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BI-OBJECTIVE OPTIMIZATION FOR REBAR CUTTING PLAN USING SYMBIOTIC ORGANISMS SEARCH

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ABSTRACT: In construction site usually fabricated the reinforced steel bars into the form of one-dimensional stocks and designed according to the structural specification. The purpose of cutting stock problems for rebar cutting plan (RCP) is to satisfy the project requirements and minimize the cutting losses. This study proposed the metaheuristic method symbiotic organisms search (SOS) to solve bi-objective rebar cutting plan (B-RCP) in one framework, to find the feasible cutting patterns along with the minimum total waste of the reinforced steel bar. To test the performance of the proposed SOS framework, the previous study case is set to be a benchmark. For real project instances of RCP are used to evaluate and validate the performance of SOS. The validation results from both cases of RCP show that SOS has better performance than those in previous studies. Thus, it is validated that SOS is a competitive algorithm for solving the RCP.

Keywords: rebar cutting plan, cutting patterns, waste, symbiotic organisms search.

1. INTRODUCTION

Construction industry is one of the biggest industries in the world, with a contribution towards the socio-economic growth and providing the infrastructure, such as bridge, warehouse, other basic building, and facilities. Due to this fact, it has also affected the consumption of construction material. Construction material such as concrete and reinforcing steel bars are commonly used in the construction project, such as foundation, columns, slabs, and beams. All of them represent a significant portion of total project budget.

Construction materials can be projected up to 60 percent of the construction costs, and reinforcing steel bar has a significant portion of the total project budget, approximately 20 percent of the entire project cost (Wang & Wang, 2010). Reinforced steel bars with ridges and grooves have a better mechanical anchoring and strength in reinforced concrete. They are used in applications such as reinforced concrete slabs, columns, prefabricated beams, and foundation. Improper management of reinforced steel bars can be directly affect the project (Salem, Shahin, & Khalifa, 2007). As there are various patterns of reinforced steel bars cutting to fulfill the demand requirement on site construction, many researchers have tried to solve the cutting stock problem of steel bars in different ways. The popular goal is to minimize the trim losses which occurs frequently in the construction sites. Thus, making a feasible cutting plan on site for steel bars is important for higher cost efficiency in construction management.

However, the availability of raw material lengths in the general market are commonly limited to 20 ft (6 m), 30 ft (9 m), 40 ft (12 m) thus waste of reinforcing rebar and surplus waste is unavoidable (Porwal & Hewage, 2012). Therefore, the raw steel bars must be cut to fit the design. To avoid these unnecessary costs, it is better to generate a cutting rebar plan in pursuit of cost-effectiveness by minimizing the waste of materials, site-place, and rebar procurement (Nikakhtar, Abbasian-Hosseini, Wong, & Zavichi, 2015). Moreover, in construction projects, minimizing material waste may not lead to complete cost saving because higher complexity of a rebar cutting plan would more likely confuse the workers and lower their productivity. Therefore to minimize the material waste should be implemented together with a simple of cutting rebar plan in order to achieve labor cost-efficient (Zheng, 2018).

The simplicity may come from a small number of cutting patterns which are a combination of various demand steel bar lengths. Overall, the following issues have been identified as significant concerns which need to be addressed in the cutting rebar plan: (1) how to provide the optimal cutting rebar plan to seek the minimum raw material, and (2) how to makes cutting plan as simple as possible to seek higher productivity of workers on-site.

In this paper, a case study is performed based on a 4-story building project in Indonesia. This case study was to give an insight of a practical steel bar cutting problem to minimize the waste with a practical constructability on site fabrication of reinforced steel bars. Therefore, a mathematical algorithm and constraints based on site construction project are used to assist the decision-making. The proposed SOS algorithm is implemented to helps the decision makers investigate the trade-off between benefits such as minimizing the raw material as well as the waste, and the number of cutting patterns in order to improve the workers productivity (Bai, Labi, & Sinha, 2012).

2. LITERATURE REVIEW

2.1 Rebar Management in Construction Industry

Reinforced steel bars are one of the most expensive materials in the construction industry. Reinforced steel bars are long narrow steel with a circular shape and it provides the tensile strength for the structure inside the concrete. It is important to manage the usage of rebars for construction because it makes up a significant cost of construction. Therefore, minimizing the raw material of reinforced steel bars not only improves the profitability of the construction projects and also has significant environmental benefits, because construction is a key pillar of the industrial sector in any country (Adjei, 2016). Rebars are generally used in several diameter sizes in the industry: 8, 10, 12, 16, 20, 25, and 32 in millimeters. Steelwork companies usually supply the reinforced steel bars in 12 m as standard sizes because it is the optimal length that average trucks can carry (Altınpulluk, 2019).

Reducing the trim losses of reinforced bars has attracted attention in the literature since it is one of the major cost items in the construction industry. A recent study published by Zheng et al (2018) considered the rebar material costs related to trim loss and rebar installation costs, including labor hours used in rebar stock processing, delivering, placing, and tying. These installation costs directly depend on the rebar layout plan. The authors claimed that benefits can be got from a trade-off between reducing waste and lowering the total cost by identifying the rebar layout arrangement plan and generating the rebar procurement plan, cutting plan, and crew installation plan. Another recent study by Benjaoran, Sooksil, and Metham (2019) studied the effect of demand variations on steel bars cutting loss and experimentally showed how the distribution of pieces of length ordered affects material utilization.

