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Development of a fuzzy logic-based loading algorithm in the selection of the most appropriate cargo package for cleaning and cosmetic products

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Abstract. Minimum space and maximum capacity based loading algorithms or software products for in-container parcel loading or in-box product placement are very common. These software products, when desired to be used for placing cleaning and cosmetics products in cargo packages, have a number of special constraints and related challenges. Breakage, disintegration or spillage can occur in products that are not placed properly during transportation and transferring of the cargo packages. For some products; there are constraints such as horizontal placement is not allowed, another product cannot be placed on top of them, or tightly placement cannot be done. On the other hand, for some products, there is freedom to put them in every cavity because of their flexible structure. Due to these constraints and freedoms, the placement algorithm needs to have product-based flexibility. In this study, cleaning and cosmetic products which have special restrictions and freedoms are taken as the primary targets. An algorithm has been developed that optimizes the placement of these products in the package. The algorithm is run and tested using the Excel database and macro code. The algorithm is integrated into a private company product line. Thanks to this software automation, which is developed to make package selection at the right size, 14,4 % monthly cargo charge and 10 % labor savings are obtained.

Key-words: Container loading problem; Fuzzy logic optimization; Container loading algorithm

1. Introduction

Loading optimization emerges as an inevitable need for the logistics sector, since placing products with minimum gap and maximum filling ratio provides a significant gain in terms of cost and time. In accordance with this aim, some commercial software products are being developed as well as academic work on product loading optimization. Constraints such as size, geometry, direction of placement, layer, order, placement time of the products to be placed in the container give rise to diversity of placement algorithms. Moreover, the container can be a ship container, a truck, or a cargo box. The diversity of these container types and their different application areas increase the diversity of the algorithms.

This study aims to select the right cargo box for the placement of health care, cleaning and cosmetic products. Some of these products have direction, layer, or geometry constraints. In some products, there is a neighborhood constraint because of the risk of spillage or squeezing. Moreover, some products have a flexible structure so that they can be placed in every spacing. Therefore, a linear algorithm is not possible, since there is no linear relation among the entire product list. Since the customer's order list is variable, it is required to prepare an algorithm that takes into account the characteristics and constraints of the products in the order list and chooses the most appropriate cargo box. In this study, an algorithm is developed based on optimizing the space inside the cargo box which is accepted as a container. As a result of the algorithm, the most appropriate cargo box is selected for the placement of the ordered products by minimizing the unused space. The algorithm is integrated to a commercial company product line and it is seen that boxes selected with this optimization made the product line safer and more economical.

2. Literature view

Algorithms for container placement problems have been developed and applied successfully according to different criteria in previous studies. These studies differ in terms of approach (heuristic, mathematical programming and meta-heuristic) [1], size (2D-3D) [2], variability (Static, Dynamic) [3], number of layers (single or multi layer loading) [4] and container type (Single or multi conteyner type). However, all of these studies are based on optimizing the container space. For example; Bortfeldt, Andreas, and Hermann Gehring (2001) [5] present a hybrid genetic algorithm (GA) for the container loading problem with boxes of different sizes and a single container for loading. Generated stowage plans include several vertical layers, each containing several boxes. In another study, Gonçalves, José Fernando, and Mauricio GC Resende (2012) [6] present a multi-population biased random-key genetic algorithm (BRKGA) for the single container loading problem (3D-CLP) where several rectangular boxes of different sizes are loaded into a single rectangular container. The approach uses a maximal-space representation to manage the free spaces in the container. Their algorithm hybridizes a new placement procedure with a multi-population genetic algorithm based on random keys. In another study, Zheng, Chien & Gen (2015) [7] aims to develop a multi-objective multi-population biased random-key genetic algorithm for the three-dimensional single container loading problem. In particular, their genetic algorithm applied multi-population strategy and fuzzy logic controller (FLC) to improve efficiency and effectiveness. Indeed, their approach maximizes the container space utilization and the value of total loaded boxes by employing Pareto approach and adaptive weights approach. In another similar study, Ramos et al., (2016) [8] propose a container loading algorithm with static stability constraints based on the static mechanical equilibrium conditions applied to rigid bodies, which derive from Newton's laws of motion. The algorithm is a multi-population biased random-key genetic algorithm, with a new placement procedure that uses the maximal-spaces representation to manage empty spaces, and a layer building strategy to fill the maximal-spaces.

