Selective Breeding Model for Optimizing Multi Container Loading Problems with Practical Constraints

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Abstract. Multi container loading problem have been considered in this research for optimization of its packing pattern to yield maximum utilization of the container volume by satisfying the practical constraints such as boundary crossing constraint, weight constraint, stability constraint and placement constraint using selective breeding algorithm. To be useful in real time packing, developed model also checks the feasibility of packing pattern and also uses best fit tuning algorithm for forbid possible empty spaces inside the container with the available bins and thereby avoid cargo displacements at the travel. The boundary crossing constraint conforms that the pallets are completely packed inside the containers without any overlap between themselves and with container boundary. Weight constraints are to check the total weights of the bins to be packed are within the threshold limit. Stability constraint is to satisfy the centre of gravity of the cargo is in line with the container and also the load bearing capacity of the bins. Placement constraint is to build pallets by considering the ease in loading and unloading respectively. In order to validate the developed model, the computational study had performed with large number of instances from ORLIB and the obtained solutions were satisfactory in most cases.

1. Introduction
The primary objective of Multi Container Loading Optimization Problems (MCLOP) is to pack the maximum number of available bins or boxes into the minimum number of containers by satisfying the practical constraints, if exist. Among the many variants of the MCLOP, in this research, the problem of categorizing the available bins into pallets and packing those pallets into the containers to reduce the freight rate and to serve the customers by delivering to the desired locations in time have been considered. Achieving an optimal packing solution for the container loading problems are having many economic and environmental pros such as reduced freight rate, ease in loading and unloading at multiple delivery points, maximum utilization of available container volume, avoiding the bin damages and maintain dynamic stability of bins and the containers.

In order to reduce the computational complexity and for easy in execution diagnosis, the entire research have been divided into five module, palletizing module, selective breeding module, pallet
optimization module, Tuning module and post processing module. In the first palletizing module, the user defined boxes are categorized based on the shape and size in the ascending order. Items of the similar product are categorized and arranged together to form a pallet. Similarly ‘m’ numbers of pallets have been formed with the available ‘n’ number of bins. The remaining bins are left unpalletized and will be used by the tuning algorithm in the tuning module later. Again the pallets are categorized with respect to the height to form the pallet layers. The packing pattern of this pallet layers will be optimized in this research using selective breeding methodology. The dimensions of the pallet layers of each product type have been identified and will be given with the unique identifiers. Thus the computational complexity reduces by reducing the bin packing problem into the pallet loading problem. The second module is the selective breeding module, in which the algorithm have been developed for optimization and the parameters of the developed algorithm have been fine-tuned through sensitivity analysis to yield best result for the application.

The fitness function developed for this research is the combination of volume maximization and constraint satisfaction penalty function. The third module is the optimization of the pallet packing. The consideration taken into account for packing are that the company uses identical rectangular front open type containers, container are large enough to fill all the orders and are of standard sizes, number of containers are more than the required, pallets are loaded in layer by layer arrangements and so on. In logistics transportation, it is severely monitored for the safety reasons which include the safety for both the containers and the products to be transported. This safety transportation introduces specific constraints such as the total weight of packed bins should be less than the container threshold weight carrying capacity and packed bins should be stable without empty spaces to prevent the bins from damages during transportation to various locations. Moreover, the stability of cargo has been obtained by making the center of gravity of the packed bins as close as possible to the center of gravity of the truck/container. The fourth module is the tuning module, in which the left out empty spaces have been filled with the remaining unpacked bins using best fit algorithm. Thereby the best packing pattern have been obtained in container loading. To be useful in practice, the final module is the post processing module, in which the graphical format of the identified packing pattern have been generated in the Cartesian coordinate system to make the packers or layman for ease in understanding the loading and unloading pattern.

Solutions to the MCLOP have been feasible and stable, because the realistic constraints such as dynamic stability, equilibrium of the items, risks in the loading and unloading processes, displacement of items during the journey, safety, etc. had considered in the fitness function of the optimization problem itself. Thus the developed modules had tested with the data sets available in the ORLIB and the results obtained are in satisfactory level. The major researches carried out in the considered research area are given in the following section.