2.2 An Overview One-Dimensional Cutting Stock Problem

The first analytical method and most significant advance in solving cutting problems was the seminal work of Gilmore and Gomory (1961), in which they described their pattern generation technique for solving the one dimensional trim loss minimization problem using linear programming. Thus, the cutting stock problem can be modelled as:

$$\text{Minimize}: \sum_{i=1}^{n} X\text{i} \tag{1}$$

subject to:

$$\sum_{i=1}^{n} P_{ji}\, X_i \geq D_{j,}\, j = 1,2,..,S \tag{2}$$

$$\sum_{j=1}^{S} P_{ji}\, l_j \leq L \tag{3}$$

$$P_{ji} \geq 0 \text{ and integer}$$
$$X_i \geq 0 \text{ and integer}, \quad i = 1,2,\dots,Z$$

where:
L = the length of raw material rebar;
l_j = the length of each demand rebar cut, j = 1,2,…,S;
D_j = the demand of rebar j, j = 1,2,..,S ;
P_{ji} = (P_{1i},…, P_{2i},….) will be the cutting pattern, j = 1,2,…,S, where P_{ji} is the number of items j in the cutting pattern ;
X_i = The number of pattern i should be cut
And the objective is to minimize the trim loss can be formulated as :

$$\sum_{j=1}^{n} L_{ji}\, X_j - \sum_{j=1}^{n} l_j\, X_j \tag{4}$$

Many researchers have improved this method, and this method has been used widely, mainly to solve the cutting stock problem. Zheng (2018) developed an integer programming technique that can be applied to get the optimal rebar stock procurement plan and cutting plan in terms of minimal trim losses. Recently, along with the development of technology, many metaheuristic methods have been developed to solve the one-dimensional cutting stock problem with various models, Salem et al. (2007) presented a genetic algorithm to reduce the trim losses. C. Cheng and Bao (2018) proposed an improved artificial fish swarm algorithm to solve the cutting stock problem.

2.3 Simplicity in Rebar Cutting Plan (RCP)

In construction industry, construction projects seem to be complex as a result of the uncertainty created by different workers and factors. Identifying the nature of complexity, reducing unnecessary complexity, and increasing the simplicity in construction projects might lead to better management of the construction process (Pannanen & Koskela, 2005). Simplicity in the construction itself means that something is easy to understand, easy to work on it and to improve the constructability.

Thus, a previous study revealed a new application for simplifying the cutting rebar process in the industry, to limit the number of cutting patterns. Thus, reducing the number of different patterns will result in faster time more stable results of the production process for cutting rebar orders (Kolen & Spieksma, 2000). For instance, in a steelwork company or the construction project, during the process of rebar cutting the positions of the cutting knives in the machine will have to be adjusted for each new cutting pattern. Thus, it is advantageous to organize the cutting plan with a limited number of patterns (Yanasse, Limeira, & Research, 2006). Also, the previous study mentioned that in some situations, the cost of production may vary depending on pattern changes in terms of the time and workers needed to prepare equipment (Cerqueira & Yanasse, 2009).

2.4 Metaheuristic Methods to Solve the RCP

The purpose of the one-dimensional cutting stock problem is to minimize the trim losses as well as the raw material. The first step to solve this cutting stock problem is to generate all the cutting patterns. After generating the cutting patterns, then find the combination of cutting patterns to create the rebar cutting plan. The new approach of optimization called metaheuristics as proposed by Glover and Laguna (1998a), is local search heuristic has the ability that can allow escaping local optima. In recent years, the number of metaheuristic algorithms is growing significantly because researchers are quite interested to create a more powerful metaheuristic to solve the optimization problem. These metaheuristic algorithms that have been applied to solve cutting stock problem (CSP) are ant colony optimization (ACO), tabu search (TS), and genetic algorithm (GA).

The ACO is the probability algorithm used for searching optimization paths, proposed by Marco Dorigo in his doctoral dissertation in 1992 (Dorigo, Birattari, & Stutzle, 2006). This algorithm is adapted from ants' social or behavior to search a portion of food or paths and it is called pheromone. From the early nineties, when the first ant colony optimization algorithm was proposed, ACO attracted the attention of researchers and it has many successful applications that are now available. Thus, there are many improvements for the ACO algorithm, including the improvements of the algorithm in self-adaptive, increasing the diversity of the various group, improvements for each local search, and combining with the global optimization algorithm (Pei, Wang, & Zhang, 2012). In the previous study, a revised version of ant colony algorithm to solve the one-dimensional cutting stock problem is presented by Eshghi, Javanshir, and Practice (2008).

Tabu search is a metaheuristic search method employing local search methods used for mathematical optimization proposed by Glover in 1990 (Glover & Laguna, 1998b). One of the important parts of tabu search is its use of adaptive memory, which creates a more flexible search behavior. In the previous research, an improved tabu search with mixed objective function for one-dimensional cutting stock problems is presented by Yang, Sung, and Weng (2006), because the simple tabu search is weak in solving the problem efficiently and effectively.

The GA is a metaheuristic inspired by the process of natural selection such as reproduction, crossover, and mutation in searching the space of problem as chromosomes, and developed by John Holland and his colleague in 1970 (Holland, 1984). The GA have been successfully applied in numerous fields to solve the CSP, such as the GA applied to solve the CSP of reinforced steel bars with minimum waste (Salem et al., 2007), and an application of GA to optimize the multiple length cutting stock problem (Chen et al., 2019).

