usable [8] and longer than or equal to the shortest L_i. And given that $nLS = (\sum_j X_j + \sum_k Y_k)$ and *nDiffPat* is defined as the number of patterns of which X_j are more than zero.

LS	i	Li	Bi	Tw	nEffPat	nSLoop	Sum(Aij)	Bi/sum(Aij)
10.00	1	0.95	25	0.20	30	100	25	1.00
	2	1.40	18				18	1.00
	3	1.75	14				6	2.33
	4	1.80	23				18	1.28
	5	1.88	7				7	1.00
	6	2.67	22				8	2.75
	7	2.88	10				2	5.00
	8	3.05	36				8	4.50
	9	3.20	4				3	1.33
	10	3.75	15				4	3.75
	11	5.00	26				5	5.20
	12	5.40	19				4	4.75
	13	6.35	7				2	3.50
	14	7.00	23				4	5.75
	15	7.19	12				4	3.00
		Total Bi	261					
		Avg. Bi	17.4					

Pc	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26	P27	P28	P29	P30
	1	1	1								2	1		1	4					3		1				1	1	7		1
	1								1	7							1		1		2		2	1		1		1		
			1				1		2			2																		
				1			1									2	3	1	2			5					1			2
	4													1											1			1		
				1							3		1											2	1					
		1						1																						
		2			1										2			1											2	
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						2			1									1	1											
				1								1													1					1
							1									1														
								1						1						1			1							
			1										1								1						1			
Tc	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20	T21	T22	T23	T24	T25	T26	T27	T28	T29	T30
10.00	0.13	0.07	0.11	0.13	0.00	0.00	0.10	0.12	0.10	0.20	0.09	0.15	0.14	0.17	0.10	0.05	0.00	0.15	0.00	0.15	0.01	0.05	0.20	0.06	0.05	0.15	0.06	0.07	0.15	0.05
Xj																														
Limit Xj	1	10	12	19	4	13	7	10	7	2	7	7	12	7	6	7	4	23	11	8	9	4	9	4	7	7	12	3	15	11

Figure 1. Test problem data and an example of the set of efficient patterns.

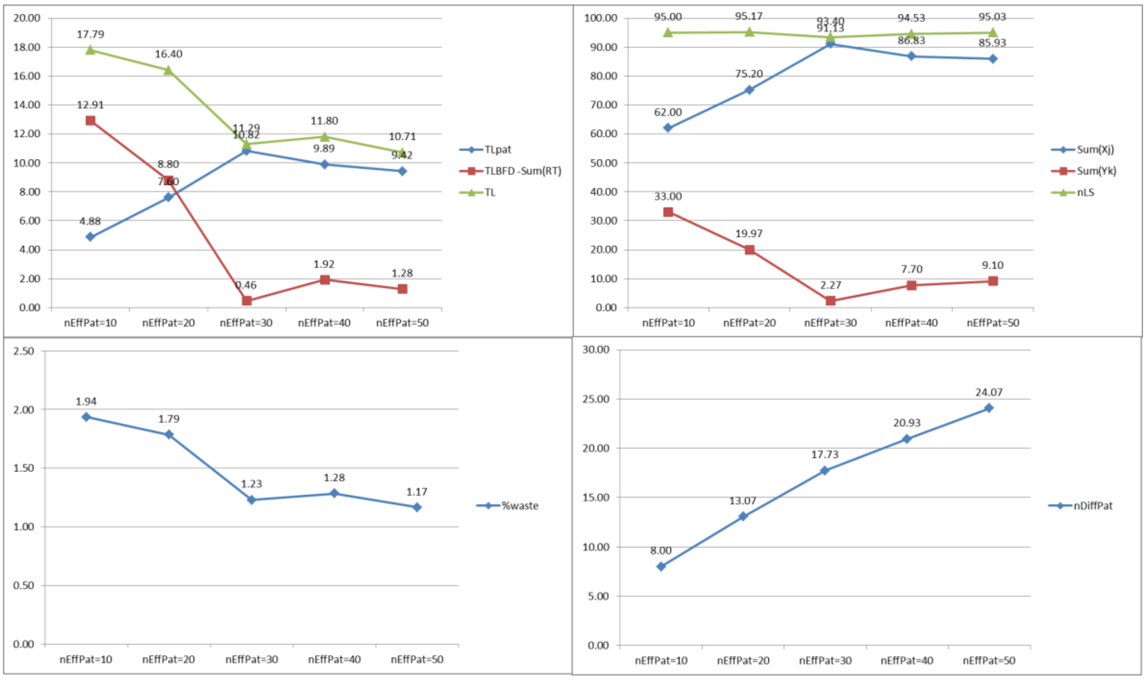

Figure 2. Results from the *nEffPat* test-set.

