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Article

Optimization of Bar Cutting Lists in Reinforced Concrete Columns Utilizing the Particle Swarm Optimization Algorithm: A Case Study of a High-Rise Building

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Abstract. In the construction of reinforced concrete structures, rebar bending and cutting lists are commonly developed. However, in practice, engineers often develop them based on ease of design. This involves specifying splicing patterns manually, rather than using optimization techniques. To address this issue, a framework for optimizing rebar cutting and splicing patterns using Particle Swarm Optimization (PSO) is proposed in this study. Two areas of a high-rise building were used as a case study to demonstrate the practical application. The framework first organizes the columns by reinforcement patterns before further subdividing the column categories' rebars by diameter and end patterns. Next, it randomizes splicing positions to serve as initial positions for PSO. Then, the corresponding cutting lengths are calculated and used for waste calculation. These processes are iterated to minimize waste. The results showed a significant reduction in waste across both areas, from 13.86% to 2.88%, compared to the as-built bar cutting list. This highlights the effectiveness of the framework in improving material efficiency and supporting sustainability. To validate practicality, the cutting and bending processes using machinery integrated with a QR code reader at a factory were demonstrated. This ensures the precise execution of the optimized list and enhances its robustness in real-world applications.

Keywords: Bar cutting list optimization, optimization, particle swarm optimization, high-rise building, reinforcement concrete, sustainability.

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1. Introduction

Construction material waste poses a significant economic and environmental challenge on a global scale [1]. Achieving sustainable construction practices hinges crucially on the efficient utilization of materials. Within the construction industry, particularly in the domain of reinforced concrete structures, minimizing material wastage has been a persistent issue, with inefficiencies in rebar cutting processes standing out as a notable contributor to this challenge [2-6]. Given that rebar represents over 30% of the total cost in civil engineering projects [7], optimizing bending schedules and cutting lists not only serves to reduce waste but also plays a pivotal role in lowering overall project costs and lessening the environmental impact.

In contemporary construction practices for reinforced concrete structures, the creation of rebar bending schedules and cutting lists is essential for optimizing the use of rebars, minimizing material waste, and ensuring the structural integrity of buildings [8]. Traditionally, engineers in developing countries like Thailand, generate these schedules based on design convenience and practical considerations. This approach often involves manually defining a limited number of splicing patterns, rather than leveraging advanced optimization techniques. In addition, the focus of existing optimization software is frequently restricted to improving the efficiency of rebar cutting based on these predefined splicing patterns, overlooking further opportunities for enhancing efficiency and reducing waste. Moreover, the progress in utilizing optimized splicing patterns is impeded by the lack of advanced cutting and bending machinery, which further constrains the industry's ability to adopt more efficient practices. Consequently, rebar cutting waste arises from purchasing market-length rebars based on the inefficient cutting patterns [9], and thus rebars have been identified as a major component of construction waste in Thailand, according to a comprehensive survey conducted in 2002 [10-11].

As advancements in computational algorithms as well as cutting and bending technologies continue to emerge, coupled with a growing emphasis on sustainability, there is a compelling need to develop a more comprehensive framework for optimizing both rebar cutting and splicing patterns.

Various techniques have been employed for the task in a variety of reinforced structural components. For instance, Zahra et al. [12] applied Linear Integer Programming (LIP) to optimize lap splicing patterns in reinforced concrete columns and shear walls of an existing six-story building to minimize steel waste, and the results demonstrated a significant reduction. Zheng et al. (2018) [13] developed a sophisticated three-stage optimization framework, employing Integer Programming (IP) in the initial phase to generate optimal rebar stock procurement and cutting plans for alternative layout arrangements in a reinforced concrete slab case study. The subsequent stages incorporated comprehensive analyses of crew installation costs and field productivity metrics, encompassing rebar cutting, handling, and installation processes. The framework proved effective in generating balanced solutions that simultaneously addressed material waste reduction and total cost optimization, demonstrating the potential for achieving multiple operational objectives through systematic optimization approaches. This methodology particularly highlighted the importance of considering both material efficiency and labor-related parameters in achieving optimal construction outcomes. Salem et al. (2007) [14] demonstrated the effectiveness of combining Genetic Algorithm (GA) with Linear Programming (LP) and IP. This framework was validated through three real-world case studies, where the framework exhibited superior performance in minimizing cutting waste compared to conventional as-built cutting schedules. Their empirical findings substantiated the framework's significant potential for waste reduction in practical construction applications, establishing a compelling case for the adoption of advanced algorithmic solutions in construction resource optimization. Additionally, the application of various stochastic optimization algorithms was demonstrated in [15-17]. While existing research has made significant contributions to understanding cutting waste optimization, there remains a notable scarcity of studies employing continuous optimization algorithms like Particle Swarm Optimization (PSO) [18], a computational technique inspired by the collective behavior of birds and fish designed to tackle non-linear and non-convex optimization problems, in cutting pattern optimization. Furthermore, the application of PSO specifically for bar-cutting optimization in actual high-rise building reinforced concrete columns incorporating mechanical splicing couplers represents an especially underexplored area in the current literature.

In response to this need, this study introduces an innovative framework to address the concerns through the application of such the optimization algorithm. The framework aims to enhance both the cutting and splicing patterns by employing PSO to identify optimal configurations considering ease of construction and practicability. To validate the practical applicability of this framework, it was applied to two critical areas of a newly constructed high-rise building in central Bangkok, Thailand, adhering to the American Concrete Institute (ACI) standards.

The proposed framework starts by organizing reinforcement rebars into groups based on their diameter, structural component type, and location to which the component belongs, simplifying the optimization process and ensuring that the outcomes are practically viable. Then, splicing positions are initialized randomly to serve as the starting points for the PSO algorithm. The framework then calculates the corresponding cutting lengths based on design and construction standards while considering the available market lengths of rebar. These are used to assess material waste. This iterative process continues until the results are refined to minimize waste effectively. Subsequently, splicing pattern and cutting position diagrams are developed for illustration, and bar cutting and bending schedules are generated alongside corresponding QR codes. To further validate the practicality of these results, the cutting and bending processes were integrated with QR codes and barcode readers at a factory as a demonstration. This ensures precise execution of the optimized cutting plans and reinforced the real-world applicability of the approach.