3. METHODOLOGY

This study implements the SOS algorithm with an ε-constraint method and use MATLAB 2019b to solve the bi-objective rebar cutting plan (B-RCP). The optimal solution of the cutting pattern will manually export to Microsoft Excel. In Microsoft Excel, the optimal solution will be presented Pareto front and the result will be compared with the PSO algorithm to verify the result of the proposed algorithm. Figure 1 shows the flowchart of the bi-objective optimization procedure using the ε-constraint method.

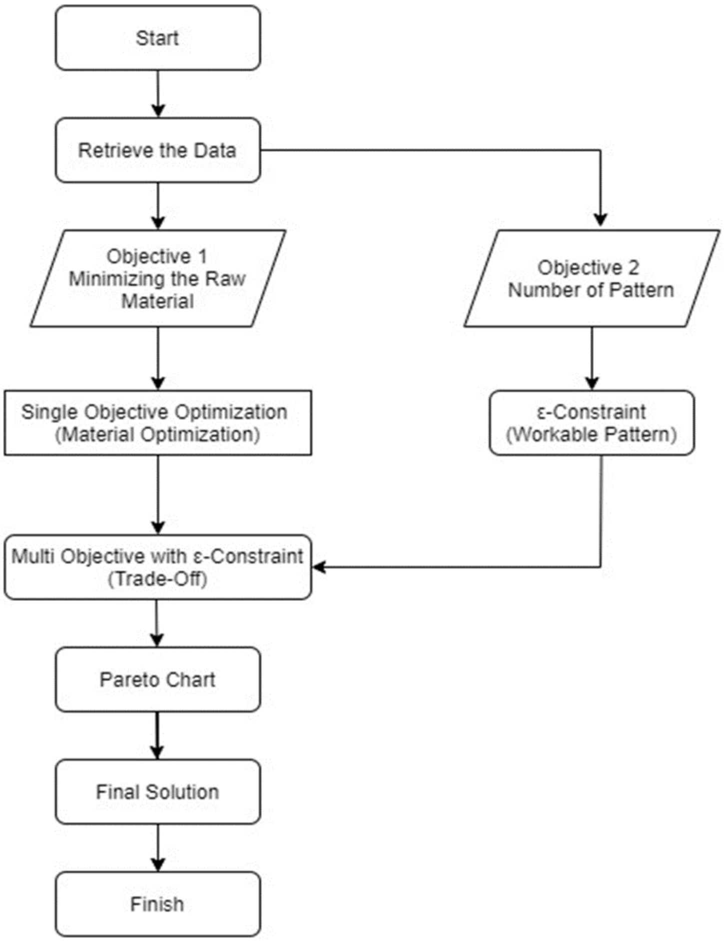

Figure 1. Flowchart of the bi-objective optimization

3.1 Symbiotic Organisms Search

Symbiotic organisms search (SOS) is a metaheuristic optimization algorithm to solve the numerical and engineering problem, proposed by M.-Y. Cheng and Prayogo (2014). SOS simulates the symbiotic interaction strategies between each organism to live in the ecosystems and employs a population-based search strategy to search for the optimal solution to a given objective function. The major advantage of SOS is that it has no algorithmic parameter, thus saving the effort of parameter tuning.

The first step of SOS is to create an initial population called the ecosystem. In this ecosystem, SOS creates a random group of organisms for the search space. Each organisms represents each candidate's solution to the problem. Each organism in the ecosystem is associated with a certain fitness value, which reflects the degree of adaptation to the desired objective. Figure 2 shows the flowchart of SOS for solving the bi-objective optimization rebar cutting plan.

