DYNA
ISSN: 0012-7353
ISSN: 2346-2183
Universidad Nacional de Colombia

Aluminum bar cutting optimization for door and window manufacturing

de Araujo-Machado, Ageu; Zayatz, João Carlos; Melluzzi Neto, Guilherme; da Silva, Marcos Meurer; Lapasini Leal, Gislaine Camila; Palma Lima, Rafael Henrique

Aluminum bar cutting optimization for door and window manufacturing
DYNA, vol. 87, no. 212, 2020
Universidad Nacional de Colombia
Available in: http://www.redalyc.org/articulo.oa?id=49663642019
DOI: 10.15446/dyna.v87n212.82636

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

Artículos

Aluminum bar cutting optimization for door and window manufacturing

Optimización de corte de barras de aluminio para la fabricación de puertas y ventanas

Ageu de Araujo-Machado [a] ageu.mga@gmail.com
Universidade Estadual de Maringá, Brazil
João Carlos Zayatz [a] jcarloszay@gmail.com
Universidade Estadual de Maringá, Brazil
Guilherme Melluzzi Neto [a] gui.mlz@gmail.com
Universidade Estadual de Maringá, Brazil
Marcos Meurer da Silva [a] marcosmeurer50@gmail.com
Universidade Estadual de Maringá, Brazil
Gislaine Camila Lapasini Leal [a] gclleal@uem.br
Universidade Estadual de Maringá, Brazil
Rafael Henrique Palma Lima [ab] rafaelhlima@utfpr.edu.br
Universidade Estadual de Maringá, Brazil

DYNA, vol. 87, no. 212, 2020

Universidad Nacional de Colombia

Received: 03 October 2019
Revised document received: 04 December 2019
Accepted: 20 January 2020

DOI: 10.15446/dyna.v87n212.82636

CC BY-NC-ND

Abstract: This study aims to optimize the one-dimensional cutting process of aluminum bars for the production of aluminum doors. Reducing the use of bars and the amount of material that becomes scrap is a key factor in process efficiency, reducing the need for raw material procurement. The mathematical model used considers the size of the bar, the number and size of cuts, the size of the leftovers that can be used and the size of the leftovers that are considered scrap. Based on real data from a company in the aluminum frame segment, the mathematical model was used to simulate three different scenarios. Three different objective functions were used in the simulations, and the results obtained in each scenario were described in order to indicate the advantages and disadvantages of using each objective function. For the instance sizes studied, the model is able to obtain optimal solutions with little computational time.

Keywords: one-dimensional cut, mathematical modeling, aluminum.

Resumen: El presente trabajo tiene como objetivo optimizar el proceso de corte unidimensional de barras de aluminio para la producción de puertas de aluminio. Reducir el uso de barras y la cantidad de material que se convierte en chatarra es un factor clave en la eficiencia del proceso, reduciendo la necesidad de adquisición de materia prima. El modelo matemático utilizado considera el tamaño de la barra, el número y el tamaño de los cortes, el tamaño sobrante a que se puede usar y el tamaño sobrante que se considera chatarra. Basado en datos reales de una compañía en el segmento de marcos de aluminio, el modelo matemático se utilizó para simular tres escenarios diferentes. Se utilizaron tres funciones objetivo diferentes para el mismo modelo en las simulaciones y se describieron los resultados obtenidos en cada escenario para las tres funciones con el fin de indicar las ventajas y desventajas de usar cada función objetivo. Para los tamaños de instancia estudiados, el modelo puede obtener soluciones óptimas con poco tiempo computacional.

Palabras clave: corte unidimensional, modelo matemático, aluminio.

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

1. Introduction

The need for increasingly diverse products has demanded increasing flexibility from companies in response to customer needs. Therefore, manufacturing industries, facing the trend of high variety and smaller production volume, have adopted the custom manufacturing mode. Therefore, they only start production after the order has been entered with the required characteristics. These industries usually have cut stocks and the production process starts from the arrival of a project on demand and individual characteristics. Thus, the inventory cutting step is the first operation that promotes subsequent ones [1].

An appropriate cutting plan can lead the company to reducing costs of material, waste as well as reducing order lead time. Losses in cutting processes are aspects that must be taken into consideration from both the environmental perspective, due to waste generation, and the economic one, regarding the reduction of waste in the production process [2].

According to Cherri et al. [3], harnessing waste from the cutting process is common for organizations due to the significant financial impact it can have, especially when the cost of raw material is a considerable part of the total cost of production composition. Thus, it is evident the need for a cutting planning, whose leftovers are avoided as much as possible and not discarded.

Several studies address the use of optimization models applied to the cutting problem [3-12]. In this context, this paper aims to apply and test a one-dimensional bar cutting optimization model in a company of the aluminum frame segment using three objective functions, in order to reduce the leftovers from the bar cutting, as well as the number of bars used for the door production process. The optimization model adopted in this work is the one proposed by Abuabara and Morabito [8] for the one-dimensional bar cutting problem, since it considers the leftovers of the process and allows classify them as reusable and leftover that becomes loss. In this study, the latter becomes aluminum scrap.