In recent years, it is observed that there is drastic increase in the number of studies in the area of container loading problems with the practical constraints. Alonso et al (2019) developed the mathematical models which can generate the packing pattern for the multi container loading problems with practical constraints, but the author had some restriction in applying the model for universal problems. Antonio et al (2018) introduced the new load balance methodology for optimizing the container loading problem based on the weight in road transportation applications. Bischoff and Ratcliff (1995) explored various constraints involved in the development of optimization methodologies for the container loading problems and used the BR instances, which has been used in this research for experimenting the developed selective breeding algorithm. Bortfeldt and Gehring (2001) enhanced the performance of the genetic algorithm by hybridization and proved that the hybridization yields better result compared to the raw algorithm for the container loading optimization problems. So in this research, the selective breeding algorithm has been hybridized with the best fit algorithm to yield best result.

Brand and Pedroso (2016) developed a generalized arc-flow formulation with graph compression methodology for solving the bin packing and the related problems and proved that the methodology produces better performance. Correcher et al (2017) took up the real world problem of loading the cars
into the large multi containers for an car manufacturing industry and the authors achieved the better performance by considering heuristic rules. Dell’amico et al (2019) developed the mathematical model using decomposition technique for multiple knapsack problems. Delorme et al (2018) created the library for bin packing and cutting stock problems and can be used as the instances for the experimentation of the developed algorithms. Furini et al (2018) developed a heuristic algorithm for the knapsack problem with setups. Huang et al (2016) developed an effective placement strategy for packing bins into the single container. Jaisree et al (2016) used the evolutionary approach for optimizing 3D heterogeneous bin packing problems. Lingaraj et al (2019) implemented the firefly algorithm for solving 1D bin packing problem with the associated constraints. Moura and Bortfeldt (2017) experimented the two-stage packing procedure which produced better packing with minimal empty spaces inside the container. Rajesh and Dinesh kumar (2011) enhanced the performance of the genetic algorithm by overloading orientation constraint for packing of 3D heterogeneous bins. Rajesh Kanna and Malliga (2012) developed the binary coded genetic algorithm for multi-constrained optimization of rectangular bin packing problem. Rajesh kannaat et al (2012) solved the arbitrary sized heterogeneous bin packing problem using hybrid genetic approach. Rajesh kannaat et al (2015) optimized the 3D bin packing problem using recursive ant colony algorithm. Rajesh kanna and Udaiyakumar (2017) developed a complete framework for multi-constrained 3D bin packing optimization using firefly algorithm. Rajesh kanna et al (2018) used the genetic algorithm for 3D heterogeneous bin packing.

Ramos et al (2016) concentrated on the mechanical equilibrium stability for the container loading problem. Rodolfo et al (2019) developed the hybrid approach for a multi-compartment container loading problem. Serairiand Haouari (2018) conducted the theoretical and experimental study on the 2D bin packing problems. Sheng et al (2016) concentrated specifically on the loading of infill boxes using heuristic algorithm. Sivasankar et al (2019) explored the graph theory approach for optimizing 3D bin packing problems. Thitipon et al (2016) extended the priority-based hybrid genetic algorithm for container loading problem. Toffolo et al (2017) used the heuristic decomposition approach for solving multi container loading problem.

2. Problem definition

Based on the order placed by the customers, the distribution center started serving the needs by sending the product to the logistic centers. The lists of ordered products 'n' by the customer have to be completely transported to the customer location can be through the containers. Each and every product received by the logistic industries are having a predetermined pattern, with dimensions length, width and height represented by li, wi, and hi respectively, weight wti and constraint ci. In general, the logistic companies are using pallet packing by categorizing the available boxes either based on dimension or on delivery locations. The dimension of the pallets are represented by its length, width and height represented by lpwp, and hp respectively, weight wtp and constraint cp. Once the bins are categorized, similar bins have been piled up on pallet bases. These pallets are then loaded into trucks for delivering them to the required locations. The logistic companies are having set of ‘P’ identical containers of standard sizes and are off rectangular prismatic shapes of standard dimensions (L, W, H) and maximum threshold weight (WT). This weight includes the weight of the container and the packed bins, which will be assumed to be distributed equally. The mathematical equations for identifying the possible positions of the segregated pallets into the container are given in the Equation 1.

\[
\frac{L}{l_p} \times \frac{W}{w_p} \geq \frac{L}{l_p} \times \frac{W}{w_p}
\]

The Equation 1 is used to identify the number of permissible positions to pack the pallets inside the container along the length and width. Heights of the pallets have not been considered, in order to reduce the computational complexity and layer by layer packing doesn’t have much influence over the
positioning. In this research, the longitudinal axis of the container is represented as columns and the transverse as rows as represented in the Figure 1.