Container loading problem is approached analytically or mathematically for some studies even if the product geometries are not uniform. For example; Chen, C. S., Shen-Ming Lee, and Q. S. Shen (1995) [9] consider the problem of loading containers with cartons of non-uniform size and presents an analytical model to capture the mathematical essence of the problem. The container loading problem is formulated as a zero-one mixed integer programming model. Reasonable solutions have been produced with heuristic methods in cases where the loading time of the container has come to the fore. In these solutions, the result is acceptable even if the result is not 100 % accurate. For example; Toffolo, Túlio AM, et al. (2017) [10] present a decomposition approach embedded in a multi-phase heuristic for the problem. Feasible solutions are generated quickly, and subsequently improved by local search and post-processing procedures. Experiments revealed that the approach generates optimal solutions for two instances, in addition to good quality solutions for those remaining from the Renault set.

Heuristic methods as well as loading models, which are important for sorting, have also been developed. For example; Ren, J., Tian, Y., & Sawaragi, T. (2011) [11] proposed a priority-considering heuristic approach to solve the multiple container loading problem, i.e., the problem of packing a given set of three-dimensional rectangular items into multiple containers to make the maximum use of the container space. In another study, Huang, Yao-Huei, F. J. Hwang, and Hao-Chun Lu (2016) [12] investigate a three-dimensional single container loading problem, which aims to pack a given set of unequal-size rectangular boxes into a single container such that the length of the occupied space in the container is minimized. In another study, Bian, Zhan, Qian-qian Shao, and Zhihong Jin.(2015) [13] present a two-phase hybrid dynamic algorithm aiming at obtaining an optimized container loading sequence for a crane to retrieve all the containers from the yard to the ship.

In existing studies, a pure fuzzy logic approach has not been found in the construction of loading algorithm. However, relevant studies are seen. Chuang et all [14], for example, develop an algorithm which not only takes market demand, shipping and berthing time of container ships into account simultaneously but also is capable of finding the most suitable route of container ships.

3. Preliminary studies

In this study, an algorithm was developed to optimize the placement of cleaning and personal care products in the box, and to select the appropriate box size for a group of products ordered. It is seen as a very important expectation for marketing companies to be able to ship with the smallest possible package in order to ensure that products are not damaged during carriage and the cost of cargo is minimum. A sample placement of the products in a box is seen in figure 1.

Fig. 1. A sample placement of the products in a box

In order to evaluate the solid outputs of the work, the products produced and marketed by a certain company is taken as an example. The results are evaluated by integrating the developed algorithm with the existing software of the same company.

Previously, for the products ordered, a staff member decides on the basis of experience which one of the three different box dimensions will suffice and sends the dispatch bill to the product selection department. The dispatch bill indicates which size cargo box should be used and which products are to be placed in it. If a box of the correct size is selected for the ordered products, the products are placed safely and manually with experience and sent to cargo. However, the mistakes made in the selection of cargo boxes have a number of additional costs. Cargo costs are increased if a large box is proposed. If a too small box is recommended, the products will not fit and are taken back to the planning department and this causes time lost. The product selection and packaging department which works in a sequential manner is heavily influenced by the loss of this time and the daily capacity is decreased. For this purpose, when a package is selected by a software program instead of an experienced member;

1. In the Planning Department, an additional worker who manually chooses boxes to be used is not necessary
2. Cargo costs will be reduced, as the choice of larger boxes will be minimized
3. Wrongly selection of a small box is minimized which is common for manual selection of boxes that causes time loss on the dispatch bill change and extra work load.