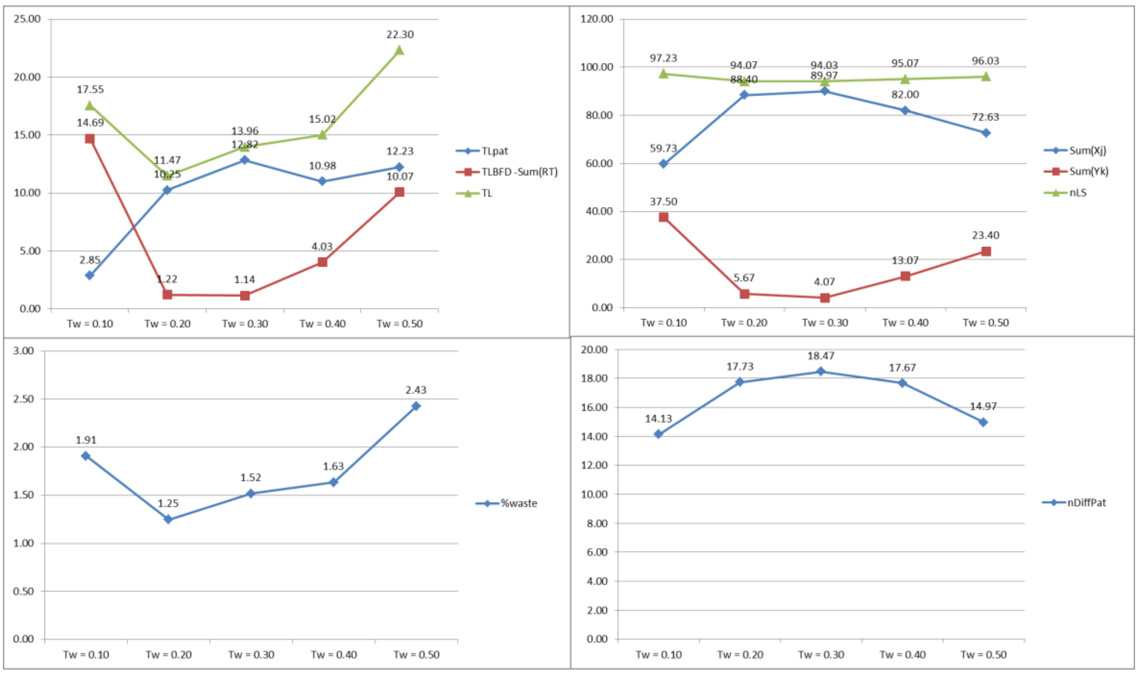

Figure 3. Results from the T_w test-set.

A. *nEffPat* test-set

The results graphs on Fig. 2 showed that *TL* and *%waste* decreased when *nEffPat* increased. This decreasing rate changed at around *nEffPat* = 30. It implied that results were better when using *nEffPat* more than 30. The *nLS* varied in a narrow range around 93 to 95. The $\sum_j X_j$ fell when the *nEffPat* was less than 30. It implied that good pattern-based solutions were hard to find when there were not enough *nEffPat*. The solutions from the *nEffPat*=50 group gave the smallest *%waste* = 1.17 but they could not give the smallest *nLS*. The solutions had to produce more Retails. On the other hand, the solutions from the *nEffPat*=30 group gave *%waste* = 1.23 which was slightly larger and they gave the smallest *nLS* = 93.40. The *nDiffPat* and *nEffPat* had a direct correlation with a declining acceleration; therefore, the ratio of (*nDiffPat*/*nEffPat*) was going down.

B. *Tw Test-set*

The results graphs on Fig. 3 showed that the relationship between *TL* (and *%waste*) and T_w was a u-shaped curve which had a bottom point at about T_w = 0.20. This implied that the solutions were good when using the suitable T_w (around 0.20), neither too large nor too small. The *nLS* varied in a range around 94 to 97. The solutions could be worse when the T_w was too large or too small. The solutions from the T_w=0.20 group gave the smallest *%waste* = 1.25 and also gave the smallest *nLS* = 94.07 (there were fewer Retails). The correlation of *nDiffPat* and T_w was an inverted u-shaped curve. The top point was around T_w=0.30 and it gave the largest ratio of (*nDiffPat*/*nEffPat*). However, at this point did not give the best solutions.

IV. CONCLUSIONS

This research contributed a development of a new procedure of the cutting-plan arrangement for construction reinforcement steel. The procedure help create low-trim-loss and low-stock-used cutting-plans. With this tool engineers and steel workers do not rely on their own intuition and can cut a bulk of reinforcement steels more efficiently. The general characteristic of the cutting reinforcement-steel problem is a strongly heterogeneous demand items which the pattern-based solution approach is suitable for.

A set of various and efficient cutting patterns are generated using the Intensive Search Algorithm and then used in the 1D-CSP optimization to determine the cutting repetitions. The constraints are set as the quantities of supplied items must not exceed the quantities of demand items or the oversupply constraints. This is different from the existing 1D-CSP optimization models and helps prevent oversupplied items which become wastes. However, the result will remain few undersupplied items which need to be cut with the Best Fit Decreasing algorithm.

The test including two test-sets was conducted. The results showed that the model gave slightly different solutions from different runtimes because the solution procedures were based on stochastic searching methods. However, they gave much smaller percentage of wastes compared to the current field practice. Also, the results showed that parameters: *nEffPat* and T_w could significantly affect the solutions. The small number of efficient cutting patterns (*nEffPat*) ruined a chance of getting a complete set of demand lengths. The large *nEffPat* increased the difficulty of the optimization process. The suitable *nEffPat* from the test-set was 30. The suitable T_w was 0.20 which was enough to generate a set of all different patterns and also restricted the trim loss of a pattern to a small amount.

The test results ensured that the developed model could create efficient cutting plans which gave low percentage of waste and number of stocks used. This research conducted the test based on one set of problem data (the demand list). The future research could investigate the effects of problem data because the results should depend on them to some extent.

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