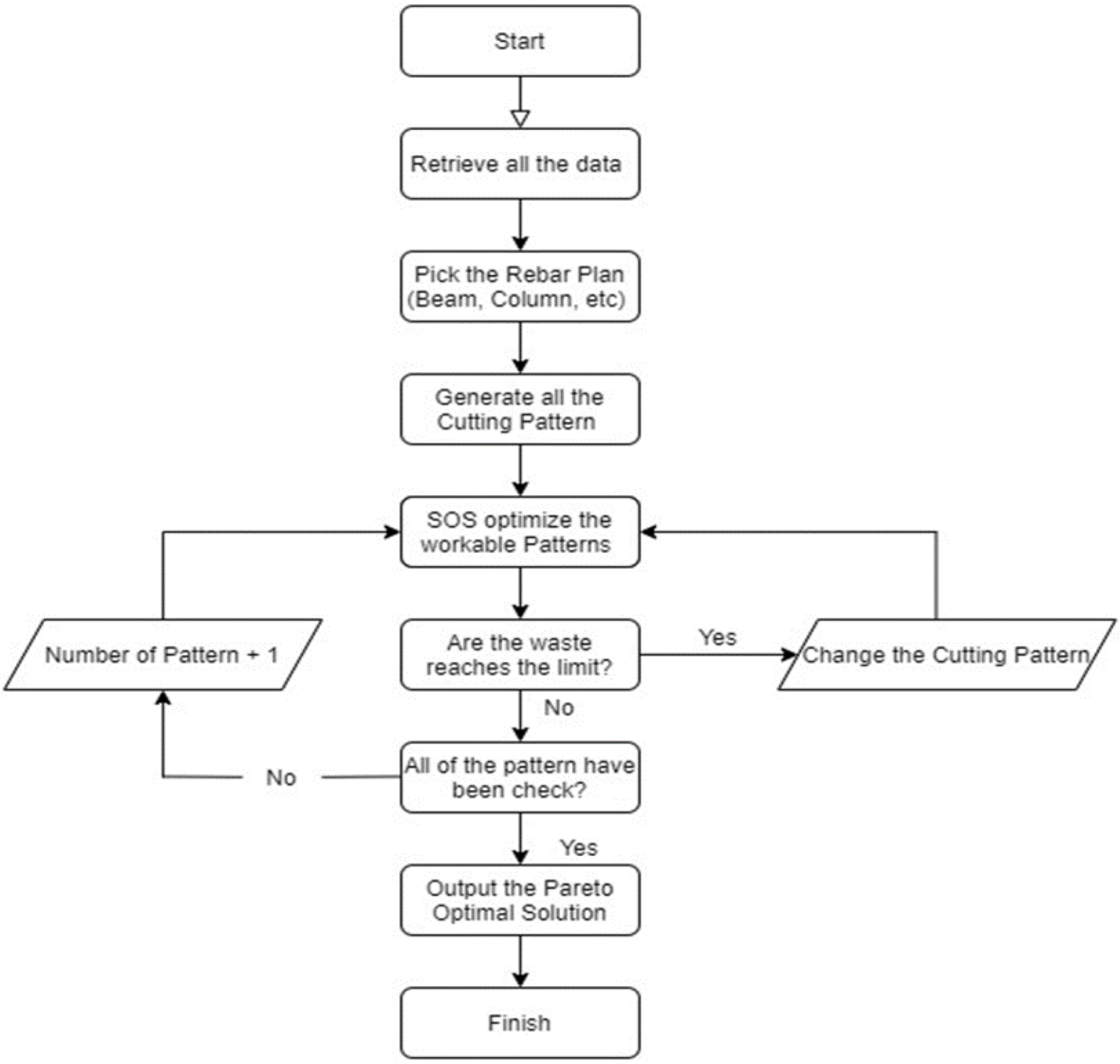

Figure 2. SOS for bi-objective rebar cutting plan flowchart

After the material waste and the number of the cutting pattern are calculated, the next step is to seek non-dominated solutions between these objectives, minimizing the waste by considering the number of cutting patterns. For the bi-objective optimization problem, a Pareto optimal solution is applied to simultaneously optimize the objective (Bakasoglu, Owen, & Gindy, 1999). Then, the Pareto optimal solutions are chosen by comparing all the result alternatives between minimum waste and the number of cutting patterns. Because the main objective function is to minimize the waste of reinforced bars along with the minimum number of cutting patterns, the ratings of non-dominated solutions will be sorted in an ascending order: smaller goes first.

For an illustration of the Pareto front, the data sets have been given in Table 1. After completing the ranking assessment, the Pareto front will be made based on the above assessment of the non-dominated solution in order to investigate the trade-off between the material waste and the number of cutting patterns. Figure 3 is shown to illustrate the Pareto front for Table 1.

Table 1. Data illustration for Pareto front

Summarize for Illustration						
Number	**Total Waste**	**Rank Based on T_w(1)**	**Number of cutting pattern**	**Rank Based on N_{cp} (2)**	**Total Rank (1) + (2)**	**Rank**
1	11.94%	17	3	1	18	8
2	12.88%	18	3	1	19	13
3	11.24%	16	3	1	17	4
4	9.56%	13	4	4	17	4
5	9.67%	14	4	4	18	8
6	10.34%	15	4	4	19	13
7	9.32%	11	5	7	18	8
8	8.45%	9	5	7	16	2
9	8.24%	8	5	7	15	1
10	9.42%	12	6	10	22	18
11	8.67%	10	6	10	20	16
12	7.23%	7	6	10	17	4
13	6.34%	3	7	13	16	2
14	7.05%	6	7	13	19	13
15	6.94%	5	7	13	18	8
16	5.21%	2	8	16	18	8
17	4.68%	1	8	16	17	4
18	6.89%	4	8	16	20	16