The selected company has 80 kinds of products. Some products look very similar to each other but have different contents. Some products have different sizes, but their volume are very close to each other. The products which are very close to each other in terms of volume and geometrical properties are classified in 18 groups, 6 of which are shown in figure 2.

Fig. 2. Grouping of products

Some items can be placed in any way because they are resistant to bumping. However, when a shampoo or tube creams are compressed, there is a risk that the cover is opened. Moreover, it is advisable to put liquid products in a vertical position to minimize the risk of flowing. On the other hand, some products like cloths can be freely placed in any spacing due to their flexible structure. In order to classify the products according to their placement restrictions and freedoms, 3 property indicators are assigned to 18 previously formed groups.These groups are ”Lying position allowed”, ”Tightly placement allowed” and ”Flexibility”. these properties are answered as ”Yes” or ”No” in the algorithm.

It is expected that the box loading algorithm to be prepared will meet the above-mentioned special cases while, existing algorithms in the literature are insufficient to meet these special needs.

A significant portion of the backordered orders of the pilot company has been analyzed beforehand. It is seen that manually selected boxes have been transferred to a chart for the order of 57.000 pieces of 440.000 products in total.

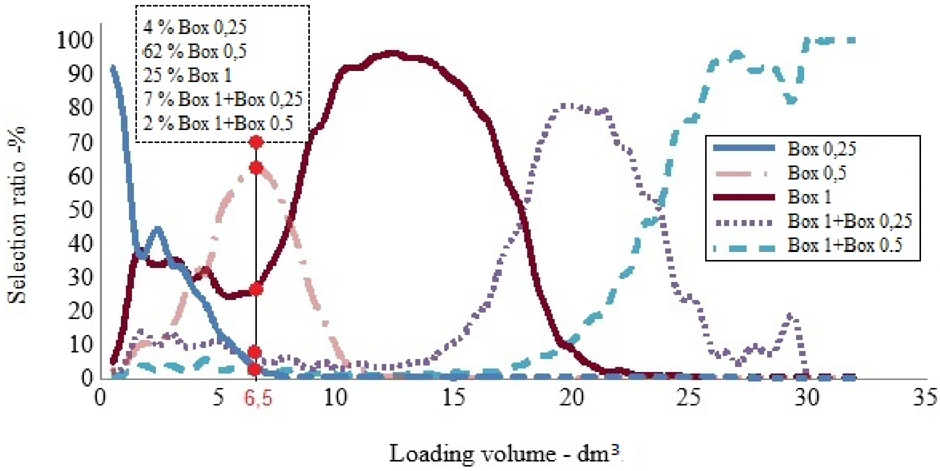


Fig. 3. Volumetric loading rates (for 57000 parcels)

Figure 3 shows statistical data of which box was selected by the manual way according to the total order volume. Significant conclusions arise when the graphic in figure 3 is analyzed in detail. If there was only one volume criterion in the box selection, the problem could be resolved with a simple software. In that case, the above graphs would be straight lines attached to each other. In fact, they would all seem to be a single line. However, due to special restrictions and freedoms, different boxes for the same order volume can be suggested which forms the intersections in figure 3. However, the number of box selection choices should be at most 2, but it is observed in figure 3 that, even 5 different box selections had been used by the manual way for the same order volume (6,5 dm^3 case for instance). When we take out the parts that we can say that is definitely wrong choice, an image like figure 4 will appear.

