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Cutting Stock Problem (CSP) applied to Structural Optimization for the minimum waste cost

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Abstract

In this study, an optimization method to design simple truss structures for the evaluation of the optimal stock of existing elements is introduced. To achieve this goal, the well-known Bin Packing Problem (BPP) will be implemented within the structural optimization procedure. Specifically, among all the BPP variants, one of the most common applications in real-world cases is the Cutting Stock Problem (CSP) in which the objective is to produce d_j copies of each item type j by employing the minimum number of bins. In the civil engineering field, structural optimization is often employed aiming to improve the load-bearing capacity of the structure itself, i.e. maximization of the performance ratio through the minimization of the structure weight. However, this goal doesn't guarantee maximum efficiency in terms of minimization of waste during the industrial production phase. To overcome these limits, authors propose a stock-constrained structural optimization in which a heuristic search technique is adopted and the best arrangement of bars whit the lowest cut-off waste is obtained for a 10-bar-truss case study. For completeness reasons, a comparison between the solution obtained by the classic minimum weight optimization problem and the stock-constrained one is discussed.

Keywords

Structural optimization, Bin package problem (BPP), Cutting stock problem (CSP), Reusing, Steel structure.

1 Introduction

In the last decade, the Scientific Community challenged on minimizing the structures' price by manipulating material, fabrication and maintenance costs. Specifically, in the structural optimization field, great attention was dedicated to materials cost minimization aiming to achieve a slender structure with optimal resource utilization. In this sense, the traditional approach adopted by researchers and practitioners is to optimize the design cost of structures while at the same time satisfying safety recommendations provided by specific standard regulations.

As demonstrated in this paper, a significant part of the expenses is also the waste of material from the cutting process. In other words, minimising the amount of material involved in the construction process without a carefully cutting design, for the minimization of waste, leads to inefficient cost optimization. Moreover, an higher environmental impact can be also recognized and evaluated as the CO_2 emission recorded at the production phase.

Construction and demolition wastes were expected to account for around 23% of the overall solid waste stream. This waste ratio equates to more than 100 million tonnes every year. Over the world, several surveys corroborate the estimates from the United States. A percentage of the waste created by stock reduction is preventable, which means it is generated as a result of improper material utilisation. The quantity of superfluous acquired materials, needless workmanship, wastes and trucking and tipping fees required to discharge the garbage would be reduced if the supplies were used more efficiently [1].

Indeed, efficient resource use is not just in the interests of the industrialist, but also of the world at large. The disposal of trash from a stock-cutting operation may cause pollution, and excessive wasting may deplete our planet's precious supplies [2]. Cutting losses is possibly the most major source of steel waste. Cutting losses arise when normal steel lengths are shortened to fit the project's required lengths. A significant amount of the created steel waste according to Adham et al. [3] is related to cutting losses, which are mostly caused by:

- dividing an order into separate, smaller orders typically results in more waste due to fewer cutting alternatives;

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- using inefficient cutting patterns in the cutting schedule results in the generation of avoidable waste that could be avoided through better stock-cutting planning;
- using the optimum cutting patterns may result in unavoidable waste which is the minimum waste generated if the optimum cutting patterns are used.

In order to minimize waste, the cutting stock problem (CSP) represents a significant source of one-dimensional stock waste in the construction industry.

2 State of Art

Cutting and packing (C&P) problems of concrete and abstract objects appear under various specifications (i.e. cutting problems, knapsack problems, container and vehicle loading problems, pallet loading, bin packing, assembly line balancing, capital budgeting, changing coins, etc.) within disciplines such as Management Science, Information and Computer Science, Engineering, Mathematics, and Operations Research. All of these problems have essentially the same logical structure [4].

The most famous of these problems is the bin packing problem (BPP) which determines how to pack as many items as possible into a container or, in other words, minimize the number of containers (bins) used for the same stock of goods. Specifically, the BPP can be stated as follows. There are given *n items*, each with an integer weight w_j $(\mathrm{j} = 1\ldots,\mathrm{n})$ and an infinite number of identical bins with integer *capacity c*. The goal is to load all the products into as few bins as possible so that the total weight packed in each bin does not exceed the limit [5].