![Figure 1. Pallet Position on the Container Bottom.](image)

The position of the first pallet should be on the lower left most corner of the container represented as placement point 1 in the Figure 1. Further pallets to be filled based on the best placement positions. The possible placement position for the second pallet is either p2.1 or p2.2 or p2.3. Equation 2 is used to identify the feasible position for the placement of the pallets. The Equation 2 satisfies for the placement points P2.1 and P2.3 in the Figure 1, but the placement point p2.2 didn’t satisfied. So the pallet to be placed should not be in the position P2.2.

\[
\begin{align*}
    P_jy &= P_{i-y} \text{ or } W_i; \\
    P_jx &= P_{i-x} \text{ or } L_i; \\
\end{align*}
\]

Once the unfeasible points have been eliminated, then the best placement point needs to be identified. The best placement point is the point which is having the higher placement ratio \([\text{if } l_i > w_i, \text{ then } (l_i/w_i)] \text{ else } (w_i/w_i)\)] in the final stage, if the ratios are less than 0.5, then the pallets have to be placed in the row wise placements without exceeding the container boundary. Thus the pallets have to be loaded into the container.

The benchmark data set used in this research for experimenting the packing has been taken from the BR model. In the data set, the number of product varies from 1 to 142 and with the objective of identifying the minimum number of containers required for packing all the products. For the considered instances in the dataset, the constraints considered are the boundary crossing, weight, stability and the placement constraint. The boundary crossing constraint ensures that all the products are within the container boundary and the boundary includes the pallets and the spacers. The weight constraint ensures that the weight of all the packed products should be less than the threshold weight of the container i.e. \(\sum_{i=1}^{n} w_i \leq W_t\). The stability constraint checks the overhanging of the pallets in each and every layer and ensures that the base of the pallet has to be placed completely over the top of the bottom layer pallets. Also stability constraint checks the weight carrying capacity of the bottom bins. The placement constraint ensures that the products to be packed based on the delivery locations and in this research, it has been given with less penalty value, because this tendency has not been uniform compared to the other constraints and completely conflicts with other constraints and packing pattern.

In this research, in order to compute the packing pattern by satisfying the constraints in less computation time, selective breeding algorithm have been used. The adapted selective breeding algorithm consider all the constraints described and always returns a feasible solution for the corresponding configuration in every iterations, the advantage of the adopted algorithm is to identify the best from the same breed i.e. feasible solution again and again to yield the better optimal packing pattern.
3. Proposed selective breeding algorithm

Selective breeding algorithm (SBA) mimics the behaviour of the chicken or animal breeding methodology, i.e. identifying the best chromosome property from the existing and producing the ‘n’ number of breeds from the identified chromosomes. Thus the generated breeds having the desired properties. Again the same procedure has to be repeated till the termination condition achieved. The finally obtained breeds are having the user desired properties. In this research, each bin/pallet is assumed to be a gene in the chromosome. The length of the chromosome is equal to the number of instances in the set or the number of bins in the set to be packed into the container. This chromosome is allowed to breed its child to minimize the empty space inside the container. The consideration made in this research is that the size of the bins includes the bin size along with the size of spacer/wooden layer used for lifting the bins in loading and unloading. SBA algorithm consists of five steps. The first step is the initial population generation stage. In this stage, the chromosome size is set to the number of bins in the set to be packed into the container. This chromosome is allowed to breed its child to minimize the empty space inside the container. The consideration made in this research is that the size of the bins includes the bin size along with the size of spacer/wooden layer used for lifting the bins in loading and unloading.

SBA algorithm consists of five steps. The first step is the initial population generation stage. In this stage, the chromosome size is set as that of the instances size. For example, a need arises to pack 1000 bins, then the chromosome size is set to 1000. These sizes will be dynamically varied or reduced if all the iterations are exceeds the container volume in the step of 10%. Each gene or string in the chromosome represents the bin in the packing order. The sample initially generated 10 number of chromosome are shown in the Figure 2. The decimal numbers represents the bins types and the repetition of the numbers denotes the bins in the sequence of arrangement.