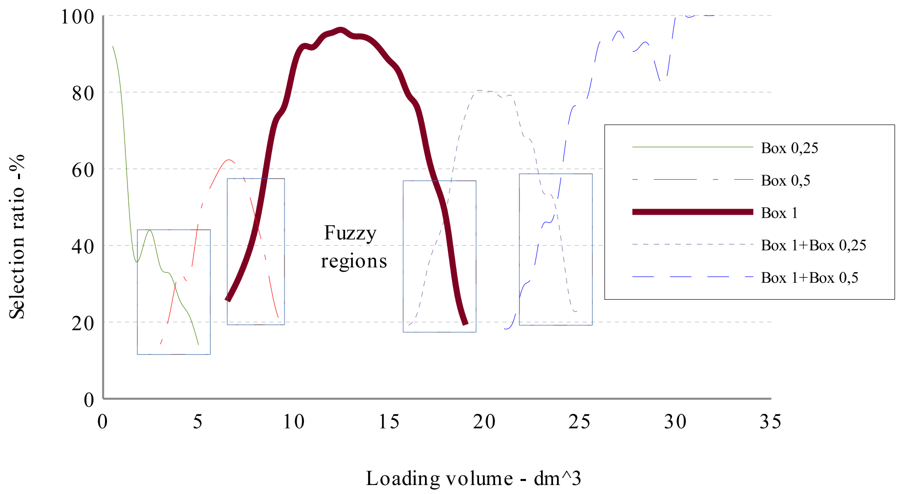


Fig. 4. Volume dependent loading rates (Strictly incorrect loads have been removed and fuzzy loads have been marked)

The main idea behind the algorithm is to use the volumetric choice in the beginning where no intersection will happen, and then move to a fuzzy logic based solution to estimate the best choice for the fuzzy regions. With this algorithm about 10% absolutely wrong loading and about 20% suspicious loading which are statistically detected can be eliminated and a total of %15 improvement is envisaged if 5% of the suspicious charges are considered incorrect.

4. Fuzzy logic approach to box selection optimization

An analysis has been done based on the volume of over 57.000 orders from the past with a special algorithm developed with Excel database macro codes. As a result of this analysis;

- It has been seen that a box can never be fully loaded. Hence, an effective usage volume for each box is obtained.
- It has been seen that 3 types of box sizes previously used (Box 0,25, Box 0,5, Box 1) are not sufficient and should be increased to 5 types. Two new box sizes are proposed, Box 1,25 and Box 1,5.
- Areas considered suspicious in figure 4 were examined in terms of volume and product type and the intersection points were optimized. According to these results, the new boxes and features obtained are listed in table 1.
- It is not straightforward to define a net volume for each product. Due to non-orthogonal geometry, there will be volume losses when two products are placed next to each other. If these volumes are thought to be lost completely, a maximum volume value is obtained. If

Table 1. Updated box properties

boxes type	net volume (dm^3)	effective usage volume (dm^3)
Box 0,25	9.083	6.600
Box 0,5	13.133	11.200
Box 1	25.855	23.500
Box 1,25	36.153	32.860
Box 1,5	41.870	38.057

these volumes are thought to be used completely with flexible other products, an absolute volume value is obtained. However, practically, a value in between maximum and absolute volume is more valuable, and this value is statistically obtained to be effective volume for each product. When these effective volumes are summed up for a certain order, the total effective volume (ev) for that order is obtained.

After the above preliminary studies, the membership functions of box types are shown in figure 5.

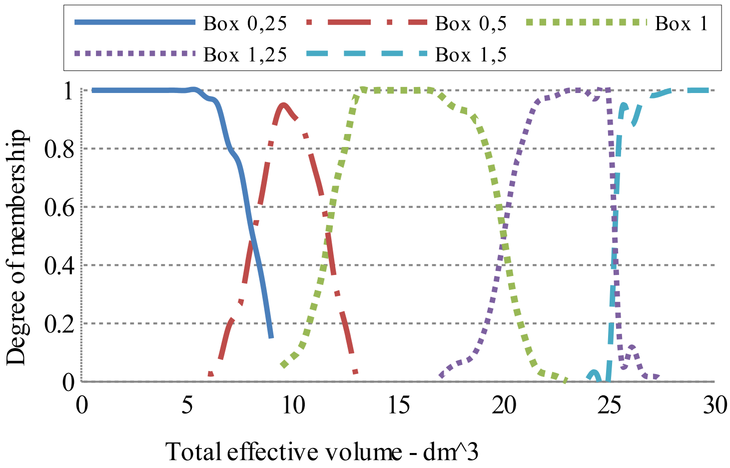


Fig. 5. The membership functions of box types

If the degree of membership value is 1 for a certain total effective volume, it is certain to select the appropriate box type. These regions are indicated by a straight line in figure 5. These regions account for approximately 50% of the total orders. That is, selecting which box to be used for the half of the orders arriving during the day can be determined by the volume calculation only, and the fuzzy estimation will be made in the box selection of the other half. In the clarification of the fuzzy zones, special cases of the products ordered will be taken into consideration.