By comparing actual rebar wastage observed in as-built bar cutting and bending schedules with outcomes achieved through PSO-based optimization, this research aims to demonstrate the effectiveness of computational optimization techniques in enhancing construction efficiency and sustainability. These advancements not only promise to reduce environmental impact but also contribute to the economic viability of construction projects, aligning with broader goals of sustainable development in the built environment.

The manuscript begins with an introduction to the adopted optimization algorithm and the proposed framework, detailed in the second and third sections respectively. Following this, the proposal is applied to a case study to demonstrate its practical application. The results of this case study are then presented and discussed in the fourth section. Finally, the manuscript concludes with a comprehensive analysis of the findings and their implications in the concluding section.

2. Particle Swarm Optimization (PSO)

PSO [18] is a metaheuristic optimization algorithm inspired by the collective behaviors observed in bird flocking or fish schooling search for food. This technique is extensively applied to solve diverse optimization challenges as shown in various studies [19-21] such as engineering design, resource allocation, as well as scheduling by simulating a swarm of particles i.e., candidate solutions that systematically explore the d-dimensional search space to locate the best possible solution while avoiding local optima. Each particle dynamically adjusts its position and velocity based on its own historical best position and the best positions achieved by neighboring particles so far. This cooperative strategy enables the swarm to progressively converge towards the optimal solution through successive iterations. The flowchart of the algorithm is illustrated in Fig. 1.

PSO begins by initializing the positions of all particles, $\mathrm{X} = [\mathrm{X}_i \text{ for } i = 1, 2, \ldots, n^{th} \text{ particle}]$, where $\mathrm{X}_i = [x_{ij} \text{ for } j = 1, 2, \ldots, d^{th} \text{ dimension}]$, and setting each X_i as the initial best position denoted by $\mathrm{P}_{best,i}$. The initialized positions should uniformly cover the search space, and literature suggests drawing these positions randomly from a uniform distribution, i.e., $\mathrm{X}(t=0) \sim \mathrm{U}(\mathrm{X}_{min}, \mathrm{X}_{max})$, where X_{min} and X_{max} are the minimum and maximum boundaries of the search space respectively. Next, the cost function $f(\mathrm{X})$ is calculated and compared across all particles to determine the swarm's initial best position namely G_{best} corresponding to the particle with the lowest cost function. Positions and velocities of all particles $V = [V_i \text{ for } i = 1, 2, \ldots, n^{th} \text{ particle}]$, where $V_i = [v_{ij} \text{ for } j = 1, 2, \ldots, d^{th} \text{ dimension}]$, are then updated using $P_{best,i}$ and G_{best} according to Eq. (1) and (2). The cost function is recalculated and compared to update $\mathrm{P}_{best,i}$ and G_{best} following these logics:

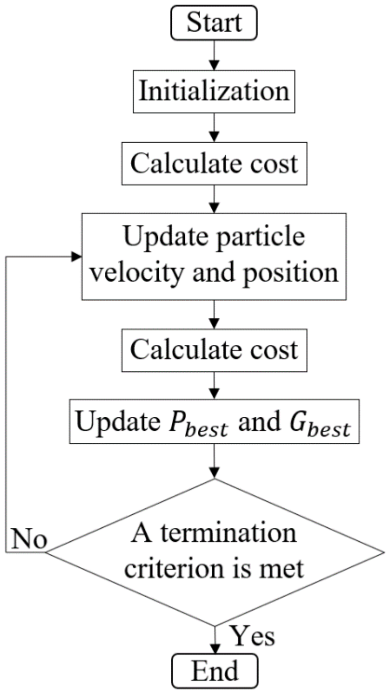


Fig. 1. Flowchart of the conventional PSO.

a) Update P_{best} :
If $f(\mathrm{X}_i(t+1)) \leq f(\mathrm{P}_{best,i}(t))$ then
$\mathrm{P}_{best,i}(t+1) = \mathrm{X}_i(t+1)$

b) Update G_{best} :
: If $f\left(\mathrm{P}_{best,i}(t+1)\right) \leq f(\mathrm{G}_{best,i}(t))$ then
$\mathrm{G}_{best,i}(t+1) = \mathrm{P}_{best,i}(t+1)$

This iterative process continues until the maximum number of iterations is reached or the cost function values for all particles are sufficiently low and stable within the same region of the search space.

$$V(t+1) = wV(t) + c_1 R_1 \odot \left(P_{best} - X(t)\right) + c_2 R_2 \odot \left(G_{best} - X(t)\right) \quad (1)$$

$$X(t+1) = X(t) + V(t+1) \quad (2)$$

where t denotes the current iteration, and $\odot$ represents the Hadamard product. The scalars c_1 and c_2 are acceleration constants that balance the importance between a particle's personal best position and the global best position. It is generally recommended to set c_1 and c_2 within the range of 0.0 to 4.0 [22]. The matrices R_1 and R_2 are $n \times d$ metrics containing values randomly drawn from a uniform distribution $\mathrm{U}(0, 1)$ in each iteration to introduce stochasticity to the search. The scalar inertia weight w regulates the influence of the particle's previous velocity.

It is important to carefully select parameters such as the number of particles and the maximum iterations for PSO. The number of particles determines the swarm size in PSO, affecting the algorithm's balance between exploring the search space and refining solutions. While a larger number of particles can improve exploration, especially for high-dimensional and complex problems, it also increases computation time. The maximum iterations define how many times the PSO will run before stopping. This number should be chosen based on the complexity of the problem, with more complex or higher-dimensional problems typically requiring more iterations to converge. To determine the optimal number of particles and maximum iterations, one approach is to run the PSO multiple times with different combinations and observe the algorithm's convergence behavior. It is crucial to consider the problem's dimensionality, available computational resources, and the desired balance between exploration and exploitation when selecting the number of particles. The maximum iterations should be large enough to allow convergence to a reasonable solution but not so large that unnecessary computation occurs.