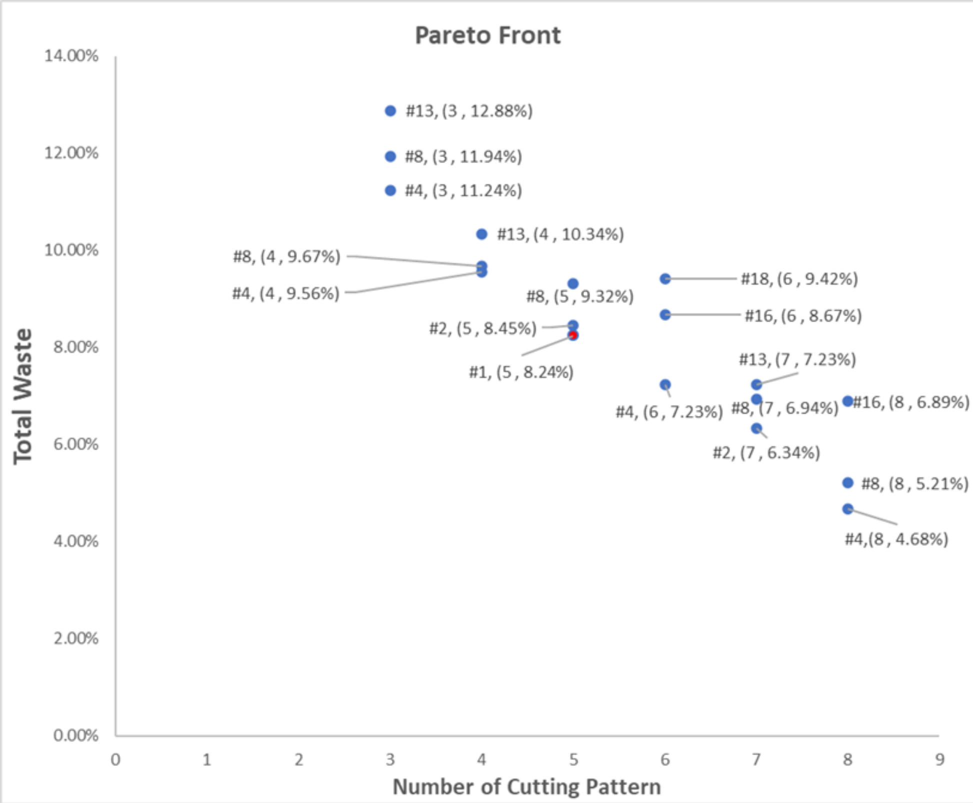

Figure 3. Pareto front between total waste and number of cutting patterns

In Figure 3, the red point shows rank number #1, with the number of cutting patterns, N_{cp}, of 5 and the total waste, T_w, of 8,24%. Some practical engineers suggest if the construction scope is small such as a warehouse, and residential house construction, they choose simplicity rather than waste. However, if the construction scope is quite large such as bridges, and tall buildings, they choose minimum waste rather than simplicity. Still, the decision-maker can make their choice based on their preference.

4. CASE STUDY

4.1 Evaluation with Previous Benchmarks

The benchmarks data is retrieved from the previous study by Melhem, Maher, and Sundermeier (2021). This set of data is a part of the demanded reinforce steel bars for the power plant project, namely SD3-Ø20. The original paper considers the minimum waste of rebars along with two different pairs of lengths and the 12-m standard lengths. However, this study will ignore the multiple lengths and focus on the single standard lengths, then search for the minimum waste along with minimizing the total utilization of reinforced steel bars and lowering the number of cutting patterns in a construction project. The detail of the data can be seen in Table 2.

Table 2. Demand rebar of SD3-Ø20; Source: (Melhem et al., 2021)

Data Demand of Rebars from Previous Paper (Ø-20)				
Length (m)	Number of Pieces	Length (m)	Density (kg/m)	Weight (kg)
0.80	1330	1064	2.464	2622
3.00	1330	3990	2.464	9831
4.00	1330	5320	2.464	13108
7.50	1330	9975	2.464	24578
7.85	700	5495	2.464	13540
8.15	42	342.3	2.464	843
8.50	1330	11305	2.464	27856
11.00	1400	15400	2.464	37946
Total Length (m)		52891.3	Total Weight (Kg)	130324

4.2 Cutting Plan Results (Benchmarks)

Before optimization, all of the possible cutting patterns were obtained from pattern generator by Pierce method is 102 cutting patterns. Then, the SOS and PSO algorithms are programmed in MATLAB to perform bi-objective optimization. Afterwards, the best result of cutting patterns will be manually exported to excel. The details of cutting patterns from SOS and PSO for N_{cp} = 5 will be shown in Tables 3 and 4.

Taking Tables 3 and 4 as an example, in the first column (No. Plan) refer as *Ncp*, and the second column shows how many times that the pattern type is used. The Cutting Length means the total length of each pattern type without trim losses, and the next column is the total of raw material of each pattern type. The middle columns show the ordered rebar with the cutting plan. For example, the calculation of cutting length in first row is quantity of pattern * ordered bars * the length of each ordered bar: 42 * 4 *0.8 + 42 * 1 * 8.15 = 476.7 meters, and for the calculation of total raw bars is quantity of pattern * standard length of raw: 42 * 12 = 504 meters. Afterward, the 53641.7 meters and 57624 meters is the summation of cutting length and the total raw material respectively.

At the bottom table, sum X_i is the total cutting pattern that we used. For the trim loss is the total waste in meters. Therefore, to get the total waste in meters the calculation is total raw bars – cutting length + surplus cut: 57624 - 53641.7 + 750.4 = 4732.7 meters. Thus, to calculate the final output of waste percentage is trim losses divided by total raw bars
(4732.7 / 57624) * 100% = 8.21%

The results in Table 5 show that SOS and PSO achieved better results than the original paper in all aspects, including total raw material as well as the total waste. However, only SOS is able to obtain the lowest material waste with the lowest number of cutting patterns in this case, followed by PSO which is obtain 9,53% of material waste with 5 of number cutting patterns. Both algorithms can obtain the minimum raw material with a total length of 57624 meters along with the total waste of 8,21%.