The membership function for the volume-based box selection is as shown in table 2. Algorithmic approaches will be made in fuzzy situations where there are 2 possibilities for the same interval.

Table 2. Degree of membership for the total effective volume (ev)

$$\mu A(x) = \begin{cases} \text{Box 0,25} & 0 < ev < ev1 & \Rightarrow ev1 = 5740 \\ \text{Box 0,25 or 0,5} & ev1 \leq ev < ev2 & \Rightarrow ev2 = 8800 \\ \text{Box 0,25 or 0,5} & ev2 \leq ev < ev3 & \Rightarrow ev3 = 12600 \\ \text{Box 1} & ev3 \leq ev < ev4 & \Rightarrow ev4 = 16840 \\ \text{Box 1 or 1,25} & ev4 \leq ev < ev5 & \Rightarrow ev5 = 23260 \\ \text{Box 1,25} & ev5 \leq ev < ev6 & \Rightarrow ev6 = 26000 \\ \text{Box 1,25 or 1,5} & ev6 \leq ev < ev7 & \Rightarrow ev7 = 32600 \\ \text{Box 1,5} & ev7 \leq ev < ev8 & \Rightarrow ev8 = 34000 \\ \text{Box 1,5 or 1,5+} & ev8 \leq ev < ev9 & \Rightarrow ev9 = 37800 \end{cases}$$

When the above membership grades are examined, clear and blurred areas are seen. If only a volume-based approach could be used to clarify the fuzzy areas, geometric structures could be used in fuzzy inference operations. But, since comparisons are needed for specific cases of products, fuzzy inferences can be clarified after they are made with a special algorithm.

5. Construction of the loading algorithm

Some possible layout configurations of the products are shown in figure 6. 3 different spaces are defined such as base coefficient (bas), top clearance (top) and additional base coefficient (e_bas) achieved by squeezing.

Fig. 6. Some possible layout configurations of the products

The volume of 1000cc products (they are named as B(1)) is defined as the reference volume (vr). The volumes of all the other products are scaled according to vr in the algorithm. Moreover, for all the boxes, 3 defined spaces are recalculated according to vr scaling transformation and listed in table 3.

Table 3. Box loading gap coefficients

	base coeff.(bas)	additional base coeff. (e_bas)	top clearance coeff. (top)
Box 0,25	4	1	0,85
Box 0,5	6	1	1
Box 1	12	1 or 1,5	2
Box 1,25	15	1 or 1,5	2,5
Box 1,5	18	1 or 1,5	2,8

After vr scaling, the volume of each product group is defined between 0 and 1 in vr. According to the box used, table 4 lists how many of these products can fit into a specific box. For instance, in Box 0,25, 4 of size group 1 or 2 products can be placed. In addition, 2 of size group 3 products, or 1 of size group 4 products, or 2 of size group 9 products can be placed as well.