3. Main Proposed Framework for Bar Cutting List Optimization

The proposed framework focusses primarily on reducing steel waste by optimizing both rebar cutting and splicing patterns, considering the standard steel lengths available in the reinforcement steel market and splicing standard. To achieve this, a comprehensive review of the standard steel lengths commonly used in the local construction industry as well as a detailed analysis of the current practices in rebar cutting processes should be conducted to ensure the proposed solutions are practical and applicable. The potential for improving rebar cutting processes in local areas should also be discussed to ensure seamless integration between the practices and the optimization results. This discussion should address any gaps or challenges that may arise and propose solutions to align practical implementation with the optimized cutting strategies. The comprehensive flowchart for the proposed framework, specifically for the optimization of column rebar, is illustrated in Fig. 2. The detailed discussion of each step in the flowchart is provided below.

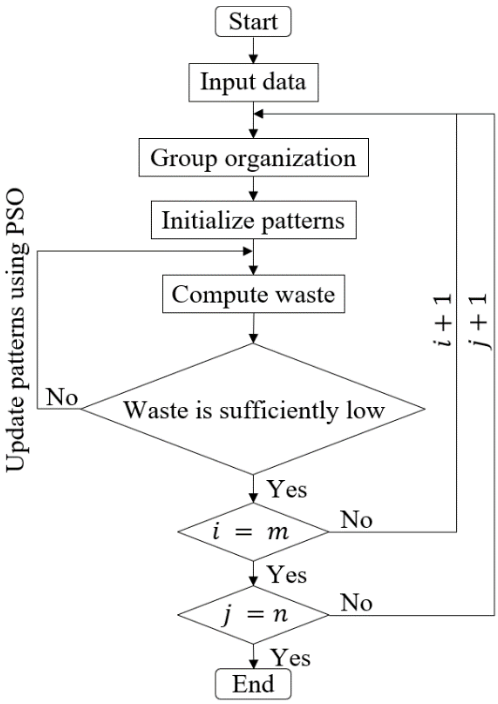


Fig. 2. The comprehensive flowchart of the proposed framework for the bar cutting list optimization.

In the first place, the referenced splicing standard and available rebar lengths in the local market should be input into the algorithm to ensure the reasonableness and practicality of the optimization outcomes. It is important to note that these details can vary significantly from one area to another and between different contractors. By incorporating specific local standards and market availability, the algorithm can produce more accurate and applicable results, tailored to the unique requirements and constraints of each project. This customization helps in achieving the most effective optimization and reducing steel waste efficiently. Additionally, reinforcement data of the whole area intended to optimize should be input to the algorithm. Please note that for the ease of application in large-scale construction, the program's user interface should be well-developed. However, the development of such an interface is beyond the scope of this study.

Subsequently, the input reinforcement data should be thoroughly evaluated and systematically organized into distinct groups based on several key factors such as the type of structural component (e.g., footing, column, beam, slab), the specific location of the component (e.g., floor level, tower section), the reinforcement patterns, and rebar diameter. For instance, columns within a particular structure can initially be categorized according to their reinforcement patterns. Columns that share identical reinforcement patterns are grouped together under the same category, which aids in more efficient data management and sets the foundation for more detailed organization. Once the columns are grouped by reinforcement patterns, the next step is to further subdivide the rebars within each column category based on their diameters and end patterns. Rebars of different diameters and end patterns have varying requirements for detailing and corresponding length computation, and organizing them accordingly helps streamline the optimization process. This step ensures that specific requirements and constraints of each floor such as rebar splicing, early stopping, and bending are taken into account during the optimization process. By meticulously organizing the reinforcement data in this hierarchical manner, the overall complexity of the optimization process is significantly reduced. This hierarchical approach ensures that the optimization outcomes are practical and tailored to the specific conditions of the construction project. Additionally, it facilitates better management of the reinforcement data, making it easier to apply necessary adjustments and meet project-specific needs.

Next, starting with the first column category on the first floor, the initial splicing patterns for all rebar sub-categories within this column category should be randomly generated to serve as the initial positions for the PSO. It is crucial to ensure that this randomization process adheres to the relevant covering, splicing, bending, and hooking standards, as well as the available rebar lengths in the market. In other words, the randomly generated splicing positions must not produce patterns that violate these constraints. Additionally, allowable regions for splicing and measurement positions from reference points should be clearly defined to facilitate construction. For example, splicing positions should be restricted to workable regions, and rebar lengths as well as measured splicing positions should be integer values that are practical for use in the field. This ensures that the splicing patterns are not only feasible but also practical for actual construction scenarios. However, it is important to note that these constraints significantly increase the nonlinearity and discreteness of the waste computation, which in turn poses substantial challenges for programming and optimization processes. This added complexity can lead to increased computational requirements and may necessitate the use of advanced algorithms like PSO to achieve global or near-global-optimal solutions. Furthermore, the intricate nature of these constraints may also affect the scalability and efficiency of the framework, making it essential to carefully design and implement strategies that efficiently balance optimality, required computational power, and indeed, the practicability of the results.

Following this, the cutting patterns should be identified to minimize waste, taking into account the predefined splicing patterns. Specifically, based on the designated splicing patterns, the optimal cutting patterns that yield the least waste are selected from all possible combinations of standard lengths. This will yield the cutting waste, which serves as the cost function for the optimization algorithm. Next, if the computed waste is sufficiently low or if the number of optimization iterations has reached the specified maximum, the optimization process for the column category on that particular floor should be terminated, and the resulting splicing and cutting patterns are considered optimal. Conversely, if the waste remains high, the current splicing patterns should be updated according to the PSO algorithm, and the process should be repeated iteratively. This cycle continues until the optimization termination criteria are met. This iterative approach ensures that cutting lengths are optimized to minimize waste while satisfying the structural requirements of the building construction. The objective function for the optimization of each j^{th} column category on i^{th} floor can be concluded in Eq. (3).