Three objective functions were used in simulations for the same model. The first one considers the minimization of the loss that is considered scrap. The second one considers the minimization of the amount of bars used. The third one combines both possibilities, seeking to minimize the amount of leftovers that is considered scrap, but offering an increase in the value of the objective function as the number of bars used rises. Based on the results obtained in the simulations, discussions were made about the advantages and disadvantages of each of the objective functions used during the simulations. Data were collected from a company that produces aluminum frames, where there is a need to establish cutting plans from a stock of bars.

Three scenarios were addressed in the simulation, where the number of necessary cuts varied, while the stock of bars remained fixed. Optimizing the use of bars directly impacts the company's performance, since aluminum is purchased per kilo, and what is not used is returned for extrusion, causing a loss.

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

2. Theoretical background

The problem of one-dimensional cutting is making an object available for production by making cuts on it in order to meet a specific dimension demand [4,13]. The cutting process refers to obtaining smaller items from cutting a larger matrix using cutting patterns or decision elements [5,14].

Cherri et al. [3] point out that the use of appropriate strategies and models for cutting problems enables the reduction of costs related to this process. Benjaoran et al. [4] mention that it is possible to minimize the stocks used and, consequently, reduce material loss. Several studies [6-9] address the cutting problem by using one-dimensional and two-dimensional approaches.

One of the common goals in the one-dimensional cutting problem is the reduction of leftovers. However, Wäscher et al. [15] point out that most cutting problems can be classified into input minimization problems, in which one seeks to minimize the amount of resources needed to achieve a goal, and production maximization problems, in which certain (limited) resources should be used to provide the best possible result.

The cutting problem has gained attention in various sectors such as the metal, paper and glass industry [1], and has been addressed from the viewpoint of both the problem [10,12] and the technique for its resolution [5,11].

Reinertsen and Vossen [10] dealt with the cutting problem by taking cutting stock and order lead time into account. Stadtler [12] presents a case of an aluminum profile manufacturer that provides its customers with the service of calculating the minimum number of aluminum profiles of a given standard length, so that the demand for lengths in orders is met. By using the Packaging-problem model, the manufacturer was able to generate optimal solutions for a large number of cutting-stock problems.

Yanasse and Lamora [5] adopted a Lagrangian approach aiming to solve a cut pattern sequencing problem, while Cui et al. [11] developed a heuristic algorithm for the one-dimensional cutting problem with usable leftovers.

3. Mathematical modeling

An ideal cutting plane is a key piece for companies working with aluminum profiles for door and window production. With a stock of bars, managing their use can help reduce leftovers in cutting planes. As much as leftovers can be sold as scrap again, the costs of included services rise and an amount of aluminum is lost. Thus, a cutting plane with minimal leftovers financially impacts the values lost with this material.

The one-dimensional cutting-stock problem occurs in various industries. The most common are metal, paper, textile and wood industries [16]. Mathematical Programming can be used to solve a number of real complex problems, allowing the integration of a

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

mathematical model supported by computational tools, as highlighted by Leão et al. [17].

The mathematical model described here was used to create a cutting plane using data from a company that produces aluminum frames. Aluminum bars are purchased in large batches in predefined sizes. From the available stock, when an order is received by the project department, it is necessary to decide how many and which bars to cut. The model takes into account a technical design issue: there is a minimum lenght value from which a piece of leftover from a bar cut can no longer be used, becoming scrap.

In order to apply the model, the profile bar stock must have sufficient material to meet the demand. Since the bars are purchased in predetermined sizes, the length of the pieces to be cut is limited to the length of the bars. These features are present in the application scenario and, therefore, the model proves to be feasible.

3.1. Model parameters and variables

The model proposed by Abuabara and Morabito [8], applicable to the problem of one-dimensional bar cutting, takes into account the leftover bars after the cutting process, and allows to classify these leftovers into reusable parts or losses. By losses we refer to leftovers less than an N length. This lenght value is a parameter of the model. Scraps larger than N are considered parts that can be used in a new cutting process.

To understand the model, it is necessary to define the indexes presented below.

i= 1,..., m: demanded profile piece

j= 1,..., n:: stock profile bars

The model considers the following parameters:

b_j : bar length j in stock;

d_i : quantity of profile piece demanded i;

l_i : length of profile piece demanded i;

M: very large value;

N: minimum length to be considered as surplus;

R: maximum number of leftovers.

The value of M assumes the value of a sufficiently large number, which in this article will be calculated by, $M = max_j \{b_j\} - min_i \{l_i\}$,that is, the value of the largest bar minus the value of the smallest profile piece [8].

The decision variables used in the model are presented below:

δ_j :bar leftover value ;

t_j: bar loss value i;

z_j : binary variable indicating whether bar j will be used (z_j =1) or not (z_j =0);

u_j : binary variable that indicates whether bar j has leftover (u_j =1) or not (u_j =0);

x_{ij} : quantity of demanded profile piece i allocated in bar j.