Almost all the other C&P problems are variants (e.g. pallet loading problem) or generalizations (e.g. cutting stock problem) of the BPP. In particular, in civil engineering, the most common problem of diminishing waste due to the steel element cutting process can be solved with the cutting stock problem. In summary, the cutting stock problem (CSP) tackles the practical question of cutting off needed pieces from stock material with the least trim loss. In more technical terms, the CSP can be defined starting from the BPP definition as follows. There are *m item* kinds, each with an integer weight w_j $(\mathrm{j} = 1\ldots,\mathrm{n})$ and an integer *demand* d_j $(j = 1,\ldots,m)$, as well as a huge number of identical integer *capacity c* bins. In the CSP literature, the bins are typically referred to as rolls, a word derived from early implementations in the paper industry, and *cutting* is commonly used rather than *packing*. The goal is to manufacture d_j copies of each item type j (i.e., cut/pack them) using the fewest number of bins possible while ensuring that the total weight in every bin does not exceed the capacity.

Moreover, the cutting stock problem can be classified as a one-dimensional and two-dimensional problem. A specified set of order lengths must be extracted from stock rods of a defined length in order to solve the one-dimensional cutting stock problem (1D-CSP). Usually, the goal is to use the fewest number of possible rods (material input). The two-dimensional two-stage constrained cutting problem (2D-2CP) aims to select the most valuable group of rectangular objects from a single infinite-length-rectangular plate. Furthermore, the two-dimensional CSP can involve regular or irregular shapes, in the second case, the problem is called nesting and requires a more difficult solution [4].

These kinds of problems are complex combinatorial optimization, which in mathematical terms is a strongly NP-hard problem. For this reason, many linear programming, heuristic and metaheuristic approaches were proposed over the years [6]-[7]. The first approach to the C&P problems dates back to the sixties with Kantorovich [8]. Although his approach is poor and only handles small-scale cases, it aids in understanding the statement of the problem.

Numerous heuristic approaches (i.e. by solving, at first, the linear programming LP problem and then converting the LP result to an integer solution) take advantage of the problem's linear programming (LP) relaxation technique. This problem is often formulated as an integer programming (IP) problem, and its linear programming (LP) relaxation is exploited in many heuristic algorithms. In mathematics, the relaxation of a (mixed) integer linear program is the problem that arises by removing the integrality constraint of each variable and allows solving the integer programming (IP) problem as a linear programming one. This relaxing technique converts an NP-hard optimization issue (integer programming) into a similar problem that can be solved in polynomial time.

However, this method makes it impractical to take into account all cutting patterns which can be identified by the columns in the LP formulation, especially when the length of a single item is much smaller than the roll length. By solving the related knapsack issue, Gilmore and Gomory provided a novel method to identify the cutting patterns required to enhance the LP solution. Gilmore and Gomory [9] proposed a column generation approach inspired by Dantzig and Wolfe [10] for decreasing stock and bin packing concerns (BBP). Because enumerating all possible cutting patterns would take an inordinate amount of time, it reduces valid patterns repeatedly and adds them to the issue based on their contribution to the objective function. The column generation approach made large-scale cutting stock issues solvable in a reasonable amount of time.

In the following years, many algorithms were developed to solve the problem. While the most precise but computational and time-consuming are the more rigorous procedure based on integer linear programming. However, in the last decade, several metaheuristic procedures have been implemented (e.g. Genetic Algorithm, Simulated annealing and Tabu search, etc.) for this purpose.

2.1 Use of cutting stock problem in truss solutions

In the previous section, the general formulation of the Cutting Stock problem has been introduced. In recent years, Academicals and practitioners have focused on the reuse of construction materials. Researchers have noted that performing cost and environmental optimization by managing sectional and/or layout properties of structures result be insufficient for reaching the best outcome. The building sector is a major contributor to material consumption, energy use, greenhouse gas emission, and waste production (see e.g. [11], [12]).

This problem can be solved basically in two ways: by minimizing the waste in the fabrication phase or by reusing stock materials from other structures. The first approach has been not sufficiently explored and this justifies the attempt of authors to cover the gap in the research. The second path was deeply explored by Brütting et al. in various publications that treated the reuse of the construction stock elements. The idea of Brütting et al. is to use the principle of circular economy in order to reduce the cost and the environmental impact of structures. In a circular economy, manufactured goods are kept in use as long as possible through closed loops, which consist of repair, reuse, and recycling. In particular, they were concerned about reuse because less energy is spent on reprocessing with respect to recycling.