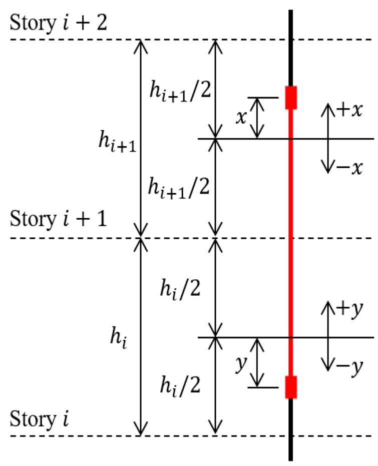
$$\text{Minimize} \qquad \sum_{k=1}^{p} W_{ijk} \tag{3}$$

with respect to

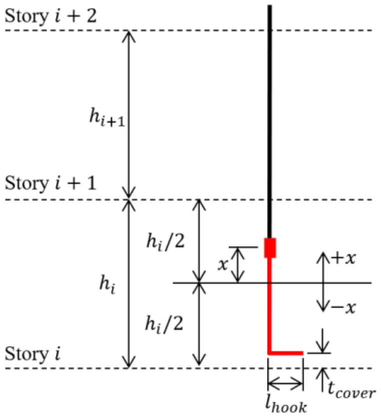
X_ij=[x_ijk for k=1,2,…,p^th rebar-subcategory]
Y_ij=[y_ijk for k=1,2,…,p^th rebar-subcategory]

where W_{ijk} is the total waste produced from k^{th} rebar sub-category within the j^{th} column category on i^{th} floor. The cost function can be computed by summing this waste across all rebar sub-categories within the specified column category, based on the predetermined cutting patterns, i.e., X_{ij} and Y_{ij}. The cutting patterns, serving as candidate solutions for the PSO to iteratively update, can be expressed by positions at the upper (x_{ijk}) and lower (y_{ijk}) ends of k^{th} rebar sub-category, measured from the center of i^{th} floor. To compute rebar lengths accurately from these coordinate patterns, each end is associated with specific rebar starting or ending patterns. These patterns include mechanical splicing, 90-degree hooking, continuation from or to the previous or next floor, and other configurations. At this stage, the referred standards should be taken into account when calculating rebar lengths. Equations for computing rebar lengths (l_i), based on typical starting or ending patterns, are provided in Eq. (4), with the corresponding variables illustrated in Fig. 3. Where l_{hook} denotes length of 90-degree standard hook calculated from Fig. 5 and Table. 1 while t_{cover} is concrete cover depth.

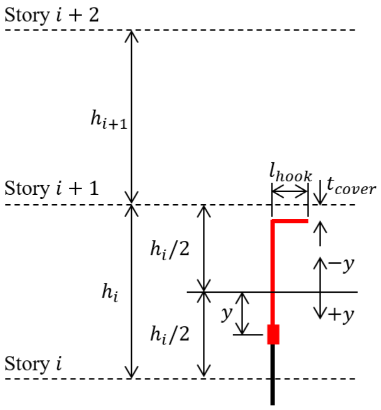
$$l_i = \begin{cases} \frac{h_i + h_{i+1}}{2} + x - y & \text{; mechanical splicing } (\textbf{Fig. 3a}) \\ \frac{h_i}{2} + x + l_{hook} - t_{cover} & \text{; begin with } 90^{o} \text{ hook } (\textbf{Fig. 3b}) \\ \frac{h_i}{2} + y + l_{hook} - t_{cover} & \text{; end with } 90^{o} \text{ hook } (\textbf{Fig. 3c}) \end{cases} \tag{4}$$



(a) Mechanical splicing



(b) Begin with 90° hook



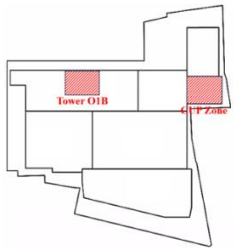
(c) End with 90° hook

Fig. 3. Typical starting or ending patterns of reinforcing steel.

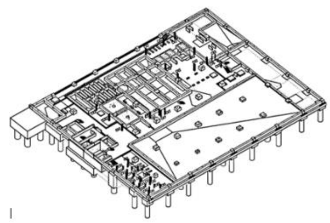
Then, the aforementioned processes should be repeated for the i^{th} floor until the specified number of m floors in the structure is reached. Once this is complete, proceed to the next j^{th} column category and repeat the processes until reaching the specified number of n column categories.

4. Application of The Proposed Framework on a Case of High-Rise Building

The proposed framework discussed comprehensively in the previous section is illustrated in this part. The high-rise building in this study is a newly constructed landmark within a large-scale development project located in the heart of Bangkok, Thailand, that integrates both commercial and residential infrastructures. This comprehensive project aims to create a dynamic, mixed-use environment, enhancing convenience and fostering a vibrant community. To investigate the possibility of further increasing the sustainability of the project, the bar cutting list optimization was applied to columns within two critical areas of the building including CUP Zone and Tower O1B as shown in Fig. 4. The former features 12 main floors, while the latter comprises 47 main floors. Please note that some column categories may terminate before reaching the rooftop due to a reduction in carrying loads on the upper floors.



(a) Key plan of the building



(b) An exemplar 3D illustration of the 1st floor of the CUP

Fig. 4. Layout of the targeted building: location of the CUP Zone and tower O1B.

Prior to the optimization process, a comprehensive survey was conducted in the local area. This survey included a thorough investigation of several key factors: the standard steel lengths available in the local market, the prevailing rebar detailing standards, and common practices in rebar cutting processes. The survey findings revealed that the typical rebar production lengths from local factories are 8, 10, and 12 m denoted as L8, L10, and L12 respectively. In terms of rebar detailing standards, construction practices in Thailand predominantly adhere to the guidelines set forth by ACI 318 [23]. Two key aspects of rebar detailing: the use of 90-degree hooks and the permissible locations for mechanical splicing using couplers are shown in Fig. 5 and 6 as well as Table. 1. Note that bar sizes are adjusted from the design to the available sizes in Thai market. These available lengths and standards were implemented as one of constraints for the optimization.