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

3.2. Functions purpose of the ILP model

In this study, we chose to carry out a comparative analysis among three objective functions. The first function, $F0_1$, (Eq. 1), which is described below, is intended to reduce the amount of leftovers generated. As shown in Eq. (1), this objective function sums the amount of losses observed for each bar.

$$FO_1 = min \sum_{j=1}^{n} t_j \tag{1}$$

The second objective function $F0_2$, (Eq. 2) is characterized by the minimization of the number of bars used in the cutting plane, defined as follows:

$$FO_2 = min \sum_{j=1}^{n} z_j \tag{2}$$

The objective functions $F0_1$ and $F0_2$ can be combined into a single objective function. The objective function $F0_1$ remains the main objective of the model, that is, the reduction in material loss, while $F0_2$ enters the objective function with a penalty which, in this case, is the reduction in number of bars. As observed in a study [8], a multi-objective function which minimizes loss, while also providing a penalty for the number of bars used, generates the third objective function, $F0_2$Eq. (3), considered in this paper.

$$FO_3 = min \sum_{j=1}^{n} t_j + \frac{\sum_{j=1}^{n} b_j * z_j}{\sum_{j=1}^{n} b_j} \tag{3}$$

As for $F0_3$, as the input parameters of the model are assumed to be integers, the first term of this expression will always be an integer, that is, total compensation loss. Therefore, since the second term always generates a value between 0 and 1, this term disables minimal loss alternative solutions in favor of solutions that minimize the total length cut of the object [8].

3.3. Model Restrictions of ILP

Model constraints are described below.

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

$$\sum_{i=1}^{m} l_i * x_{ij} + \delta_j = b_j \qquad \forall_j \tag{4}$$

$$\sum_{j=1}^{n} x_{ij} = d_i \qquad \forall_i \tag{5}$$

$$\sum_{j=1}^{n} u_j \leq R \tag{6}$$

$$N * u_j \leq b_j * z_j - \sum_{i=1}^{m} l_i * x_{ij} \qquad \forall_j \tag{7}$$

$$b_j * z_j - \sum_{i=1}^{m} l_i * x_{ij} \leq t_j + u_j * M \qquad \forall_j \tag{8}$$

$$\delta_j \in N \qquad \forall_j \tag{9}$$

$$t_j \in N \qquad \forall_j \tag{10}$$

$$u_j \in \{0,1\} \qquad \forall_j \tag{11}$$

$$x_{ij} \in N \qquad \forall_{ij} \tag{12}$$

$$z_j \in \{0,1\} \qquad \forall_j \tag{13}$$

Eq. (4) ensures that bar length will be respected by determining that the sum of the amount of each profile piece added to the leftover is equal to the size of the bar. Eq. (5) ensures that the demand will be met, showing that the number of pieces from each bar is equal to the demand placed. Eq. (6) ensures that the amount of leftovers will be limited to parameter R. Eqs. (7) and (8) make up the set of restrictions related to leftovers. Eq.

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

(7) verifies that the minimum size defined as N is less than or equal to the unused length. Eq. (8) ensures that the unused bar length is less than or equal to the sum of the loss with parameter M. Eqs. (9), (10), (11), (12) and (13) represent the domain of variables.

4. Results

4.1. Data collection

Data were collected from an industry of the metal-mechanical sector, which uses, among other items, aluminum profiles in the production of frames. The input is purchased prior to the orders due to supplier lead time. Thus, there is a certain number of bars stocked to be cut when an order is received. The raw material is purchased in predefined sizes and stocked to feed a make-to-order production system.

Production orders are issued according to purchase orders. When a production order or a set of grouped orders is released for production, one wants to optimize the use of stock inputs. Aluminum is purchased in bars of predetermined length. The problem is cutting the aluminum into smaller pieces, which will make it possible to assemble the frames. Loss is intended to be minimal. The cost of raw material, purchased per kilogram regardless of bar length is not considered as a parameter in this model. There is a production order with demands for items and lengths to be cut, as shown in Table 1.

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

Table 1
Production Order.

Indice	Dem.	Size (mm)	Indice	Dem.	Size (mm)
1	4	52	53	2	2300
2	1	200	54	2	2302
3	5	260	55	2	2315
4	2	282	56	4	2350
5	3	290	57	2	2352
6	1	300	58	2	2353
7	2	350	59	2	2362
8	5	540	60	2	2366
9	1	850	61	2	2367
10	2	1017	62	4	2386
11	2	1022	63	2	2420
12	4	1030	64	2	2425
13	4	1262	65	4	2442
14	6	1310	66	2	2457
15	2	1350	67	2	2502
16	3	1500	68	2	2517
17	2	1548	69	3	2560
18	5	1555	70	1	2643
19	2	1600	71	2	2760
20	4	1684	72	1	2860
21	2	1750	73	2	2890
22	2	1820	74	2	2892
23	6	1826	75	4	2990
24	4	1872	76	2	2995
25	3	1900	77	3	3060
26	3	1920	78	4	3070
27	2	1950	79	2	3097
28	3	1970	80	2	3104

Table 1 (cont.)
Production Order.