The first way to approach the reuse optimization problem has been developed in [13]. In this study, structural optimization with stock constraints has been shown.

For clarity, the term *member* has been used for a position or bar in a reticulated structure and *member length* is the distance between nodes at this position. The term *element* is used for the individual component of a stock. The stock has been reused from materials which have different dimensions.

In Figure 1, it is possible to see the two ways to approach the problem: the 1-to-1 *assignment* of elements to positions in the truss (as in Stock A), and a *cutting stock approach*, where multiple members can be cut from individual elements (as in Stock B).

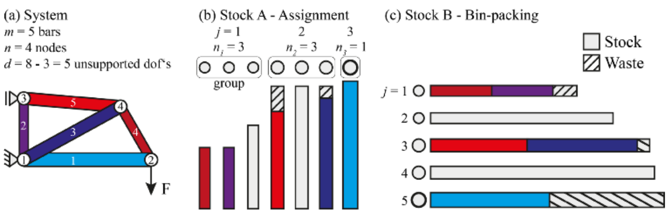

Figure 1 (a) Cantilever truss, (b) stock A and assignment, (c) stock B and cutting stock configuration, used with permission from Brutting et al. [11].

In case (a), which is the *assignment* problem, the objective of the optimization is to avoid waste by minimizing the long distance between members and stock elements. In case (b) a cutting pattern which minimizes global waste is evaluated (number of required bins). Both cases were solved through a MILP (mixed-integer programming) procedure. Another problem addressed in the investigated paper is that the lengths of the chosen elements may not correspond exactly to the lengths of the structure's members once both problems have been solved. For this reason, shape optimization is then used to reduce cut-off waste for the globally optimal assignment or bin-packing solutions by changing the placements of the structure nodes (coordinates).

Finally, in this work, Brütting et al. exposed also a procedure to optimize the configuration of stock or kit-of-parts such that its elements can be reused in various structures. This last consideration allowed to spread of the stock of reusing items in many structures and the outcome is an ulterior minimization of the waste.

Ulterior amendments, with specific regard to the assignment problem, were done by using the basic formulation in [14] where the assignment was coupled with a topological optimization. After that, the truss was subjected to shape optimization. Is also noticeable the introduction of an absolute *buffer/problem relaxation* such that the inclusion of short items in an optimal cutting pattern, during the selection phase, has been allowed.

Moreover, in 2020, Brütting et al. [15] reported an entire structural optimization based on the principles introduced above. In this work simultaneous analysis and design approach have been performed, structural analysis is part of the optimization formulation by treating member end forces as well as nodal displacements and rotations as continuous state variables.

Furthermore, designing a custom kit of parts whose components have been prepared to be combined in various structural configurations, serving diverse purposes, represents an alternate approach to component reuse.

In a recent paper, Brütting et al. [16] pointed out an interesting comparison between results obtained by optimization by using the assignment approach and the CSP technique. A kit of parts has been evaluated for three different real-world application case studies. The kit-of-parts bars are tubular components joined with bolts at spherical joints. The structures' original topology and geometry are provided as input. The process consists of two steps. To allow for the reuse of similar bars in different structures, the structural geometries and kit-of-parts bars' length and cross-section dimensions are optimised in the initial stage. The second stage optimises the hole pattern for the spherical joints' connection details, allowing each joint to be reused in many constructions.

3 Mathematical formulation of the problem

This section introduces the mathematical formulation of the CSP by using the column generation technique to reduce the problem's computational cost.

3.1 Bin Packing Formulation

In order to understand how the cutting stock problem works it is necessary to introduce the mathematical formulation of the one-dimensional bin packing problem. This problem aims to allocate a set of items into the minimum number of bins. At the initialization problem, the following parameters have been assumed:

- $\mathbf{I}$: set of items, indexed by i ;
- $\mathbf{B}$: set of bins, indexed by b ;
- $\boldsymbol{L_i}$: length of item i ;
- $\boldsymbol{L}$: length of each bin;
- $\boldsymbol{x}_{\{i,b\}} \in \{\mathbf{0}, \mathbf{1}\}$: unitary if item i is allocated to bin k, 0 otherwise;
- Item $\boldsymbol{y}_{\{i,b\}} \in \{\mathbf{0}, \mathbf{1}\}$: unitary if bin b is used, 0 otherwise.