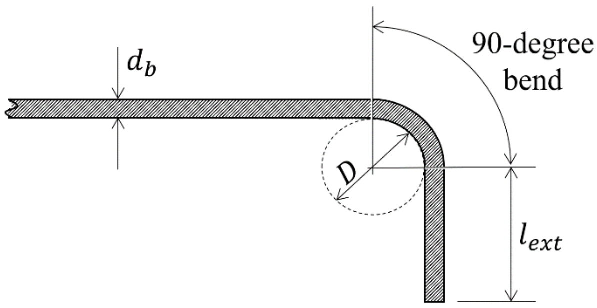


Fig. 5. 90-degree standard hook.

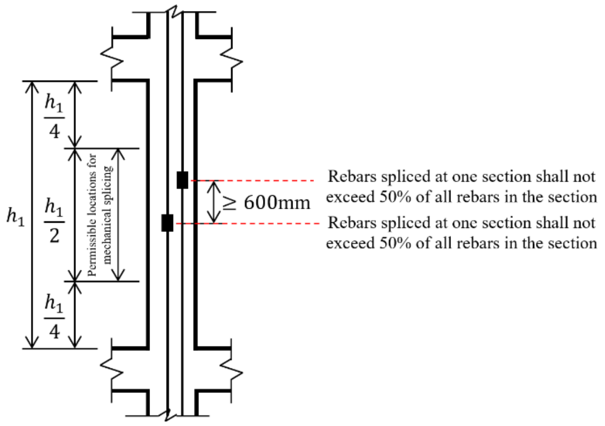


Fig. 6. Permissible locations for mechanical splicing.

Table 1. 90-degree standard hook.

Bar size, d_b	**Minimum inside bend diameter, D (mm)**	**Straight extension, l_{ext} (mm)**
DB10 to DB16	$4d_b$	MAX($6d_b$, 75mm)
DB20 to DB25	$6d_b$	$12d_b$

Following the specification of constraints, the rebars were systematically categorized into distinct groups based on the location and reinforcement pattern of the columns as well as rebar diameter and end pattern. Initially, columns were classified according to their reinforcement patterns, grouping those with identical reinforcement configurations into the same category. After that, the next step involved subdividing the rebars into finer sub-categories. This subdivision was based not only on rebar diameter but also on the end patterns, including the starting and stopping configurations such as 90-degree hooks, continuation patterns, and mechanical splicing. Rebars that shared the same diameter and end patterns were organized into the same sub-category. It is important to note that, due to the 50% splicing constraints, each column must be equally divided into at least two sub-categories to ensure compliance with the detailing requirements. As a result, columns in the CUP Zone and Tower O1B were organized into 8 and 18 column categories, respectively, with varying number of rebar sub-categories within each column category. An example of column category C2 in the CUP Zone is presented in Fig. 7.

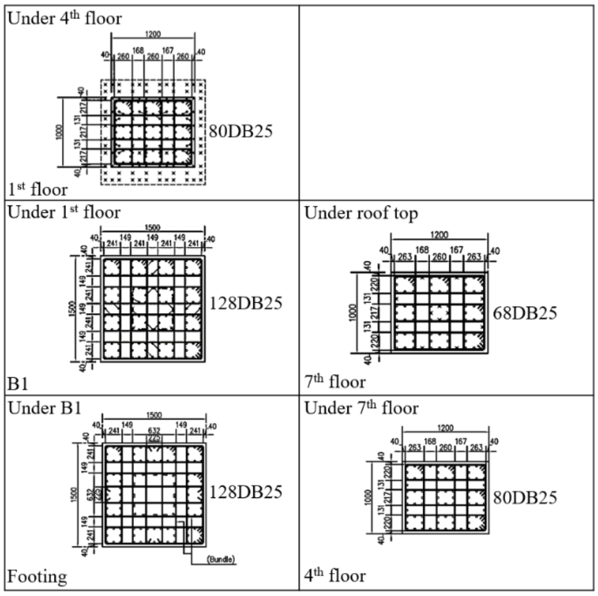


Fig. 7. An example of C2 column category in CUP Zone.

Next, once the group of rebars was organized, the optimization routine commenced. This iterative process started with the first column category on the first floor and continued until the rooftop, then moved on to the next column category, repeating until the last column category was reached. The hyperparameters for the PSO were tuned by balancing between exploration and exploitation until satisfactory convergence of all particles was observed. A summary of the PSO configurations employed is presented in Table. 2. Please note that, for the validity of the results, mechanical splicing using couplers was employed in this study, as it reflects the actual practice in this building construction. Additionally, the number of couplers used was fixed to match the actual construction to limit potential cost increases due to the number of couplers.

Table 2. Summary of PSO hyperparameters.

Hyperparameter	Value
Number of particles (n)	200
Maximum iterations (t_{max})	100
Acceleration constants (c_1 and c_2)	2.0
Random matrices (R_1 and R_2)	$\sim\mathrm{U}(0.0, 1.0)$
Inertia weight ($w(t)$)	Linearly decrease (Eq. (5)) [24]
w_{min} for $w(t)$	0.1
w_{max} for $w(t)$	1.0

$$w(t) = w_{max} - (w_{max} - w_{min}) \times \frac{t}{t_{max}} \tag{5}$$

Following the optimization, detailed splicing patterns and cutting position diagrams were created for visualization. Alongside these diagrams, bar cutting and bending schedules were generated, each accompanied by QR codes to facilitate practical implementation. These QR codes can be scanned by cutting and bending machines equipped with barcode readers at the factory. An example of the optimized splicing pattern and cutting position diagrams for a column in the CUP Zone is shown in Fig. 8 and 9 respectively. Additionally, Table. 3 and 4 summarize the optimization results across all categories in both study areas.

It can be seen in the exemplar splicing pattern diagram of column category C2 of the CUP Zone in Fig. 8 that all details such as rebar beginning, ending, mechanical splicing using couplers, as well as rebar bending were considered within the optimization routine since these details significantly influence the optimized rebar cutting positions and lengths. Moreover, a number of cutting patterns and cutting lengths were also controlled to be reasonable for the practicability of the optimization results. To illustrate, the number of cutting patterns was limited to reasonable patterns and not too much so that the cutting and installation works would not much increase from the common practice. In addition, the cutting length was controlled to be reasonable i.e., to be suitable integer values so that the optimization results were practically possible. The standard for rebar beginning, ending, and mechanical splicing was also considered during the optimization as discussed.