Table 3. Cutting pattern results from the SOS (N_{cp} = 5)

No. Plan	Quantity of Pattern	Number of Bars (B_{ij})of Length Vj To be cut from the standard length								$X_i * V_i * B_{ij}$ (Cutting Length)	Xi * L (Total Raw Bars Length)
		V1 (m)	V2 (m)	V3 (m)	V4 (m)	V5 (m)	V6 (m)	V7 (m)	V8 (m)		
		0.8	3	4	7.5	7.85	8.15	8.5	11		
5	42	4					1			476.7	504
	700	3				1				7175	8400
	1330		1					1		15295	15960
	1330			1	1					15295	15960
	1400								1	15400	16800
	Demand	1330	1330	1330	1330	700	42	1330	1400	53641.7	57624
	Cut	2268	1330	1330	1330	700	42	1330	1400		
	Surplus	938	0	0	0	0	0	0	0		
	Surplus Total	750.4	0	0	0	0	0	0	0		
					Total Surplus (m)		(Sum Surplus Cut)			750.4	
					Sum		(Sum X_i)			4802	
		Length of Raw Bar (m)		12	Trim Loss		(TRB - CL + SC)			4732.7	
					Total Waste (%)		(Trim Loss/ TRB)*100			8.21%	

Table 4. Cutting pattern results from the PSO (*Ncp* = 5)

No. Plan	Quantity of Pattern	Pattern -Number of Bars (B_{ij})of Length Vj To be cut from the standard length								$X_i * V_i * B_{ij}$ (Cutting Length)	Xi * L (Total Raw Bars Length)
		V1 (m)	V2 (m)	V3 (m)	V4 (m)	V5 (m)	V6 (m)	V7 (m)	V8 (m)		
		0.8	3	4	7.5	7.85	8.15	8.5	11		
5	700	4	0	0	0	1	0	0	0	7735	8400
	42	4	0	0	0	0	1	0	0	476.7	504
	1400	0	1	0	0	0	0	1	0	16100	16800
	1330	0	0	1	1	0	0	0	0	15295	15960
	1400	0	0	0	0	0	0	0	1	15400	16800
	Demand	1330	1330	1330	1330	700	42	1330	1400	55006.7	58464
	Cut	2968	1400	1330	1330	700	42	1400	1400		
	Surplus	1638	70	0	0	0	0	70	0		
	Surplus Total bar(m)	1310.4	210	0	0	0	0	595	0		
					Total Surplus (m)		(Sum Surplus Cut)			2115.4	
					Sum		(Sum X_i)			4872	
		Length of Raw Bar (m)		12	Trim Loss		(TRB - CL + SC)			5572.7	
					Total Waste (%)		(Trim Loss/ TRB)*100			9.53%	

Table 5. Comparison of the results with previous study by Melhem et al. (2021)

Metaheuristics	Number of Cutting Patterns	Total Length of Raw Material (m)	Total Waste (%)
SOS	**5**	**57624**	**8,21**
	6	57624	8,21
	7	56724	8,21
PSO	5	58464	9,53
	6	57624	8,21
	7	57624	8,21
Melhem et al. (2021)	8	57636	8,23

4.3 Further Analysis

In a further analysis, the contractor lists the demand bars D-16 for 4 story building, which will be cut simultaneously for this project. This data set contains 8 types of lengths to satisfy the requirement in the project. The data that has been listed by the contractor can be seen in Table 6.

Table 6. Data Rebars D-16 for pile caps, sloofs, and columns

Demand of Rebars D-16 for Pile Cap ,Sloof and Columns				
Length (m)	Number of Pieces	Length (m)	Density (kg/m)	Weight (kg)
1.55	480	744	1.58	1176
2.3	560	1288	1.58	2035
3	36	108	1.58	171
4.15	12	49.8	1.58	79
5.5	832	4576	1.58	7230
6	3676	22056	1.58	34848
8	162	1296	1.58	2048
9	342	3078	1.58	4863
	Total Length (m)	33195.8	Total Weight (Kg)	52449

4.4 Cutting Plan Result (Further Analysis)

In this case study, there are several feasible alternatives for cutting patterns. The best result of cutting patterns from the SOS and PSO are shown in Table 7 and Table 8. These tables including the total waste, the cutting patterns, demand of rebar, and the total of pattern types, and the total feasible cutting pattern results from pattern generator by Pierce method is 124 possible cutting patterns.

Table 7. Cutting pattern results using the SOS (N_{cp} = 7)

No. Plan	Quantity of Pattern	Pattern -Number of Bars (B_{ij})of Length Vj To be cut from the standard length								$X_i * V_i * B_{ij}$ (Cutting Length)	Xi * L (Total Raw Bars Length)
		V1 (m)	V2 (m)	V3 (m)	V4 (m)	V5 (m)	V6 (m)	V7 (m)	V8 (m)		
		1.55	2.3	3	4.15	5.5	6	8	9		
7	17	3	0	1	1	0	0	0	0	200.6	204
	83	3	0	0	0	1	0	0	0	842.45	996
	19	1	3	1	0	0	0	0	0	217.55	228
	162	1	1	0	0	0	0	1	0	1919.7	1944
	342	0	1	0	0	0	0	0	1	3864.6	4104
	749	0	0	0	0	1	1	0	0	8613.5	8988
	1464	0	0	0	0	0	2	0	0	17568	17568
	Demand	480	560	36	12	832	3676	162	342	33226.4	34032
	Cut	481	561	36	17	832	3677	162	342		
	Surplus	1	1	0	5	0	1	0	0		
	Surplus Total bar(m)	1.55	2.3	0	20.75	0	6	0	0		
					Total Surplus (m)	(Sum Surplus Cut)				30.6	
					Sum	$(Sum X_i)$				2836	
		Length of Raw Bar (		12	Trim Loss	(TRB - CL + SC)				836.2	
					Total Waste (%)	(Trim Loss/ TRB)*100				2.46%	

Table 8. Cutting pattern results using the PSO (N_{cp} = 9)