The mathematical formulation of the problem is:

$\min \sum_{b \in B} y_b$ (1)

subjected to the following constraints:

$\sum_{b \in B} x_{i,b} = 1 \ \forall i \in I$ (2)

$\sum_{b \in B} L_i x_{i,b} < L y_b \ \forall b \in B$ (3)

$x_{i,b} \leq y_b \ \forall i \in I, b \in B$ (4)

$x_{i,b} \in \{0,1\} \ \forall i \in I, b \in B$ (5)

$y_b \in \{0,1\} \ \forall b \in B$ (6)

The principal equation of the bin packing problem (1) simply minimizes the number of bins used to obtain the requested items.

The mathematical equation was subjected to some constraints. In particular, the (2) equation means that each item must be assigned to a bin (i.e. each item should be cut from one of the paper rolls available). Additionally, the second condition (3) assures that the length of all items associated with a bin should not exceed the length of the bin and the third (4) entails that an item can be assigned to a bin if and only if that bin is used. Finally, equations (5) and (6) express the domains of the two decision variables $x_{i,b}$ and y_b.

3.2 Column generation

The bin packing problem is a very complex combinatorial problem. For simplifying this problem the Column Generation formulation is used in this work.

In this formulation, the main element is no longer the bin, but the feasible cutting pattern, that is, the possible arrangement of items in a bin. Since enumerating all feasible cutting patterns is prohibitively time-consuming, it generates valid patterns iteratively and adds them to the problem according to their contribution to the objective function.

The first step is to set up the restrained master problem (RMP). The parameters involved in the column generation model are:

- $\mathbf{I}$: set of unique items (subset of items with unique distinct lengths), indexed by i ;
- **P**: set of paths, indexed by p ;
- $\boldsymbol{L_i}$: length of item i ;
- $\boldsymbol{Q_i}$: quantity needed for item i;
- $\boldsymbol{L}$: length of each bin;
- $\boldsymbol{M_{i,p}}$: matrix whose element (i,p) defines the number of times item i is included in path p;
- $\boldsymbol{x_p \in Z}$: number of times path p is chosen.

The mathematical formulation of the problem is:

$\min \sum_{p \in P} x_b$ (7)

subjected to:

$\sum_{p \in P} M_{i,p}\, x_p \geq Q_i \ \forall i \in I$ (8)

$x_p \in Z$ (9)

The objective function of the RMP is the minimization (i.e. Equation (7)) of the number of paths used which is strictly correlated with the minimization of the number of bins. The objective function is subjected to two constraints. First, it needs to select the number of paths in a way such that every unique item appears at least as many times as needed and this is what is done in (8). In the second equation (9), a new constraint is introduced for the definition of the x_p domain.

The next step is to write the dual problem. The dual problem is a formulation correlated with the principal problem exposed above which is the primal. The dual problem is written in such a way that:

- A mostly horizontal constraint matrix becomes a mostly vertical constraint matrix;
- A minimization problem (see eq.s (1)-(7)) becomes a maximization problem (see Equation (10);
- The objective value coefficients of the primal become constraint right-hand side values of the dual;
- The objective value coefficients of the dual are the dual values of the primal.

Specifically, the dual problem can be formalised as follows:

$\max \sum_{i \in I} Q_i \lambda_i$ (10)

subjected to:

$\sum_{p \in P} M_{i,p}\, \lambda_i \leq 1 \ \forall p \in P$ (11)

$\lambda_i \in Z$ (12)

The λ_i is the dual value referring to a specific item constraint. Each dual value gives an indication of how profitable is to add the associate item to a new path.

Moreover, to determine the best path to add it is necessary to set up the pricing problem where a new decision variable y_i which represents how many times a certain item i appears in the new path.

More in detail:

$\max \sum_{i \in I} \lambda_i y_i$ (13)

subjected to the following constraints:

$\sum_{i \in I} L_i y_i < L$ (14)

$y_i \in Z$ (15)

Where Equation (14) ensures that the newly added path is feasible, and Equation (15) imposes the y_i domain.