In addition to the residual steel waste generated by the proposed framework, the actual steel waste was also derived from the as-built rebar schedules for validation purposes. Specifically, the actual residual steel waste was calculated by evaluating all possible combinations of standard-length rebars to identify the combinations that minimize waste, based on the splicing positions specified in the as-built schedules.

According to the optimization results, the total waste length across all column categories was significantly reduced compared to those computed from the as-built rebar schedules, from 14.20% to 2.99% for the CUP Zone and from 12.91% to 2.59% for Tower O1B. This dramatic reduction in waste demonstrates the effectiveness of the PSO in minimizing steel waste and enhancing resource efficiency. While not explicitly illustrated in this manuscript, it is important to highlight a notable trend observed in the results: the waste generated by rebars on the top floor is consistently higher than that on other floors. This phenomenon can be attributed to the fact that the optimization was conducted in each column category from the first floor to the top floor, meaning that the splicing patterns and cutting positions were determined based on the constraints and conditions of the preceding floors. As a result, by the time the optimization reached the top floor, the splicing patterns were already fixed according to the previous floor's configuration. This limitation prevented further adjustments that could have achieved an optimal solution for the top floor. The increased waste on the top floor underscores a potential area for improvement in future studies. One possible approach could involve developing a more efficient framework that considers the entire building's rebar requirements simultaneously, rather than in a floor-by-floor sequence. Additionally, the results will be further improved by considering all column categories at the same time. This could help ensure that the splicing patterns are optimized not only in isolation but also in the context of the overall structure, potentially reducing waste even further. However, adopting this approach may introduce challenges related to the curse of high dimensionality [25] and the significant computational power required.

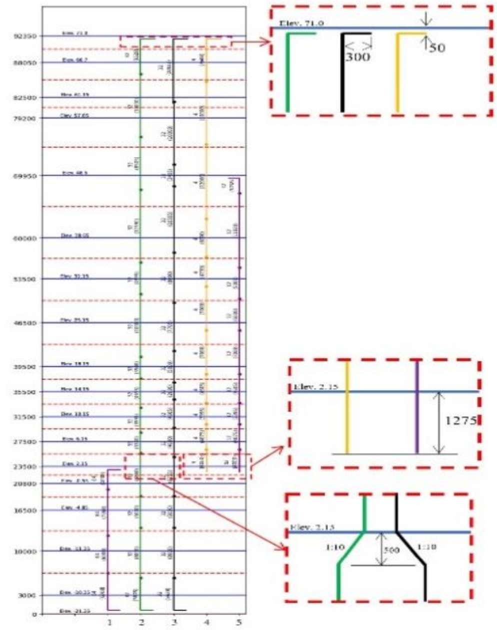


Fig. 8. An example of splicing pattern diagram of column category C2 in CUP Zone.

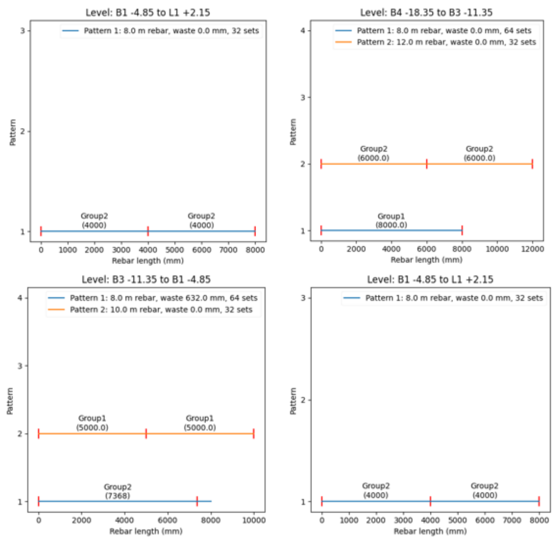


Fig. 9. An example of cutting position diagram from footing level to under 1st floor of column category C2 in CUP Zone.

Table 3. Summary of rebar optimization results for the CUP Zone.

Column category	Level	Bar size, d_b	Length of required rebar (m)	Baseline from as-built schedules				Optimal			
				Standard bars to cut			Waste (%)	Standard bars to cut			Waste (%)
				L8	L10	L12		L8	L10	L12	
C1	Footing (-21.85) to L7 (+48.60)	DB28	6617.816	409	216	179	14.54	252	307	137	1.70
		Subtotal	6617.816	409	216	179	14.54	252	307	137	1.70
C2	Footing (-21.85) to Roof (+71.00)	DB25	19200.880	1664	528	240	11.83	906	336	751	2.18
		Subtotal	19200.880	1664	528	240	11.83	906	336	751	2.18
C3	Footing (-21.85) to Roof (+71.00)	DB25	4679.532	256	151	142	12.45	166	103	217	6.04
		DB28	4047.708	354	84	84	15.62	193	171	76	2.92
		Subtotal	8727.240	610	235	226	13.92	359	274	293	4.59
C4	Footing (-21.85) to Roof (+71.00)	DB28	8124.512	660	264	88	10.48	379	176	290	1.82
		Subtotal	8124.512	660	264	88	10.48	379	176	290	1.82
C5A	Footing (-21.85) to L1 (+2.15)	DB32	1969.760	160	0	80	13.72	88	46	69	1.13
		Subtotal	1969.760	160	0	80	13.72	88	46	69	1.13
C5B	Footing (-21.85) to Roof (+71.00)	DB25	3530.640	160	263	13	15.16	38	245	72	2.47
		DB28	1978.960	36	80	94	11.98	3	43	133	3.59
		DB32	1969.760	160	0	80	13.72	16	97	73	0.22
		Subtotal	7479.360	356	343	187	13.94	57	385	278	2.17
C5C	Footing (-21.85) to Roof (+71.00)	DB25	3450.024	148	229	45	16.35	236	72	92	7.59
		DB28	1978.960	57	80	80	11.98	57	32	103	1.67
		DB32	1865.760	180	20	40	13.63	103	65	34	0.87
		Subtotal	7294.744	385	329	165	14.47	396	169	229	4.27
C6	Footing (-21.85) to L1 (+2.15)	DB25	1838.880	200	0	40	13.11	61	70	55	0.50
		Subtotal	1838.880	200	0	40	13.11	61	70	55	0.50
Total			61253.192	4444	1915	1205	12.91	2498	1763	2102	2.59

Note: The quantities were calculated from one column per column category.