Table 4. Various loading coefficients according to size groups

	size gr.	effective volume	base coeff.	Box 0,25	Box 0,5	Box 1			Box 1,25			Box 1,5		
Big sizes	1	1531	1	4+	7+	12+	13+	14+	15+	16+	17+	17+	19+	20+ $\Longrightarrow$ **vr**
	2	1150	1											
	3	850	0,5	2	0	2	2	1	2	2	2	2	2	2
	4	700	0,5	1	0	2	1	0	4	2	0	4	2	0
	5	736	0,6	0	0	2	2	1	2	2	2	2	2	2
	6	600	0,5	0	0	3	2	1	3	3	3	0	0	3
	7	510	0,34	0	0	3	2	1	4	4	4	0	0	3
	8	610	0,4	0	0	2	2	0	4	4	4	0	0	2
	9	292	0,33	2	0	5	2	1	10	8	4	5	3	4
$\Uparrow$	10	465	0,25	0	0	8	2	1	10	8	4	6	4	4
$\Downarrow$ Small sizes	11	275	0,3	2	0	4	2	2	8	6	4	10	8	4
	12	230	0,22	2	0	8	2	2	12	9	4	15	12	4
	13	236	0,2	5	0	8	2	3	12	9	9	12	12	9
	14	326	0,25	5	2	8	2	1	10	9	6	6	6	6
	15	229	0,15	6	2	20	8	2	14	11	8	8	8	8
	16	234	0,2	6	2	10	4	3	14	11	10	12	8	12
	17	250	0,2	5	2	16	4	2	22	20	16	16	12	16
	18	210	0,15	max	max	max	max	max	max	max	max	max	max	max

When the placing operation is carried out, first of all, if the base space of the box is insufficient, the upper space is taken into account and if it is not sufficient as well, the additional base space is targeted by compressing.

By utilizing the volumetric coefficients created for the product volumes and box spaces, a strict sequence is adopted from the easy to the hard, from certain toward blurred, such as;

1. Volume based comparison; Each box has a total effective volume (ev), which can be loaded at maximum. The products in the orders also have an effective volume (ev) and order quantity (tp). If the volume of each product in the order is V (i);

   $\sum_{i=1}^{tp} V(i) < ev$ must be achieved

2. *ev(i)*; as seen in table 2, it is a variable obtained by looking at past statistics and expressing effective volumes. By comparing *ev(i)* with *V*, which is the total order volume, it is determined that the box choice is fuzzy or clear. If there is no certainty, the algorithm passes to step 3.

3. At this step, 2 box choice options remain, large and small box. The algorithm in this step makes it clear whether the orders will definitely not fit in the small box or not. If it is certain that the orders will not fit, it chooses the large box and terminates. If there is still an uncertainty, it passes to step 4.

   According to different product and box volume options listed in table 4, the sum of the coefficients of the products of the order is compared with the box volume in vr derived from table 3. If the sum of products in vr is more than the box volume in vr even after considering top clearances and squeezing, then it is certain that the small box cannot be used.

   In addition to total volume in vr, big size and small size combinations listed in table 4 are also checked and a contradiction is searched. If there is a contradiction, then the small size box cannot be chosen and the algorithm terminates.

   If the uncertainty continues, a new variable is introduced, that is the average volume of the order, which is obtained by dividing the total order volume (V) by the number of products in the order (tp). The box chosen for this variable in the previous manual loading statistics is checked (shown in figure 7) If, according to the variable and previous statistics, it is statistically not favorable to choose the small box, then the algorithm chooses the large box and terminates.