Forehead, to decide if a certain path should be added to the RMP it needs to verify the gain obtained by the addition of the new path with the following formula:

$c - z \leq 0$ (16)

Where c is the original cost from the primal problem and z is the reduced cost computed in the pricing problem. Finally, by adoperate suitable substitutions:

$$1 - \sum_{i \in I} \lambda_i y_i < 0 \quad (17)$$

The pricing problem can be rewritten in the following form:

$$\sum_{i \in I} \lambda_i y_i \geq 1 \quad (18)$$

Until the previous condition is satisfied by the new generate path this one was added to the primal RMP and the procedure was iterated. In figure (2), the flow chart related to the column generation procedure and the solution to the pricing problem is shown.

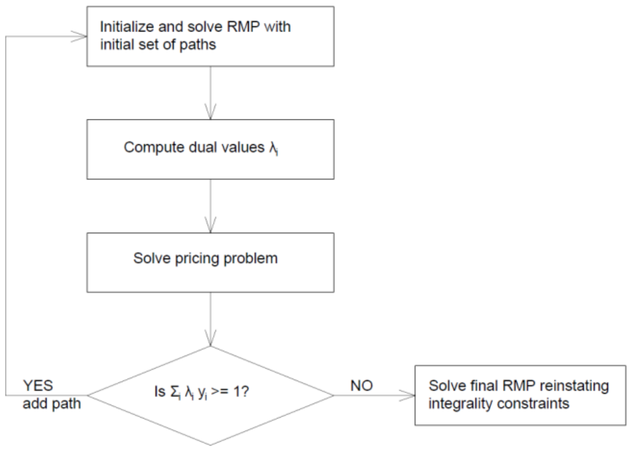

Figure 2 Column Generation algorithm for the solution of the CSP

4 CSP within the structural optimization process

In this section, practical applications in which CSP is implemented within structural optimization have been shown. At first, the mathematical formulation of the optimization process has been described by focusing on the OF chosen as the target function and the adopted structural constraints. Then, a detailed description of the case study chosen by the authors and the results obtained by the optimization process has been pointed out.

4.1 Mathematical formulation of the optimization process

Respect to traditional optimization approaches (i.e [17]-[18]) in which the OF represents the total weight of the structure as a sum of the mass of each element, in this study the target function has been evaluated by computing the amount of steel requested during the production phase. A ten-bar truss, comes from [19], has been adopted as case study for the application of the proposed method. To achieve this goal, a real-coded guided-Genetic Algorithm (GA) has been developed by the authors and cross-sectional areas of each element are chosen as design variables of the problem. CSP has been implemented within the optimization process and it has been independently solved for all groups of elements with the same cross-sectional properties. Finally, the solution obtained by the CSP for each group has been adopted for the evaluation of the OF ($W(x)$) expressed as follows:

$$W(x) = \rho \sum_{g=1}^{g=k} n_g A_g L_g \quad (19)$$

$W(x)$ represents the total mass of the purchased bars for each group g. Specifically, k represents the total number of groups of elements with the same cross-sectional areas. n_g, A_g and L_g are the cardinality, the cross-sectional area and the length of bins belonging to the same group g of elements with the same cross-sectional area A_g, respectively. ρ is the mass density assumed to be equal for all members composing the structure.

The statement of the entire optimization process is the following:

$$\min f(x) = W(x) \quad (20)$$

Subjected to:

$$\frac{N_{\{ED\}}}{N_{\{t,RD\}}} \leq 1, \quad (21)$$

$$\frac{N_{\{ED\}}}{N_{\{c,RD\}}} \leq 1, \quad (22)$$

$$\frac{N_{\{ED\}}}{N_{\{b,RD\}}} \leq 1, \quad (23)$$

$$u_{\{max,x\}} \leq u_{\{lim,x\}}, \quad (24)$$

$$u_{\{max,y\}} \leq u_{\{lim,y\}}. \quad (25)$$

Equations (21)-(25) represent the structural constraints of the problem. In detail, strength verifications about tensile stress (without any holes), compression stress and buckling instability according to Eurocode 3 (EN 1993-12005 and EN 1993-2 2006) are introduced by Equations (21), (22) and (23) respectively. Another constraint to satisfy is the maximum deflection along x and y directions (represented by Equations (24) and (25), respectively).