**Figure 2. Sample parent Chromosomes**

The second stage of the SBA is the calculation of the breeding factor (Bf) value for the randomly generated parents and is given in the Equation 3. Then the generated parents are sorted based on the breeding factor value in ascending order.

\[
Bf(x) = \frac{1}{\text{Objective Function value } f(x)}
\]

Whereas, 
\[
f(x) = 1 - \frac{\sum_{i=1}^{L} \sum_{j=1}^{W} x_{i,j} \cdot \chi_{i,j}}{L \times W \times H} - \left( \frac{\sum_{i=1}^{L} (BQ + WC + SC + PC)}{4} \right)
\]

The third stage is the segregation of the dominant and recessive set. The entire population has been segregated into two sets based on the fitness value. The higher fitness set is called as dominant set having the best chromosomes parents and remaining set is called as recessive set having worst chromosomes parents. Then one dominant and one recessive parent from each set have to be allowed to breed its children’s. In the above sample, 5 dominant and 5 recessive parents were clubbed together for breeding i.e. (1) D1r1 (2) D2r2 (3) D3r3 (4) D4r4 (5) D5r5. The fourth stage is the breeding stage, in which all the possible combinations of the chromosomes have to be breed from the available parents. The breed combinations are D1r1 x D2r2; D2r2 x D3r3; D3r3 x D4r4; D4r4 x D5r5; D1r1 x D3r3; D2r2 x D4r4; D3r3 x D5r5; D1r1 x D4r4; D2r2 x D5r5; D1r1 x D5r5. As the total, 80 breed can be generated for the above combinations. The fusion points can be the 50% of the length of the chromosome i.e. 50 fusion points and has to be generated at random for each and every breed. In the fusion points, the genes have to be swapped between the dominant and the recessive chromosomes. Thus as the result of breeding, 80 new chromosomes have been obtained along with the 10 initially generated parents. Because of the fusion in breeding, the solution may struck with the local optima and is called as in-breeding depression. To avoid this, in this work, 10% of chromosomes have been generated at random and added to the population.
The fifth stage is the identification of the best chromosomes based on the breeding factor values. The best 10 chromosomes have been selected for the next iteration and the same procedure has to be followed till the termination conditions achieved. In this experimentation, the termination condition considered are the breeding values had to reach 1 or the number of iterations reached 100. The finally obtained set of chromosomes is the optimal packing pattern which can yield maximum container volume. Further to enhance the container volume utilization, the left out bins are given as the input to the best fit algorithm and the algorithm fits the bins in the available spaces inside the container and is the tuning module.

4. Results and discussion
In this research, experiments were run on 15 instance sets BR1, BR2, ..., BR15 [4]. Each set consists of 100 instances and have been categorized in to three classes based on the bin heterogeneity. Class 1 of the bins are of one types i.e. strongly homogeneous, whose instances are in BR0. Class 2 of the bins are of few different types i.e. weakly heterogeneous, whose instances from BR1-7. Class 3 of the bins are of different types i.e. strongly heterogeneous, whose instances are BR8-BR15. In order to validate the developed hybrid SBA module, the output obtained from the developed module has been compared with the previous research data in the Table 1.

| Classes | Parretno et al. (2008) | Goncalves&Resende (2012) | Ramos et al. (2016a) | Developed SBA with constraints | Developed SBA without constraints |
|---------|------------------------|--------------------------|---------------------|-----------------------------|----------------------------------|
| BR0     | 90.21                  | 97.35                    | 98.63               | 95.85                       | 98.75                            |
| BR1     | 80.77                  | 94.34                    | 93.36               | 89.63                       | 93.42                            |
| BR2     | 79.77                  | 94.88                    | 94.55               | 90.69                       | 95.26                            |
| BR3     | 81.07                  | 95.05                    | 94.75               | 90.42                       | 95.59                            |
| BR4     | 79.76                  | 94.75                    | 94.63               | 90.40                       | 94.79                            |
| BR5     | 80.01                  | 94.58                    | 94.38               | 89.78                       | 94.63                            |
| BR6     | 79.17                  | 94.38                    | 94.24               | 90.24                       | 94.99                            |
| BR7     | 76.72                  | 93.74                    | 93.82               | 88.78                       | 94.36                            |
| BR8     | 75.30                  | 92.65                    | 93.16               | 87.84                       | 94.02                            |
| BR9     | 74.80                  | 91.90                    | 92.62               | 87.37                       | 92.92                            |
| BR10    | 73.40                  | 91.28                    | 92.09               | 85.85                       | 92.32                            |
| BR11    | 72.80                  | 90.39                    | 91.56               | 85.54                       | 92.36                            |
| BR12    | 71.27                  | 89.81                    | 91.28               | 84.88                       | 91.95                            |
| BR13    | 70.48                  | 89.27                    | 93.93               | 84.98                       | 94.49                            |
| BR14    | 69.01                  | 88.57                    | 90.38               | 83.50                       | 90.49                            |
| BR15    | 69.52                  | 87.96                    | 90.08               | 82.92                       | 90.80                            |