Indice	Dem.	Size (mm)	Indice	Dem.	Size (mm)
29	4	1972	81	2	3238
30	2	1985	82	3	3506
31	2	1987	83	4	3510
32	2	1995	84	3	3580
33	2	2006	85	3	3586
34	2	2016	86	3	3700
35	3	2020	87	3	3863
36	2	2030	88	4	3970
37	2	2032	89	5	4180
38	2	2072	90	2	4200
39	2	2100	91	2	4285
40	2	2151	92	4	4390
41	2	2166	93	4	4460
42	2	2167	94	3	4650
43	2	2182	95	4	4780
44	2	2192	96	3	4836
45	2	2232	97	5	5250
46	2	2245	98	5	5270
47	2	2272	99	3	5486
48	2	2284	100	3	5500
49	2	2286	101	5	5530
50	1	2287	102	3	5570
51	2	2289	103	5	5970
52	2	2294	104	41	6060

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

Source: The Authors.

As the stock was large enough to meet the bar demand in the cutting process, we considered a case in which there were 170 bar units of 6.1 meters and 190 bar units of 5.1 meters, totaling 360 bars in stock. It is essential that the cutting pieces do not exceed 6 meters, which is the size of the largest bars in stock. For this study, reusable bars are those whose leftovers are larger than 500 mm, otherwise they are considered as scrap.

4.2. Model implementation

The model described was implemented with Solver Gurobi version 8.1.1, using the Anaconda Python Distribution 3.7. A 64-bit Microsoft Windows 10 operating system was used, operating on 4 GB RAM with an Intel Core I5-2450 processor, which has 2 processor cores, 4 threads, 2.50 GHz processor-based frequency.

4.3. Deployment scenarios

Three scenarios were considered to analyze the behavior performance of objective functions. In the first one, only the 52 smallest items were considered, keeping the demand. In this case, there will be a surplus of bars in stock to establish the cutting scheme, and it is important to observe the performance of the objective functions concerning the number of bars used and process losses. The R value, which represents the maximum number of bars to be used, was equal to the total of 360, thus allowing the free use of bars.

Next, we considered two new scenarios in which the demand approximates the totality of bars in stock. With that, we sought to analyze the performance of objective functions when the gap that exists between the available bars and the present demand in the production order is decreased.

The second scenario considers all 104 items, but the demand for each item has been halved. In cases where the demand value was odd, the next integer was considered higher than a half. The third scenario considers the actual production order contained in Table 1. In all scenarios the number of bars in stock was maintained.

For each scenario, the purpose of the optimization function was changed: minimizing total loss ($F0_1$) minimizing the number of bars used($F0_2$) , minimizing both loss and the number of bars used at the same time($F0_3$). (Then, the performance of the objective functions in each scenario was analyzed in relation to the number of bars used and the amount of loss associated with the cutting scheme.

4.4. Results and discussion

The structuring of the model allows the elaboration of a cutting plane, in order to identify which piece will be cut from each bar. It also

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

provides information on the number of stock bars and bars required for production, the amount of total loss identified, as well as the sum in millimeters of the material that became reusable. The detailing of loss and reusable parts is in the cutting plane, which also specifies from which bar a particular piece will be cut.

Table 2 presents the results for the three proposed scenarios. For all scenarios, the Solver was able to find an optimal solution within the proposed parameters. However, each function can be applied to different situations depending on the company's objective and strategy.

Table 2

Proposed scenarios.

Scenario 1				
		Objective Function		
		FO_1	FO_2	FO_3
Bars Used	6100	3	34	13
	5100	190	1	31
	Total	192	35	44
FU(mm)		987.300	212.500	237.400
TL(mm)		0	2.640	0
RS(mm)		777.440	0	27.540
RQ		192	0	37
NI		392	139.719	848.687
OR(s)		0,53	70,92	600,15
IUR (%)		49,22	10,59	11,83
Scenario 2				
		Objective Function		
		FO_1	FO_2	FO_3
Bars Used	6100	71	93	76
	5100	190	0	34
	Total	261	93	110
FU(mm)		1.402.100	567.300	637.000
TL(mm)		1.126	14.222	1.126
RS(mm)		847.896	0	82.296
RQ		237	0	78
NI		12.445	598.863	86.148
OR(s)		6,72	600,09	81,84
IUR (%)		69,90	28,28	31,75
Scenario 3				
		Objective Function		
		FO_1	FO_2	FO_3
Bars Used	6100	154	169	128
	5100	190	1	72
	Total	344	170	200
FU(mm)		1.908.400	1.036.000	1.148.000
TL(mm)		2.082	33.096	2.082
RS(mm)		903.414	0	143.014
RQ		298	0	141
NI		11.790	760.898	106.524
OR(s)		8,87	600,12	184,62
IUR (%)		95,13	51,65	57,23

FU: Footage Used, TL: Total Loss, RS: Reusable Surplus, RQ: Reusable Quantity Surplus, NI: Number of Interactions, OR: Optimization Runtime and IUR: Inventory Utilization Rate in mm.