In Figures (3) and (4) a graphical representation related to the flow chart of the entire optimization process and a detail of the flow chart/pseudo code of the CSP procedure are shown. The entire procedure has been based on geometrical assumptions which can be assumed fixed during the optimization process, as described within the first parallelogram of Figure (3). Then, population random generation of the first individuals has been realized and a preliminary structural verification has been performed in order to solve the CSP only for feasible individuals with specific regard to structural safety (hence, individuals of a population which satisfy constraint conditions represented by Equations (21)-(25)). Once, the grouping strategy has been performed and elements of structure with the same cross-sectional areas have been collocated into the same group, CSP can be solved (see Figure (4)) independently by considering all elements of each group.

As the output of the CSP procedure, the required number of bins and the corresponding optimal cutting patterns has been pointed out for each individual. Finally, the best individual has been selected for the evaluation of the fitness of OF. The entire procedure has been repeated until the stopping criteria (maximum number of generations) are fulfilled.

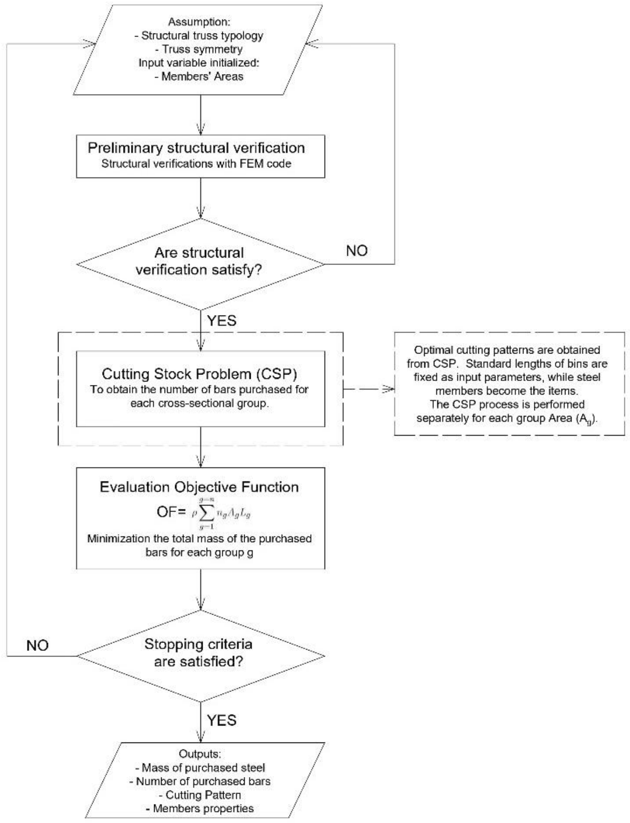

Figure 3 Flow chart of the optimization problem

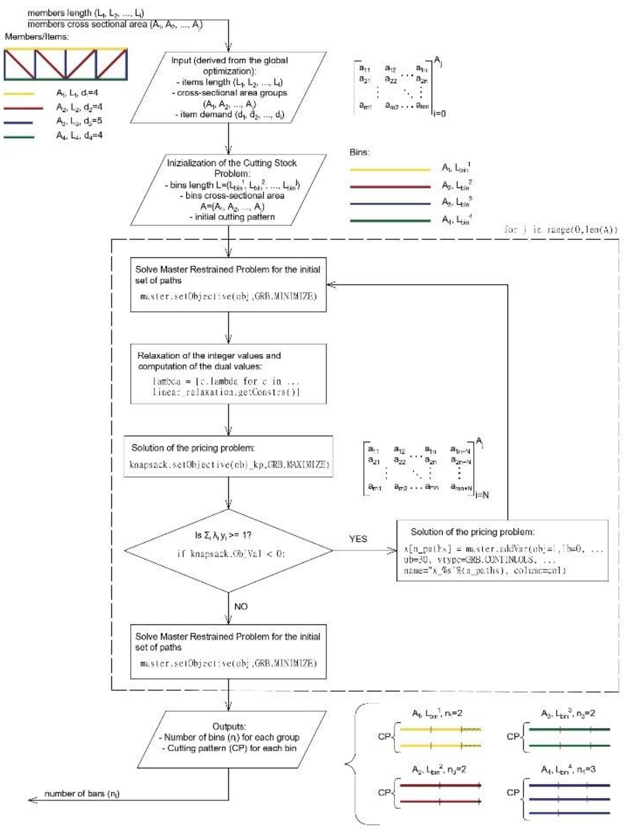

Figure 4 Flow chart/pseudo-code of the CSP procedure

More information concerning the lower and upper bounds of the adopted design variables, their mechanical and geometric features, and details concerning the threshold values of structural constraints will be provided in the next sections in which the results obtained by the optimization process will be shown.