From the experimental output is clear that the developed SBA module without any constraints, produce comparatively better results, because it analysis all the possible combinations of bins, also breed the best from the better combinations. On the other hand, by including the constraints, the results have not up to the level expected, because the constraints added negative value to the breeding factor and thereby eliminates the best combinations which yield higher volume utilization. Thus the
breeds from the best parent have eliminated and breed from the better parent only iterated. So by including the constraints, the results are not much satisfactory in using the SBA.

Stability constraint has been considered as one of the most essential issues in identifying the optimal solution, because it includes placement bin base size, allowable maximum height that the subset of layers can pile up and weight bearing capacity of the bottom bins. Similarly the placement constraint restricts some of the bin placements which can yield better packing pattern. For safety reasons, it is essential that the centre of gravity of the container should be located near to its geometric centre and in this research, layer by layer packing had been used, which automatically divides the load equally all over the container base. Thus the developed module can pack all the available bins in minimum number of containers and identifying the better results in less computational time. In addition to the solution, in this research, heuristic post processing module also developed i.e. the graphical models have also been generated for ease of packing and in layman understandable format, which is shown in the Figure 3. The layer by layer arrangement shown on the right of the Figure 3 is filled by the decimal numbers, which is filled with the bin numbers stored in the database. So that the packing layman can know the position and orientation of each and every bin. Also the developed heuristic module fills the decimal or bin numbers with the units equal to the size.

![Figure 3. Graphical Representation of the Bins/Pallets in the Container.](image)

5. Conclusion
Revolution in the digital marketing increases the need of generating the high-quality solutions for multi objective loading problems by satisfying the constraints and involving multiple containers had been addressed in this research using hybrid selective breeding algorithm. In this paper, for experimenting, 15BR instances have chosen and the results obtained are in the satisfactory level and the optimal or quasi-optimal results are produced in reasonable times. Among the BR models, the experimental results show that the optimal solutions were obtained in most cases and on the other hand, for few instances for which optimality was not proven, but a feasible solution were found. Compared to the mathematical models, the SBA model generates results from the random initial solution and is independent of the parameters and the applications. In order to get the feasible solution, the negative penalty constraint function has been included in the objective function itself, so the invalid or unfeasible solutions breeds were eliminated in the initial stages itself. The boundary crossing constraints, weight constraint, stability constraint and placement constraint have also been
considered. Also, the developed hybrid module generates the graphical loading plan to be useful in practice for the packers. In future, some interesting extensions have also been considered, such as top open truck, wall building approach, splitting demands over a time horizon, packing based on expected delivery dates, freight rate optimization, etc.