Source: The Authors.

Inventory Utilization Rate *IUR* corresponds to the percentage of material used in stock, given by Eq. (14).

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

$$IUR = \frac{FU}{\sum_{j=1}^{n} b_j} \tag{14}$$

To analyze the performance of the objective functions in each scenario, four graphs were generated. Fig. 1 shows the number of bars used per scenario. In all scenarios, the largest number of bars used was observed in $F0_1$, with high quantity in relation to the other two $F0_2$ used less bars than $F0_3$, and this difference tends to rise as the gap between the number of bars in stock and the demand for parts decreases. Fig. 2 shows the bar footage used in each scenario. In all scenarios, we noticed that $F0_1$ consumed larger footage than the other two.used less footage than $F0_3$ and this difference tends to rise as the gap between the number of bars in stock and the demand for parts decreases.

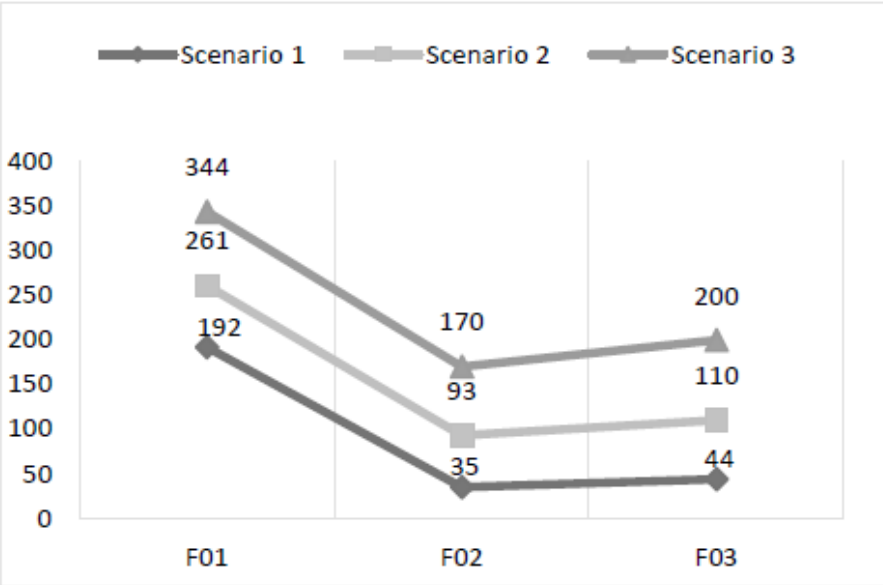

Figure 1
Bar amount graph per scenario.
Source: The Authors.

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

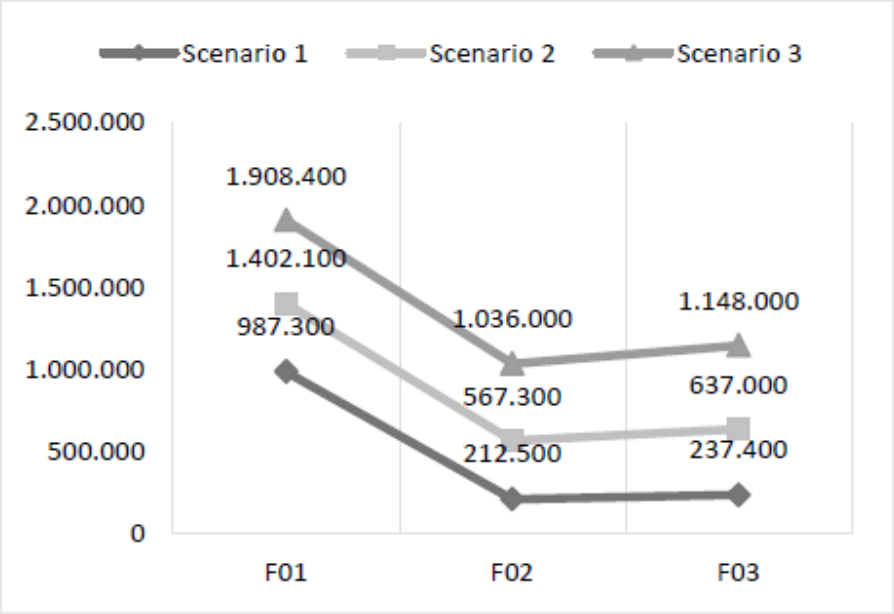

Figure 2
Graph of the footage used per scenario.
Source: The Authors.

Fig. 3 illustrates the amount of interactions per scenario. In this case, $F0_1$ required the least amount of interactions; $F0_2$ increased the number of interactions as the gap between the number of bars in stock and the demand for parts decreased. $F0_3$ presented a higher number of interactions when there was a higher gap between the number of bars in stock and the demand for parts. Also, a decrease in the number of interactions was observed as the gap between the number of bars in stock and the demand for parts decreased.