No. Plan	Quantity of Pattern	Pattern -Number of Bars (B_{ij}) of Length Vj To be cut from the standard length								$X_i * V_i * B_{ij}$ (Cutting Length)	Xi * L (Total Raw Bars Length)
		V1 (m)	V2 (m)	V3 (m)	V4 (m)	V5 (m)	V6 (m)	V7 (m)	V8 (m)		
		1.55	2.3	3	4.15	5.5	6	8	9		
9	12	3	0	1	1	0	0	0	0	141.6	144
	113	2	1	0	0	0	1	0	0	1288.2	1356
	28	2	0	0	0	0	1	0	0	254.8	336
	162	1	1	0	0	0	0	1	0	1919.7	1944
	342	0	1	0	0	0	0	0	1	3864.6	4104
	12	0	0	2	0	0	1	0	0	144	144
	1	0	0	0	1	0	1	0	0	10.15	12
	832	0	0	0	0	1	1	0	0	9568	9984
	1345	0	0	0	0	0	2	0	0	16140	16140
	Demand	480	560	36	12	832	3676	162	342	33331.05	34164
	Cut	480	617	36	13	832	3676	162	342		
	Surplus	0	57	0	1	0	0	0	0		
	Total bar(m)	0	131.1	0	4.15	0	0	0	0		
					Total Surplus (m)	(Sum Surplus Cut)				135.25	
					Sum	(Sum X_j)				2847	
		Length of Raw Bar		12	Trim Loss	(TRB - CL + SC)				968.2	
					Total Waste (%)	(Trim Loss/ TRB)*100				2.83%	

Afterward, the result comparison between the performance of SOS and PSO is shown in Table 9. It shows that the SOS and PSO achieved the same result when the number of cutting pattern is 5. When the number of patterns is 6, 7 ,8, 9 and 10, SOS is superior to PSO in minimizing the length of raw material and total waste. It is also SOS is able to obtain the lowest material waste of 2.42% in N_{cp} 10 better results than PSO in pattern types of 6,7,8,9, and 10 including total raw material along with the total waste. It is also SOS is able to obtain the lowest material waste of 2.42% in N_{cp} 10, followed by PSO which is obtain 2.83% of material waste with 9 number cutting patterns.

Table 9. Comparison of the results between the SOS and PSO

Metaheuristics	**Number of Cutting Patterns**	**Total Length of Raw Material (m)**	**Total Waste (%)**
SOS	5	38088	12.84
	6	34512	3.81
	7	**34032**	**2.46**
	8	34056	2.53
	9	34044	2.49
	10	34020	2.42
PSO	5	38088	12.84
	6	35076	5.36
	7	34200	2.94
	8	34644	4.18
	9	34164	2.83
	10	34704	4.35

4.5 Pareto Trade-off Analysis (SOS results)

In this section, Pareto bi-objective optimization was applied in order to achieve the solution between the number of cutting patterns and material waste. The number of cutting patterns and the total waste percentage for each cutting plan along with the rank of each objective are listed in Table 10.

Table 10. Results of total waste, t_w, and number of cutting patterns, n_{cp}

Summarize						
Number	Total Waste	Rank Based on T_w(1)	Number of cutting pattern	Rank Based on N_{cp} (2)	Total Rank (1) + (2)	Rank
1	12.84%	16	5	1	17	7
2	13.17%	18	5	1	19	11
3	12.84%	17	5	1	18	10
4	4.74%	15	6	4	19	11
5	3.81%	11	6	4	15	3
6	3.91%	13	6	4	17	7
7	3.58%	8	7	7	15	3
8	2.46%	2	7	7	9	1
9	3.85%	12	7	7	19	11
10	2.53%	4	8	10	14	2
11	3.78%	10	8	10	20	14
12	3.24%	6	8	10	16	5
13	2.49%	3	9	13	16	5
14	3.68%	9	9	13	22	16
15	4.51%	14	9	13	27	18
16	2.42%	1	10	16	17	7
17	2.53%	5	10	16	21	15
18	3.34%	7	10	16	23	17

Next, each of the non-domination was calculated to determine their rank for each objective, by summing the rank values of these two objectives. Thus, the new rank was made, and it can identify the optimal trade-off solution. To be seen clearly besides using the table only, the Pareto tradeoff graph is provided to illustrate the results in Table 10, as it is shown in Figure 4.