4.2 Case study one: ten-bar truss

In this section, the results of the optimization process with specific regard to the ten-bar truss case study are pointed out. Specifically, two optimization scenarios have been performed:

- **Scenario (a)**: optimization by considering CSP procedure (minimization of purchased steel bars);
- **Scenario (b)**: optimization via traditional approach by minimizing the total weight of the structure without considering the CSP procedure.

In order to have a comparison between the two mentioned-above approaches, the CSP procedure has been performed at the end of (b) such that the total number of bins requested for the assemblage of the optimized structure has been evaluated.

As reported in Figure (4), the structure is a trussed isostatic cantilever composed of 10 bars made of steel with a mass density of $\rho = 0.10\,lb/in^3$ $(2.768\,kg/m^3)$, elastic modulus $E = 10000\,ksi$ $(68.971\,GPa)$ and constrained by two pinned supports at nodes 5 and 6, respectively. A single-loading condition $P_1 = 100\,kips$ $(444.8\,kN)$ has been assumed. A set of 42 discrete values have been used for the possible cross-sectional areas for each member $A = \begin{Bmatrix} 1.62, 1.80, 1.99, 2.13, 2.38, 2.62, 2.63, 2.88, 2.93, 3.09, 3.13, 3.38, 3.47, 3.55, \\ 3.63, 3.84, 3.87, 3.88, 4.18, 4.22, 4.49, 4.59, 4.80, 4.97, 5.12, 5.74, 7.22, 7.97, \\ 11.5, 13.5, 13.9, 14.2, 15.5, 16.0, 16.9, 18.8, 1.99, 22.0, 22.9, 26.5, 30.0, 33.5 \end{Bmatrix}$ $(in.^2)$. The displacements of the free nodes in both directions had to be less than $\pm 2\,in.$ $(\pm 50.8\,mm)$ and the allowable stress was set to $\pm 25\,ksi$ $(\pm 172.25\,MPa)$. Finally, for performing the CSP procedure in both (a) and (b) optimization scenarios, the bin length for each cross-sectional area group has been imposed equal to 1020 in.

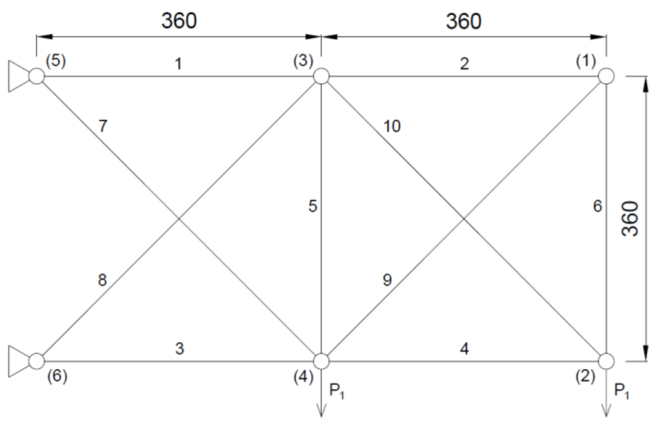

Figure 5 Configuration of the in-plane 10-bar truss, measures are expressed in inches (in.)

The algorithm has been performed by setting a population size of 200 individuals and the stopping criteria has been fixed to 200 maximum generations for an overall number of evaluations of 20,000 for both embedded CSP and traditional approach optimization. Finally, 10 runs have been performed and at each run, the optimal OF value expressed in terms of the total number of purchased bins and total structural weight has been stored. Tables (1)-(2) report the results of both optimization procedures.