6. References

[1] Alonso M T, AlvarezValdes and Ioric F Parreno 2019 Mathematical models for multi container loading problems with practical constraints Computers & Industrial Engineering 127 722-33
[2] Antonio G Ramos and ElsaSilvabJose FOliveir 2018 A new load balance methodology for container loading problem in road transportation European Journal of Operational Research 266 1140-52
[3] Bischoff E, and Ratcliff M 1995 Issues in the development of approaches to container loading Omega 23 377–90
[4] Bortfeldt A and Gehring H 2001 A hybrid genetic algorithm for the container loading problem European Journal of Operational Research 131 143–61
[5] Brand F and Pedroso JP 2016 Bin packing and related problems: General arc-flow formulation with graph compression Computers & Operations Research 69 56–67
[6] Correcher J, Alonso M, Parreno F and AlvarezValdes R 2017 Solving a large multicarrier container loading problem in the car manufacturing industry Computers & Operations Research 82 139–52
[7] Dell’Amico M, Delorme M, Iori M and Martello S 2019 Mathematical models and decomposition methods for the multiple knapsack problem European Journal of Operational Research 274 886–99
[8] Delorme M, Iori M and Martello S 2018 BPPLIB: a library for bin packing and cutting stock problems Optimization Letters 12 235–50
[9] Furini F, Monaci M and Traversi E 2018 Exact approaches for the knapsack problem with setups Computers & Operation Research 90 208–20
[10] Huang Y, Hwang F and Lu H 2016 An effective placement method for the single container loading problem Computers & Industrial Engineering 97 212–21
[11] Jaisree, Umagowri and Rajesh Kanna 2016 Evolutionary Approach For Optimizing 3d Heterogeneous Bin Packing Problems International Journal of Trend in Research and Development 3 447-452
[12] Lingaraj N, Rajesh Kanna S K, Suresh G and Sivashankar P 2019 Implementation of Firefly Algorithm for the 1D Bin Packing Problem with Multiple Constraints International Journal of Research 81188-94
[13] Moura A and Bortfeldt A 2017 A two-stage packing problem procedure International Transactions in Operational Research 24 43–58
[14] Pollaris H, Braekers K, Caris A, Janssens G and Limbourg S 2016 Capacitated vehicle routing problem with sequence-based pallet loading and axle weight constraints EURO Journal on Transportation and Logistics 5 231–55
[15] Rajesh Kanna and Dinesh Kumar 2011 Overloading Orientation Constraint over Genetic Mutation for Solving 3D Heterogeneous Bin Packing Problem European Journal of Scientific Research 66 366-376
[16] Rajesh Kanna SK and Malliga P 2012 Multi-Constrained Optimization of Rectangular Bin Packing Problem using Binary Coded Evolutionary Algorithm International Journal of Materials Manufacturing and Optimization 3 27-35
[17] Rajesh Kanna SK, Malliga P and Sarukesi K 2012 A 3D-Multi Constrained Arbitrary Sized Heterogeneous Box Packing Optimization Using Hybrid Genetic Approach Journal of Advanced Material Research 479-481 1825-30
[18] Rajesh Kanna SK, Jaisree, Balasundaram and Bharanikumar 2015 Optimization of 3D Constrained Rectangular Bin Packing Problem Using Recursive Ant Colony Algorithm
*IOSR Journal of Mechanical and Civil Engineering* **12** 65-70

[19] Rajesh Kanna SK and Udaiyakumar 2017 A Complete Framework For Multi-Constrained 3d Bin Packing Optimization Using Firefly Algorithm
*International Journal Of Pure And Applied Mathematics* **114** 267-282

[20] Rajesh Kanna S K, K C Udaiyakumar, S Dinesh Kumar and N Lingaraj 2018 3D heterogeneous bin packing framework for multi constrained problems using hybrid genetic approach
*IOP Conf. Series: Materials Science and Engineering* **402** 1-9

[21] Ramos A, Oliveira J, Gonçalves J and Lopes M 2016 A container loading algorithm with static mechanical equilibrium stability constraints
*Transportation Research Part B* **91** 565–81

[22] Rodolfo Ranck Júnior, Horacio Hideki, Yanasse Reinaldo Morabitoc and Leonardo Junqueira 2019 A hybrid approach for a multi-compartment container loading problem
*Expert Systems with Applications* **137** 471-92

[23] Serairi M and Haouari M 2018 A theoretical and experimental study of fast lower bounds for the two-dimensional bin packing problem
*RAIRO-Operations Research* **52** 391–414

[24] Sheng L, Hongxia Z, Xisong D and Changjian C 2016 A heuristic algorithm for container loading of pallets with infill boxes
*European Journal of Operational Research* **252** 728–36

[25] Sivasankar P, S K Rajesh Kanna, N Lingaraj and Suresh 2019 A Graph Theory Approach for Optimizing 3D Bin Packing Problems with Weight Constraint
*Journal of Applied Science and Computations* **6** 2645-52

[26] Thitipong Jamrus and Chen-Fu Chien 2016 Extended priority-based hybrid genetic algorithm for the less-than-container loading problem
*Computers & Industrial Engineering* **96** 227-236

[27] Toffolo T, Esprit E, Wauters T and Vanden Bergh G 2017 A two-dimension alheuristic decomposition approach to a three-dimensional multiple container problem
*European Journal of Operational Research* **257** 526–38