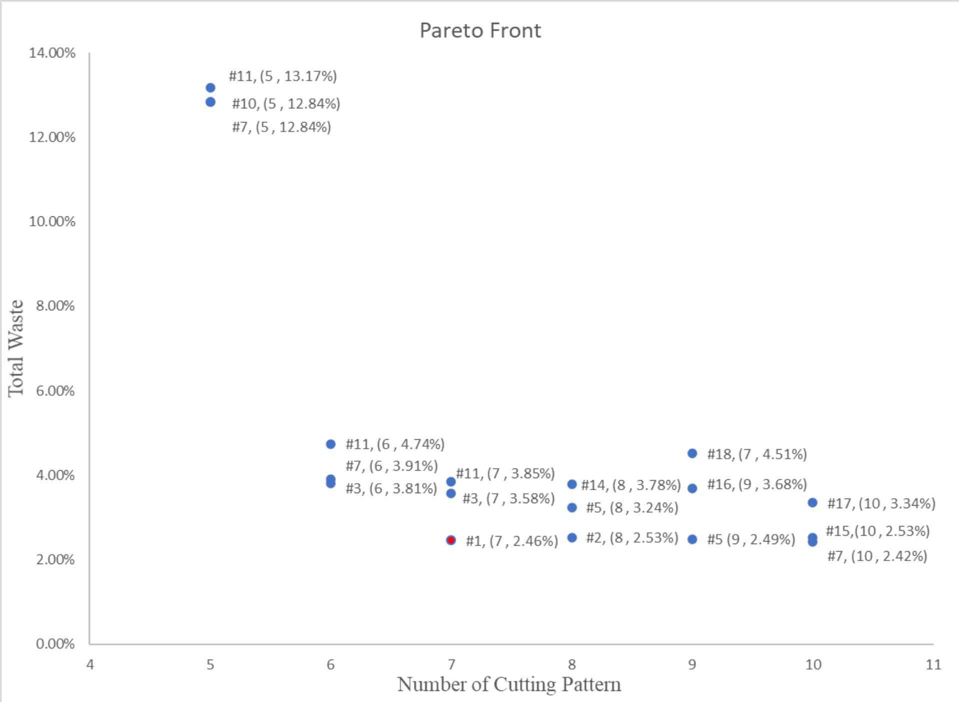

Figure 4. Pareto front between total waste and number of cutting pattern

According to the B-RCP results, the cutting pattern plan #8 in Table 10 with the red point at Figure 4 has the highest rank, thus providing the best trade-off plan with regards to each objective. Specifically, cutting plan #8 has the N_{cp} of 7, and has the second-lowest total material waste at 2.46%, among all the 18 alternative cutting plans. In Figure 5 shows the best of non-dominated solutions from each of number cutting pattern.

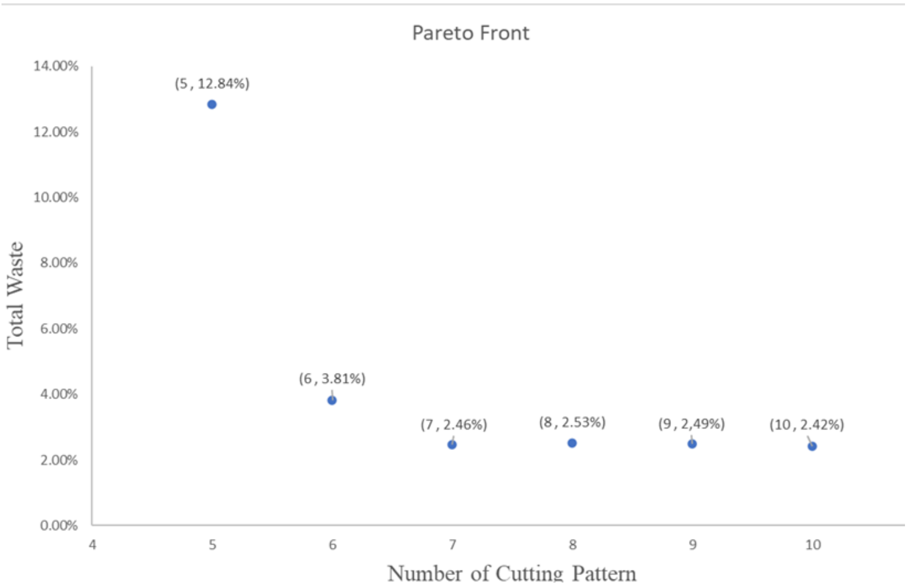

Figure 5. The non-dominated solutions in Pareto front

In Figure 5, increasing the number of cutting pattern may not always reduce the material waste, as in the example of #7 to #8. From point #7 to #8, the material waste increase around 0.07%. However, cutting plan #10 has the lowest material waste at 2.42%.

In practical cases, some of the site engineers suggest simplicity rather than waste to achieve efficient work. However, the decision makers can still make their choices according to the situation and personal judgment. Still, the presence of the non-dominated solutions provides adequate assistance to assist decision makers in determining the best cutting plan for reinforcement rebars.

5. CONCLUSIONS

This study introduces the B-RCP to investigate the optimal trade-off between reducing material waste and lowering the number of cutting patterns. The primary purpose of this study is to handle B-RCP to minimize the total waste of the utilization of reinforcing steel bars along with the number of cutting patterns that lead to simplicity to improve the constructability in construction site.

The validation results from the real project case from Melhem et al. (2021) show that SOS is able to achieve better solutions compared to PSO and the paper result in both minimum total waste along with 5 types of cutting patterns in around 5 runs the of an experiment. SOS found the minimum waste of 8.21% compared to 9.53% for PSO in 5 types of cutting patterns. It is shown that the obtained cutting patterns for the projects can satisfy the demand for steel bars. Thus, it is shown that the proposed SOS algorithm can solve B-RCP with better results efficiently.

For the further analysis results from the real project case of a 4-story building in Indonesia (D16) show that SOS could achieve better solutions compared to PSO in the minimum total waste (Tw) of each number cutting pattern in 5 runs of the experiment which indicates that SOS was not be trapped in the local optima solution and can escape to achieve better global solutions. SOS found a minimum total waste of 2.42% compared to 2.83% for PSO. From the Pareto Front, it is shown that the plan number 8 has the *Ncp* of 7, and has the second-lowest total material waste at 2.46%, among all the 18 alternative cutting plans. The Pareto front also shows that increasing the number of cutting patterns may not always reduce material waste.

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