VOLUMETRIC OPTIMIZATION OF FREIGHT CARGO LOADING: CASE STUDY OF A SME FORWARDER

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ABSTRACT

Purpose: Freight forwarders faces a challenging environment of high market volatility and margin compression risks. Hence, strategic consideration is given to undertaking capacity management and transport asset ownership to achieve longer term cost leadership. Doing so will also help to address management issues, such as better control of potential transport disruptions, improve scheduling flexibility and efficiency, and provide service level enhancement.

Design/methodology/approach: The case company currently has truck resource which is unprofitable, and the firm's schedulers are having difficulty optimizing the loading capacity. We apply Genetic Algorithm (GA) to undertake volumetric optimization of truck capacity and to build an easy-to-use platform to help determine potential costing savings that can be attained, and whether if the business should expand its internal truck fleet.

Findings: Our analysis suggests that the case company's truck resource is underutilized by about two-thirds of capacity. Through a proposed mathematical model and GA heuristic, the case company can potentially save up to S$567K per annum.

Value: By using a simple GA and incorporating a visually appealing user interface, we have helped a freight forwarder improve her financial and operational efficiency. The game changer is the scalability of the solution to include more resource optimization across the fleet and across more freight forwarding firms.

Keywords: Case study, Fleet management, Genetic algorithm, Bin packing, Freight

Type of Paper: Case study

1. INTRODUCTION

The International Federation of Freight Forwarders Association defines freight forwarding as the "services of any kind relating to the carriage, consolidation, storage, handling, packing, or distribution of the goods as well as the ancillary and advisory services in connection therewith, including but not limited to customs and fiscal matters, declaring the goods for official purposes, procuring insurance of the goods and collecting or procuring payment or documents relating to the goods." In essence, forwarders value-add in the logistics spectrum through the bundling of customer (shipper) demands, and procuring of transport capabilities with volume rebates, coordinating the many transport players, and enhancing transport management with value-added services.

The freight forwarder market is highly fragmented, driven by very low entry barriers in the industry. Basic transportation service is mainly delivered by the local players, with several large international players. Market competition is characterized by low product differentiation, causing price to be a main competitive lever. (Stålbrand et. al., 2005) (Wulyo, 2017). While there are limited value-added services that may be provided through different ancillary and advisory offerings to act as differentiators, process efficiency and network cost are key areas where the freight forwarders focus on to reduce price and maintain cost competitiveness. (Burkovskis, 2008).

In this case study, the case firm, one of the SME freight forwarders with presence across the ASEAN region, has internal freight resource which is unprofitable, and the firm's Schedulers are having difficulty optimizing the loading capacity of its freight fleet.

For the freight forwarders as such, fleet optimization among the freight forwarding community is both an art and science. For the smaller local freight forwarders, with pressing concerns on cash flows and asset utilization, there is the imperative to volumetrically optimize the freight carried in a truck wherever possible. Unfortunately, for such smaller freight players, the presence of efficient and intelligent, albeit expensive, load schedulers is often a luxury that the freight company can ill afford. Often times, the loading of the cargo (pallets or cartons or boxes) onto a truck is done by sight and with the scheduler having some prior knowledge of the shipment to realise speed and workflow efficiency. Clearly, this community of freight forwarders recognizes the need to improve this aspect of the traffic process, namely, by incorporating a smart scheduler which can allow for more flexibility in shipment request without sacrificing on capacity optimization and management.

This paper therefore presents an effort to apply mathematical modelling and Genetic Algorithm (GA) to volumetrically optimize the cargo loading for a freight forwarder.

Through this case study, the community can then appreciate the value of using mathematical techniques imbedded within a smart optimization engine and a visually acceptable user interface to rapidly load small pieces of cargo (crates, boxes, cartons) onto a truck. Specifically, we show the economic efficiency of applying this to the operations and capacity management of the freight traffic process and determine the potential cost savings of applying technology in a prudent manner.

The rest of this paper is set as follows. Section 2 presents the necessary literature review. Section 3 develops the model used on the case study. Section 4 discusses the findings, with graphical evidence of the visual interface. Section 5 concludes the paper with some recommendations for future research.

2. LITERATURE REVIEW

The bin packing problem which refers to orthogonally packing a fixed number of crates into finite sized bins using the least number of bins (Martello et al., 2000). A general classification of the bin packing problem is found in Dyckhoff (1990). For instance, the classical knapsack problem (Diedrich et al., 2008) is a combinatorial optimization packing of many different volumetric items into an allocated bin with the objective to minimize wasted space and maximize value. Gehring et al. (1990) effectively applied such combinatorial decision problems on various sizes of shipping containers using a heuristics solution. Each item is generally categorized by their mass, volume and monetary value, such that a subset of items can be packed into this knapsack to obtain the maximum profit possible subject to the total capacity constraint.

In a similar vein, there is the container loading problem which seeks to find a feasible arrangement of containers in a container yard or on board a ship. In such problems, height is generally not constrained to finite stacking, but rather used as the objective function such that it is minimized to obtain an optimal loading solution. The solution space of heuristic solutions for the container loading problem can be found in George and Robinson (1980), and Bischoff and Marriott (1990).