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

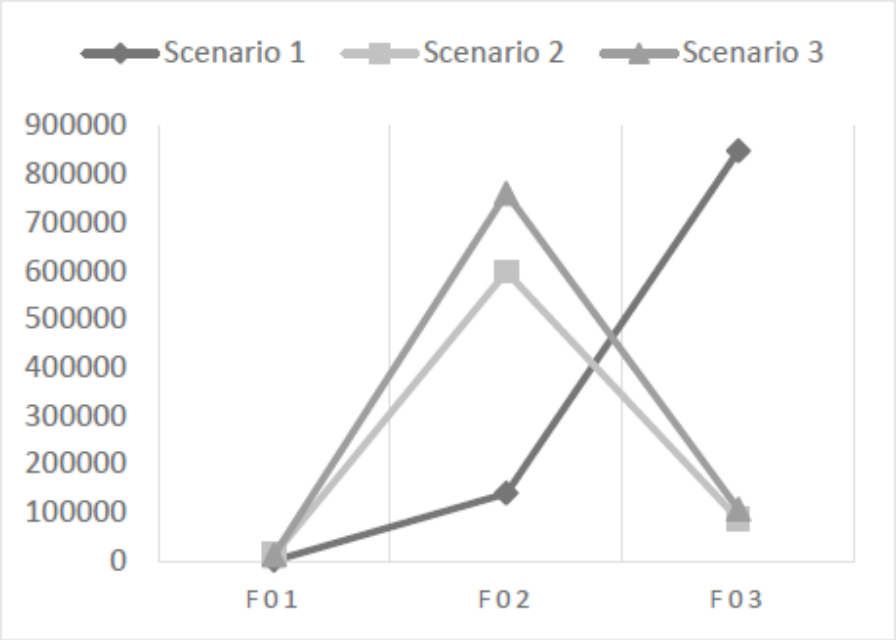

Figure 3
Graph of number of interactions per scenario.
Source: The Authors.

Fig. 4 shows the runtime per scenario.*F0* $_1$ required the shortest runtime. Runtime in *F0* $_2$ rose as the gap between the number of bars in stock and the demand for parts decreased. *F0* $_3$ had a longer runtime when there was a higher gap between the quantity of bars in stock and the demand for parts. A decrease in runtime was also observed when the gap between the quantity of bars in stock and the demand for parts decreased.

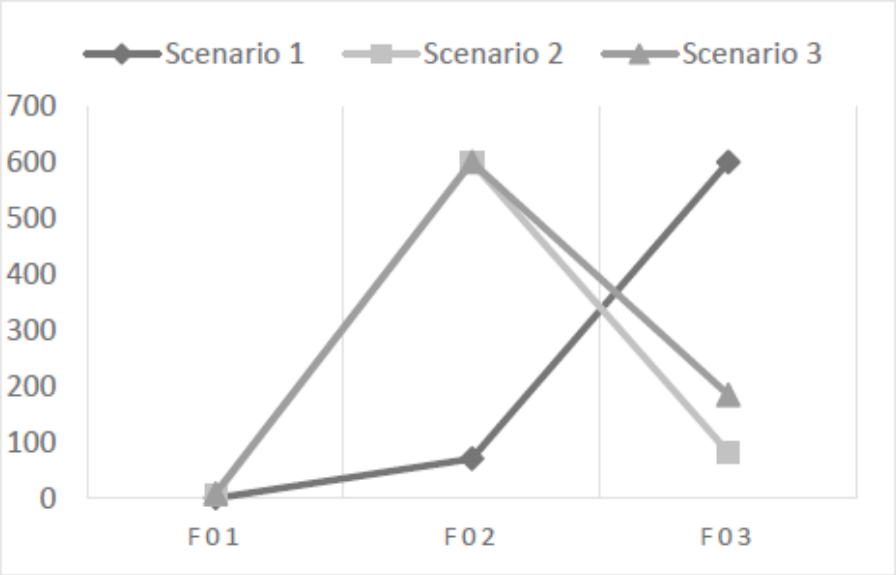

Figure 4
Runtime graph per scenario.
Source: The Authors.

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

Objective function $F0_1$ demanded a significantly higher number of bars compared to the others in all scenarios, also consuming larger footage. This can be explained due to the fact that $F0_1$ is intended to minimize loss only. In all three scenarios, a null or almost zero loss was obtained, but it caused higher consumption of bars and footage. Consequently, the usable surplus was also high, which for the production process in question was considered a disadvantage, taking into account an analysis of future material needs. One advantage of this function is that, in all scenarios, it used fewer interactions and less runtime. One possible application of this function to the model is to determine if the cutting stock can meet demand.

Objective function $F0_2$ presented the best result when analyzing the quantity of bars consumed and footage used. On the other hand, it resulted in a larger amount of loss, or non-reusable material. For the production process, high material losses become monetary losses due to the amount paid to manufacture the profile, which acquires scrap value. The number of interactions rose as demand approached total bars in stock. The same happened with runtime. This function can be used in specific projects when one wants to keep in stock as many un-sectioned bars as possible.