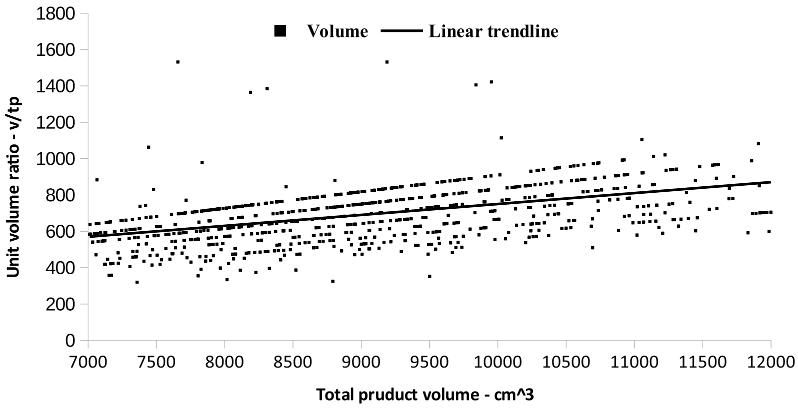
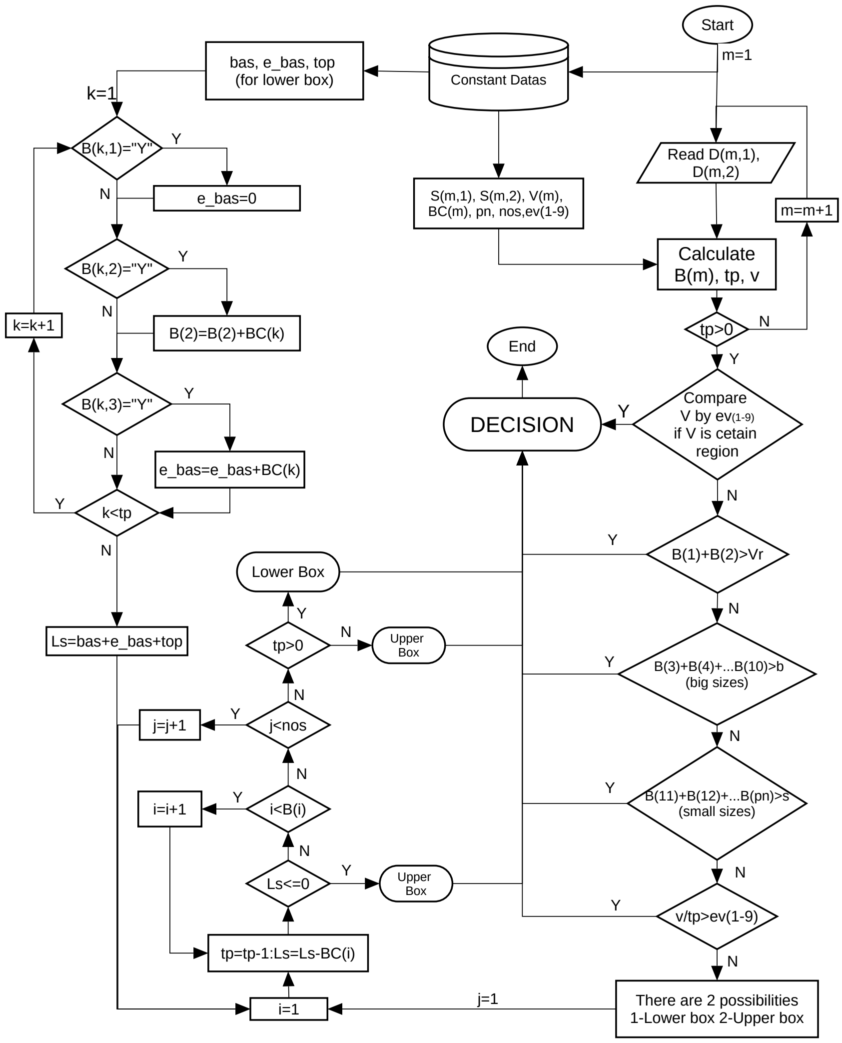


Fig. 7. Unit volume ratio (obtained by dividing the total order volume (v) by the number of order (tp))

4. In this step, the products are placed one by one starting from the first product group by the algorithm as the last option. Still two box choices, small and large remain and the algorithm tries to choose the small one. Placement starts from base and large products, product group B(1). First they are tried to be placed at the bottom as much as possible, and then placing them in the top clearance, or placing more at the bottom by squeezing are considered depending on the properties of the products. After the largest products are placed, then comes the smaller products. When spaces between the products are filled by small or flexible products, more efficient placement can be made. At the end, it is checked whether the products will fit in the small box or not and the algorithm finishes according to the answer.