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Table 4. Summary of rebar optimization results for the Tower O1B.

Column category	Level	Bar size, d_b	Length of required rebar (m)	Baseline from as-built schedules				Optimal			
				Standard bars to cut			Waste (%)	Standard bars to cut			Waste (%)
				L8	L10	L12		L8	L10	L12	
C1	Footing (-17.12) to L39 (+187.60)	DB28	3676.152	16	384	30	17.73	230	192	9	5.22
		DB32	8855.808	363	363	276	11.18	110	520	245	1.85
		Subtotal	12531.960	379	747	306	13.10	340	712	254	2.84
C1A	Footing (-17.12) to L39 (+187.60)	DB25	1807.212	66	132	22	16.87	89	102	17	7.13
		DB28	2085.028	13	232	3	17.98	143	110	0	7.62
		DB32	9398.208	433	388	262	11.60	234	460	249	0.66
		Subtotal	13290.448	512	752	287	13.31	466	672	266	2.63
C2	B2 (-9.22) to L47 (+221.90)	DB25	1077.69	6	123	0	18.59	105	30	0	5.78
		DB28	3657.432	16	384	30	18.33	230	150	39	4.12
		DB32	7849.008	252	373	250	11.43	227	239	313	1.44
		Subtotal	12584.130	274	880	280	14.05	562	419	352	2.59
C3	B2 (-9.22) to L47 (+221.90)	DB28	2607.320	88	232	6	18.74	244	75	0	3.63
		DB32	11091.712	278	705	277	13.58	371	483	299	2.65
		Subtotal	13699.032	366	937	283	14.56	615	558	299	2.84
C4	B2 (-9.22) to L47 (+221.90)	DB25	2905.052	98	260	6	18.97	140	173	26	8.84
		DB28	12184.564	384	640	355	12.70	703	479	163	1.52
		Subtotal	15089.616	482	900	361	13.91	843	652	189	2.93
C5	B2 (-9.22) to L47 (+221.90)	DB25	2679.592	96	228	10	18.23	177	74	51	3.30
		DB28	2085.028	12	234	2	17.98	143	88	11	3.40
		DB32	7260.802	230	360	223	11.78	334	257	181	2.11
		Subtotal	12025.422	338	822	235	14.29	654	419	243	2.60
C6	Footing (-17.12) to L39 (+187.60)	DB25	1807.212	66	132	22	16.87	132	70	10	3.81
		DB28	2085.028	8	236	3	17.98	11	143	55	4.46
		DB32	8210.208	339	357	240	11.59	304	407	158	2.29
		Subtotal	12102.448	413	725	265	13.48	447	620	223	2.89
C7	B1 (-5.82) to L47 (+221.90)	DB25	2987.698	118	252	7	18.75	207	127	22	6.77
		DB28	2085.028	12	234	2	17.98	136	110	1	5.51
		DB32	7134.368	238	369	196	11.38	205	170	338	3.67
		Subtotal	12207.094	368	855	205	14.31	548	407	361	4.74
C8	B2 (-9.22) to L47 (+221.90)	DB28	14900.976	410	926	364	13.47	580	527	447	2.50
		Subtotal	14900.976	410	926	364	13.47	580	527	447	2.50
C9	Footing (-17.12) to L47 (+221.90)	DB25	2963.004	130	236	8	17.99	240	108	8	4.49
		DB28	2085.028	8	240	0	18.18	139	103	0	2.73
		DB32	7995.008	300	358	247	11.87	456	166	236	1.81
		Subtotal	13043.040	438	834	255	14.27	835	377	244	2.57
C10	Footing (-17.12) to L39 (+187.60)	DB25	1807.212	66	132	22	16.87	110	88	11	4.69
		DB28	2085.028	12	234	2	17.98	95	125	11	2.73
		DB32	8066.688	395	355	196	12.34	338	362	163	2.64
		Subtotal	11958.928	473	721	220	14.01	543	575	185	2.97
C11	Footing (-17.12) to L39 (+187.60)	DB25	1533.092	48	132	8	17.41	121	66	0	6.19
		DB28	2435.576	19	240	24	16.60	127	143	13	6.83
		DB32	7451.264	291	347	212	11.95	346	276	173	2.05
		Subtotal	11419.932	358	719	244	13.68	594	485	186	3.63

Column category	Level	Bar size, d_b	Length of required rebar (m)	Baseline from as-built schedules				Optimal			
				Standard bars to cut			Waste (%)	Standard bars to cut			Waste (%)
				L8	L10	L12		L8	L10	L12	
C12	L20 (+106.65) to L47 (+221.90)	DB28	5734.540	82	600	15	19.21	486	163	29	2.29
		Subtotal	5734.540	82	600	15	19.21	486	163	29	2.29
C13	L30 (+148.15) to L47 (+221.90)	DB28	4947.544	198	423	0	17.51	264	222	66	3.57
		Subtotal	4947.544	198	423	0	17.51	264	222	66	3.57
C14	L38 (+181.35) to L46 (+216.65)	DB28	638.808	24	56	0	17.72	67	12	0	2.69
		DB32	198.436	20	6	0	10.87	27	0	0	8.85
		Subtotal	837.244	44	62	0	16.10	94	12	0	4.15
C15 and C16	L38 (+181.35) to L47 (+221.90)	DB28	985.712	7	112	0	19.30	93	28	0	3.88
		Subtotal	985.712	7	112	0	19.30	93	28	0	3.88
C17	L42 (+200.05) to L47 (+221.90)	DB28	637.112	0	56	14	14.27	42	28	7	9.87
		Subtotal	637.112	0	56	14	14.27	42	28	7	9.87
Total			167995.178	5142	11071	3334	14.20	8006	6876	3351	2.99

Note: The quantities were calculated from one column per column category.