Objective function $F0_3$, showed an equivalent loss compared to $F0_1$ but with significant advantage concerning the number and the size of bars used, which was smaller. Although $F0_3$ used more bars and larger footage than $F0_2$, it was able to distribute the cuts to minimize losses without using a high number of bars. The number of interactions was higher when there was a higher gap between the number of bars available and the demand. When the demand approached the total available bars, the number of interactions was well below the total identified in $F0_2$ The same applied to runtime.

For the production order in question, represented by scenario 3, $F0_3$ was adequate from the viewpoint of the quantity of leftovers and the amount of losses. When there are pieces that cannot be used, all unused material is turned into aluminum scrap and a monetary value is lost. The leftover bars, in this case, are large enough to be used in other projects, so they are not considered scrap. These leftovers come in a satisfactory quantity, thus, other projects can absorb them.

In some contexts where there is no certainty to use leftovers in further projects, $F0_2$ provides a contribution to the bar cutting plane that should be considered, since it minimizes the number of bars used in this process, even generating some losses. In any case, leftovers can be lost if not used at other times. Table 3 shows an overview of applications, advantages and disadvantages of the objective functions.

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

Table 3
Applications, advantages and disadvantages of the objective functions.

Objective Function	Application	Advantage	Disadvantage
FO_1	Guarantees if cutting-stock meets demand.	Less runtime and less waste of raw material.	Consumption of more bars.
FO_2	Material planning for specific projects.	Returns the smallest number of bars required for the process.	Does not consider loss.
FO_3	Productive processes that allow reusing leftovers.	Returns the best cutting plane tending to reduce the amount of loss with the least possible use of bars.	High processing time, depending on instance size.

Source: The Authors.

The penalty in the objective function of [8] guarantees two advantages in the bar cutting process when the intention is working with the use of leftovers, because it results in the least amount of losses. For the company, the first advantage ensures avoids the generation of waste considered losses during optimization, and generates reusable pieces for later production. The second advantage is that the sale price of the waste considered loss is relatively lower than the purchase price of the bar aluminum bar used in the process. Thus the smaller the material loss, the more effective the productive and financial process will be.

5. Concluding remarks

Mathematical modeling contributes to the optimization of one-dimensional cutting planes, increasing the efficiency and performance of the production process. In this work, the mathematical model by Abuabara and Morabito [8] was applied to a cutting plane of a metalworking company that needs to cut aluminum bars for the production of frames.

The mathematical model adopted allows the use of several objective functions. In this case, three distinct objective functions were analyzed. The adoption of a specific objective function depends on the rules, characteristics, and specific needs of the company. The comparative analysis of three objective functions showed that the combination of an objective function that minimizes losses with a penalty for the number of bars used provided more adequate results for the specific case of the plane studied than the individual use of these approaches.

Data on limitation of leftovers quantity, represented by the R value of the model, were not described in this study. This value tends to modify

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

the objective functions performance, which represents a limitation for the analyses. The mathematical model proved to be feasible for the considered instances, and cutting planes with larger instances can have a significant impact on runtimes or on the number of interactions. Future research points to the need to consider the size of the cutting blade in process losses. Future work points to the need to consider the size of the cutting blade in process losses.

Acknowledgements

This study was partially financed by the Coordination for the Improvement of Higher Education Personnel (CAPES) - Brasil - Finance Code 001.

References

[1] Wang, W., Shi, Z., Shi, L. and Zhao, Q., Integrated optimisation on flow-shop production with cutting stock. International Journal of Production Research, pp. 1-17, 2018. DOI: 10.1080/00207543.2018.1556823

[2] Coelho, K.R., Cherri, A.C., Baptista, E.C., Jabbour, C.J.C. and Soler, E.M., Sustainable operations: the cutting stock problem with usable leftovers from a sustainable perspective. Journal of Cleaner Production, 167, pp. 545-552, 2017. DOI: 10.1016/j.jclepro.2017.08.153

[3] Cherri, A.C., Arenales, M.N. and Yanasse, H.H., The usable leftover one#dimensional cutting stock problem- A priority#in#use heuristic. International Transactions in Operational Research, 20(2), pp. 189-199, 2013. DOI: 10.111/j.1475-3995.2012.00868.x

[4] Benjaoran, V., Sooksil, N. and Metham, M. Effect of demand variations on steel bars cutting loss. International Journal of Construction Management, 19(2), pp. 137-148, 2019. DOI: 10.1080/15623599.2017.1401258

[5] Yanasse, H.H. and Lamosa, M.J.P., An integrated cutting stock and sequencing problem. European Journal of Operational Research, 183(3), pp. 1353-1370, 2007. DOI: 10.1016/j.ejor.2005.09.054

[6] Kłosowski, G., Kozłowski, E. and Gola, A. Integer linear programming in optimization of waste after cutting in the furniture manufacturing. In: International Conference on Intelligent Systems in Production Engineering and Maintenance, 2017, pp. 260-270.