Other abbreviations and meanings used in the algorithm are listed in the flow chart of the algorithm is shown in figure 8;



Constant Datas: *(Changes as the product range is updated)*
S(1,1) = product code
S(1,2) = size group
VP(i) = product volume information
BC(i) = product base coefficient
pn = product number
nos = number of sizes

Variable Datas: *(Changes with each order)*
B(i) = The order quantity for each product group
D(1,1) = Product code
D(1,2) = Number of products
V(i) = Size-based number of items ordered
tp = The quantity of the ordered products on a piece basis
ev = Total effective volume of ordered products

Fig. 8. The flow chart of the algorithm

6. Results and discussion

With this work, an algorithm has been implemented that makes the right box selection for a quantity of products ordered. Because of the complexity of this selection due to the special cases of the products, the solution has been approached by fuzzy logic, but the inference and refinement has been obtained by an algorithm. Placement planning has been done by using a set of data such as the geometric properties of the products, the characteristics of stacking and the resistance it shows against external bumps. The results have been tested by integrating into a private company's own software. According to these test results;

1. The correct box selection rate has increased to %99. If the product range was fixed this rate could be %100. However, when new products are added, the flexibility of integration into the existing software has been provided by the user, and this definition has been linked to a number of coefficients.

2. As shown in figure 9, a comparison of the box selection made for the 5700 actual order was made, a %14 improvement in shipping costs has been achieved between manual selection and algorithm selection.

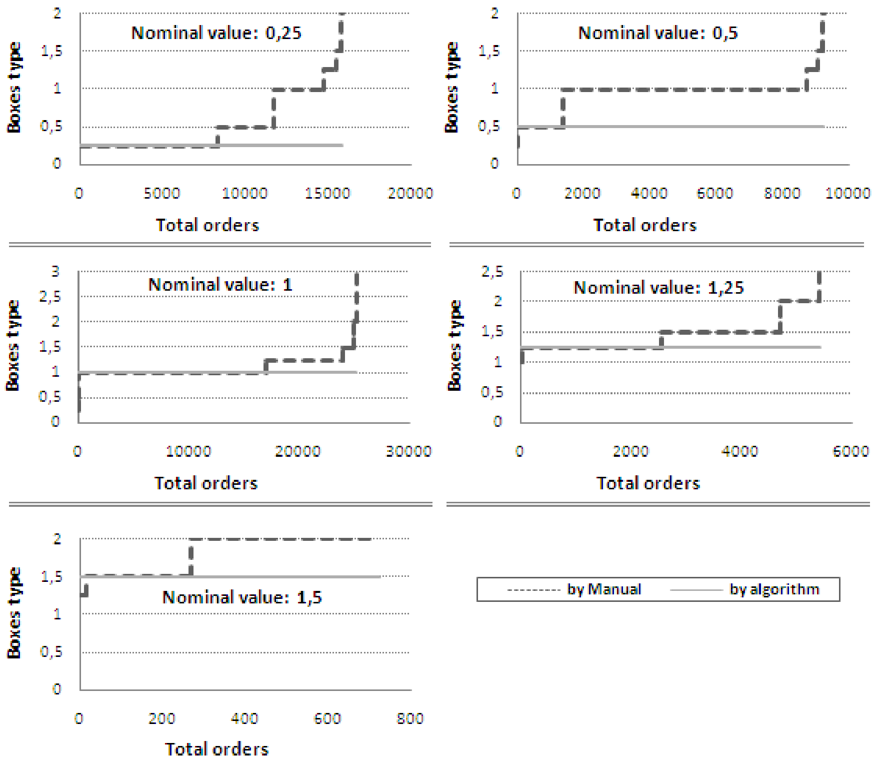


Fig. 9. Comparison between manual selection and algorithm selection

When each nominal box volume is examined, the space between the two graphs represents the wasted volume

3. As box selection work is done entirely by automation, there is a gain in personnel expense
4. The time lost in the re-selection process due to wrongly selecting a small box has been reduced to zero.
5. Wasting incorrectly selected boxes as they have already labels on them is prevented.
6. The order adjustment delay between the head office and the factory has been removed.

The developed algorithm is still being used by the private company and it is open for further enhancement according to the product list.

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