To further validate the practicability and illustrate the use case of the optimization results, an example of the generated bar cutting and bending schedules of column category C6 of CUP Zone was implemented at an actual rebar cutting and bending factory. These schedules, along with the corresponding QR codes as illustrated in Fig. 10, were utilized by machines equipped with QR codes and barcode readers in Fig. 11. The integration of QR codes facilitated the seamless transmission of cutting and bending instructions directly to the automated machinery, ensuring precise execution of the optimized patterns. Additionally, the well-planned cutting and bending workflow and well-organized cut and bent rebar inventory management system contributed to improved operational efficiency, reduced errors, and further minimized steel waste. This systematic approach not only streamlined the production process but also ensured that the rebars were accurately tracked and managed throughout the entire lifecycle, from fabrication to installation on the construction site. The benefits of these improvements can be further amplified through integration with Building Information Modeling (BIM). BIM provides a comprehensive digital representation of the construction project, allowing for precise coordination between design and execution. This ensures that the rebar cutting and bending schedules are perfectly aligned with the project's structural requirements. This integration facilitates better communication among project stakeholders, improves accuracy in construction, and optimizes resource use, ultimately leading to more efficient and effective project completion.

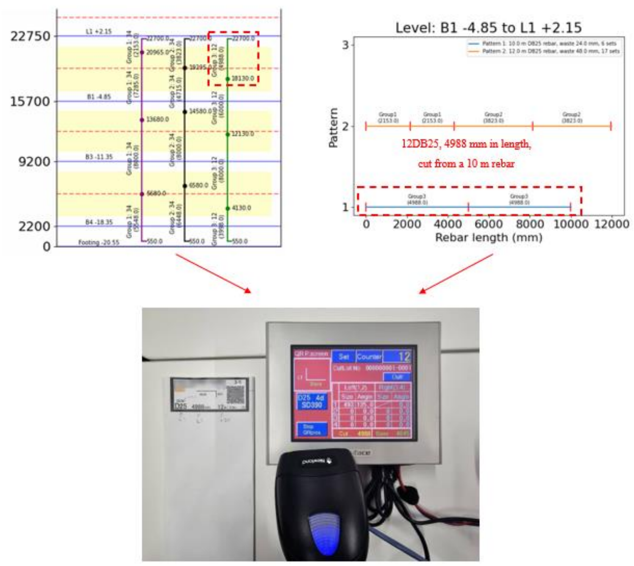

Fig. 10. An example of the generated bar cutting and bending schedules and the corresponding QR codes

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Fig. 11. A rebar cutting and bending machines equipped with QR codes and barcode readers
(Note: The figures were sourced from the rebar cutting of another project, as the actual cutting could not be performed due to the high workload at the factory.)

5. Conclusion

This study introduces a comprehensive framework for optimizing column rebar cutting and splicing patterns using the PSO algorithm. The approach begins with an in-depth survey of key factors, including the standard steel lengths available in the local market, prevailing rebar detailing standards, and common rebar cutting practices. Columns are systematically categorized into n column categories, with each category consisting of p rebar sub-categories based on column location, reinforcement patterns, rebar diameter, and rebar end patterns. This categorization aims to reduce complexity in the subsequent optimization process and ensure practical results. With the identified factors and organized column categories as inputs, the PSO initiates with randomly generated splicing positions. It then calculates the corresponding cutting lengths in line with reinforcement detailing standards and market availability, with the goal of minimizing steel waste. This iterative process refines splicing patterns through successive iterations for the i^{th} floor, continuing until the specified number of m floors in the structure is completed. The process then progresses to the next j^{th} column category and repeats until all n column categories are addressed. Once satisfactory optimization results are achieved, splicing patterns and cutting position diagrams, as well as bar cutting and bending schedules alongside the corresponding QR codes are generated for real-world implementation.

As a result of applying the proposed framework to two critical areas of a newly constructed high-rise building in Bangkok, Thailand, the total waste length across all column categories in both areas was dramatically reduced compared to those computed from the as-built rebar schedules, from 13.86% to 2.88%. This significant decrease in waste highlighted the PSO algorithm's effectiveness in reducing steel waste and carbon footprint, improving resource efficiency, and enhancing sustainable construction practices. Moreover, the implementation of the generated bar cutting and bending schedules with QR codes in rebar cutting and bending machines, equipped with QR code and barcode readers, enabled the seamless transmission of instructions directly to the automated machinery. This integration ensured the precise execution of optimized patterns. Additionally, the well-structured cutting and bending workflow, along with an organized inventory management system for cut and bent rebars, enhanced operational efficiency, reduced errors, and further minimized steel waste. This systematic approach not only streamlined the production process but also ensured accurate tracking and management of rebars throughout their entire lifecycle, from fabrication to installation on the construction site.

Last but not least, potential improvements in rebar cutting list optimization are discussed. One notable observation is that the waste generated by rebars on the top floor tends to be significantly higher compared to other floors. This indicates that the floor-by-floor optimization approach may have missed opportunities for adjustments that could have optimized the top floor more effectively. This highlights a potential area for future research: developing a more comprehensive optimization framework that considers the entire building's rebar requirements simultaneously. Such an approach could optimize splicing patterns in the context of the overall structure, potentially reducing steel waste even further. However, implementing this approach might present challenges related to high-dimensional optimization and significant computational demands. Consequently, future studies could explore and compare various stochastic optimization algorithms beyond PSO, such as Evolutionary Strategies (ES) [26] and others, to identify the most effective algorithms for tackling high-dimensional problems. Additionally, research should focus on integrating rebar cutting list optimization within the broader context of actual construction projects. This would involve examining the entire process from design and optimization to cutting, bending, transportation, installation, and project completion. Implementing BIM throughout the process ensures precise coordination between design and execution, aligning optimized rebar cutting and bending schedules with structural requirements. This integration enhances communication among stakeholders, improves construction accuracy, and optimizes resource use, leading to more efficient project completion.

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