[7] Suliman, S.M.A., A sequential heuristic procedure for the two-dimensional cutting-stock problem. International Journal of Production Economics, 99(1-2), pp. 177-185, 2006. DOI: 10.1016/j.ijpe.2004.12.017

[8] Abuabara, A. and Morabito, R., Cutting optimization of structural tubes to build agricultural light aircrafts. Annals of Operations Research, 169(1), pp. 149-145, 2009. DOI: 10.1007/s10479-008-0438-7

[9] Kallrath, J., Rebennack, S., Kallrath, J. and Kusche, R., Solving real-world cutting stock-problems in the paper industry: Mathematical approaches, experience and challenges. European Journal of Operational Research, 238(1), pp. 374-389, 2014. DOI: 10.1016/j.ejor.2014.03.027

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

[10] Reinertsen, H. and Vossen, T.W., The one-dimensional cutting stock problem with due dates. European Journal of Operational Research, 201(3), pp. 701-711, 2010. DOI: 10.1016/j.ejor.2009.03.042

[11] Cui, Y., Song, X., Chen, Y. and Cui, Y.P., New model and heuristic solution approach for one-dimensional cutting stock problem with usable leftovers. Journal of the Operational Research Society, 68(3), pp. 269-280, 2017. DOI: 10.1057/s41274-016-0098-y

[12] Stadtler, H. A one-dimensional cutting stock problem in the aluminium industry and its solution. European Journal of Operational Research, 44(2), pp. 209-223, 1990. DOI: 10.1016/0377-2217(90)90356-G

[13] Poldi, K.C. and Arenales, M.N., Heuristics for the one-dimensional cutting stock problem with limited multiple stock lengths. Computers & Operations Research, 36(6), pp. 2074-2081, 2009. DOI: 10.1016/j.cor.2008.07.001

[14] Martinovic, J., Scheithauer, G. and de Carvalho, J.V., A comparative study of the arcflow model and the one-cut model for one-dimensional cutting stock problems. European Journal of Operational Research, 266(2), 458-471, 2018. DOI: 10.1016/j.ejor.2017.10.008

[15] Wäscher, G., Haußner, H. and Schumann, H., An improved typology of cutting and packing problems. European Journal of Operational Research, 183(3), pp. 1109-1130, 2007. DOI: 10.1016/j.ejor.2005.12.047

[16] Tomat, L. and Gradišar, M., One-dimensional stock cutting: optimization of usable leftovers in consecutive orders. Central European Journal of Operations Research, 25, pp. 473-489, 2017. DOI: 10.1007/s10100-017-0466-y

[17] Leao, A.A.S., Santos, M.O., Hoto, R. and Arenales, M.N., The constrained compartmentalized knapsack problem: mathematical models and solution methods. Eur. J. Oper. Res. 212, pp. 455-463. 2011. DOI: 10.1016/j.ejor.2011.02.016.

Notes

A.A. Machado, is BSc. in Industrial Engineering in 2017 from the State University of Maringá (UEM), Brazil. Currently, he is a student in the Master's in Industrial Engineering from UEM. His research interests include optimization, process improvement and Quality Engineering.ORCID: 0000-0002-1055-1741

J.C. Zayatz, is BSc. in Industrial Engineering in 2012 from the State University of Maringá (UEM), Brazil. Currently, he is a student in the Masteer's in Industrial Engineering from UEM. His research interests include optimization and process improvement. ORCID: 0000-0003-0849-1900

G. Melluzzi Neto, is BSc. in in Industrial Engineering in 2012 from the State University of Maringá (UEM), Brazil. Currently, he is a student in the Master's in Industrial Engineering from UEM. His research interests include optimization, process improvement and logistics. ORCID: 0000-0002-3385-2387

M.M. Silva, is BSc in Industrial Engineering in 2019 from the Federal University of Grande Dourados (UFGD), Brazil. Currently, he is a student in the Master's in Industrial Engineering from UEM. His research interests include optimization, process improvement, green supply chain management and industrial symbiosis. ORCID: 0000-0002-1229-5518

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative

G.C.L. Leal, is BSc. in Industrial Engineering in 2007 from the State University of Maringá (UEM), Brazil. MSc. in Computer Science in 2010 from UEM, and PhD degree in Electrical and Computer Engineering in 2015 all of them from the Technological Federal University of Paraná (UTFPR), Brazil. Currently, she is a professor in the Production Department at UEM. Her research interests include optimization, support for decision-making and process improvement. ORCID: 0000-0001-8599-0776

R.H.P. Lima, is BSc. in Industrial Engineering in 2008 from the University of São Paulo (USP), Brazil. PhD in Industrial Engineering in 2012 from the USP. Currently, he is a professor in the Production Department at the Federal University of Technology - Paraná (UTFPR). His research interests include logistics, operations management, computational intelligence and quality management. ORCID: 0000-0002-9098-3025

How to cite: Machado, A.A, Zayatz, J.C, Melluzzi-Neto, G, Silva, M.M, Leal, G.C.L. and Lima, R.H.P, Aluminum bar cutting optimization for door and window manufacturing. DYNA, 87(212), pp. 155-162, January - March, 2020.

PDF generated from XML JATS4R by Redalyc
Project academic non-profit, developed under the open access initiative