As expected, the optimization performed in (a) pointed out the best results in terms of the total number of purchased bins with a significant reduction of total mass waste (or waste length) with respect to the minimum weight approach (b). On the contrary, the structural mass derived by (b) results to be lower than the one obtained by (a). However, the gain in terms of mass waste evaluated in (a) seems to be more significant than the loss in terms of structural weight detected in (b).

Table 1 Result of the optimization via CSP (a)

	Stock Mass (OF)	Structural Mass [lb]	Mass Waste [lb]	Waste length [in]
Best	6825.8	5792.0	1033.9	903.5
μ	7320.1	6158.4	1161.7	903.5
σ	308.6	257.1	98.4	0

Table 2 Result of the optimization via traditional approach (b)

	Stock Mass [lb]	Structural Mass (OF)	Mass Waste [lb]	Waste length [in]
Best	10323.4	5580.4	4743.0	2943.4
μ	12133.9	5632.9	6501.0	4212.5
σ	1343.2	64.2	1348.1	1021.6

According to the outcomes of the optimization reported in Tables (1)-(2), the reduction of the total number of bins and waste appears more evident by observing Figures (5) and (6). They represent the optimal cutting pattern for both scenarios (a) and (b), respectively. Specifically, along the x-axis cross-section areas deriving by the grouping strategy are depicted while on the y-axis the length of each pattern expressed in inches is reported. Waste has been defined, for each area group, by the dashed area as the remaining length of bins after the cutting procedure.

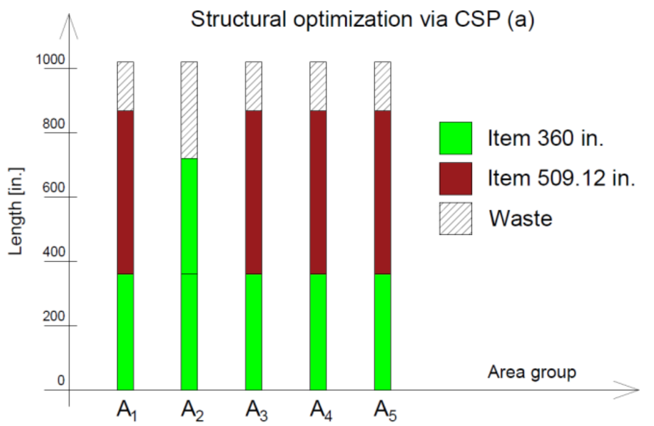

Figure 6 Optimal cutting pattern derived by optimization scenario (a)

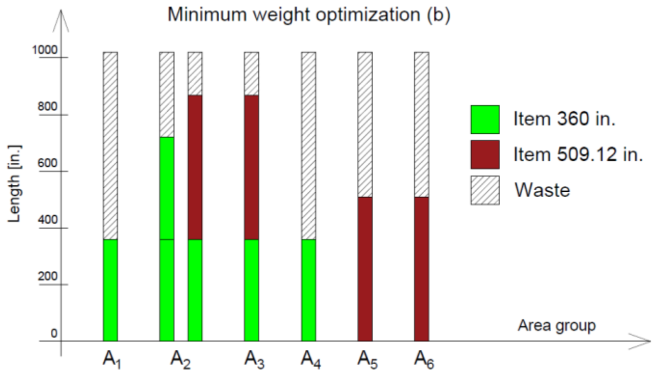

Figure 7 Optimal cutting pattern derived by optimization scenario (b)

5 Conclusion and future developments

In this paper, a novel procedure for the optimization of steel truss structures has been introduced aiming to evaluate the minimum number of bins (total mass of purchased steel bars) and the optimal cutting pattern of a stock of elements has been evaluated by solving the Cutting Stock Problem (CSP). A well-known in literature 10-bar truss case study has been adopted to demonstrate the effectiveness of the proposed method. The outcomes of the research reveal how considering the cutting procedure within the optimization process brings a significant waste reduction with respect to the traditional approach in which only the total mass target function is minimized (1033.9 vs 4743.0). Therefore, the former guaranteed a high level of performance and slenderness of the structure though a negligible loss of structural weight has been recognized with respect to the latter. In future developments, the proposed approach will be performed on realistic complex civil engineering structures such that advantages related to cost and environmental aspects will demonstrate the usefulness of adopting the CSP procedure into optimization processes.

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