Both the bin packing and container loading problems typically operate under a 3-D environment and use a cost function (Gehring et al., 1990). Due to the case company's existing concern of capacity under-utilization in managing the freight, and the need to understand how much additional load is needed to maximize the trucking capacity (so that they can cargo space more proactively), this study will focus solely on optimizing the capacity utilization, and show to the case firm the overall incremental profit that can be gained based on an optimized load plan by relying on a bin packing solution.

There are several ways to find good feasible near optimal solutions to the class of NP-hard 3-D bin packing problem, see for example, Martello et al. (1990), and Scheithauer (1991), and the references therein. The solution techniques can be categorized under three categories: (i) mathematical, (ii) heuristics, and (iii) meta-heuristic approaches.

Multiple integer linear programming (MILP) as proposed by Chen et al. (1995) and others is a mathematical approach that focuses on using mixed integer programming to pack cartons of non-uniform sizes, taking into consideration the carton orientations and overlapping of cartons in a bin. A proposed method to improve the relaxed lower bound of MILP is discussed in Hifi et al. (2010), using identical bins to minimize the number of used bins. Similarly, den Boef et al. (2005) proposed a solution approach with a softer lower bound. Fekete et al. (2007) developed a separate mathematical model with a two level tree search algorithm, however this is limited to two dimensional packing problems. Yang and Leung (2003) also developed a model, an open-ended branch and price algorithm, in which the cargo cartons follow a sequence.

Next, a popular heuristic is the wall or layer building model explored by George and Robinson (1980) with identical cartons and no boundaries to the crate orientation. Non-identical crates with stability of stacking have been studied by Bischoff et al. (1995), and Baltacioğlu et al. (2006), where a new heuristic was created that follows humanistic thinking to aid packing. Pisinger's (2002) approach was to apply the strip and layer building method to decompose the problem down into simpler sub-forms. A heuristic to generate a solution with a minimum number of bins required using a guided local search with no crate rotation is found in Faroe et al. (2003).

The meta-heuristic models generally comprise tabu search, simulated annealing, and GA. Fanslau and Bortfeldt (2010) have discussed the different meta-heuristic models used. For instance, Bortfeldt and Mack (2007) suggested integrating a layer packing heuristic model with a tree search algorithm to obtain the best layer depth, dimension, and direction. Simulated annealing has been used together with heuristic methods to solve a generic 3-D bin packing problem, as found in Zhang et al. (2007). Egeblad and Pisinger (2009) further looked at 2D and 3D knapsack problems using simulation annealing. A hybrid of layer building and GA is also employed by Goncalvez and Resende (2012). Lodi et al. (2002) used a tabu search approach to qualify the neighbouring spaces with no crate orientation.

3. RESEARCH METHOD, DATA, and ASSUMPTIONS

In this paper, we elected to use GA as the meta-heuristic to imbed into the user interface built for the case firm.

The case firm has provided three months of cargo data, consisting of the cargo dimensions, estimated charging rates and order fulfilment timing. In the 3 months' worth of data, 76 working days were identified in the freight operations. Daily operations are performed once in the morning and once in the afternoon. On Saturdays, the operations are carried out only in the morning and Sundays are designated as non-work days. This data set has a total of 140 trips of freight operations, an average daily volumetric utilization at 34.6% and an average load of 578 kg. (See Table 1 for the capacity utilization).

Table 1: Daily volumetric utilization (in percent)

	Mon	Tues	Wed	Thurs	Fri	Sat	Overall
Mean	56.3	44.1	37.4	24.8	34.7	8.8	34.6
Median	36.7	35.9	26.9	21.1	33.0	4.2	27.1
Standard Deviation	48.0	53.0	36.9	24.3	15.5	8.9	36.9
Max Vol. Utilization	166.7	207.4	137.7	97.4	61.9	25.7	166.1

At the same time, the bin packing engine had to accommodate the regulatory constraints. For starters, regulations govern how much weight can be carried based on the truck size and this serves as another important constraint to our bin packing issue. The total tonnage cannot exceed 2 tonnes. We had to collect the finer details of these constraints from the relevant agencies and from the case firm's operational team. (Table 2 shows the relevant statistics.)

Table 2: Weight capacity utilization (kg)

	Mon	Tues	Wed	Thurs	Fri	Sat	Total
Mean	911.6	540.5	573.9	486.5	723.5	115.0	578.1
Median	766.0	591.0	427.0	387.0	705.0	97.5	437.0
s.d.	790.6	289.3	530.7	537.6	332.9	108.9	544.5

From the initial data collected, a q-q plot was undertaken and it showed that as the daily total weight carried increased, so too does the total freight volume carried, albeit by a smaller margin, as expressed by the relationship *Volume = 3.929 + 0.05298 x Weight. (This suggests that weight has a greater bearing than volume in the pricing negotiations).*

Finally, the other practical constraints which had to be factored include the cargoes that were typically heterogeneous in weight and size. In the loading sequence of the cargo plan, we had to pre-plan for the sequence of unloading for delivery. In short, the cargoes had to be packed in a sequence such that it facilitates the ease of unloading in an order of priority. We assume that the cargoes are free to rotate in all directions for the packing during loading and unloading. Fourthly, we are looking at a fast solution generation which is practical and does not delay the trucking schedule as the working hours are limited and costly.

4. MODEL SELECTION AND RESULTS

The mathematical model used to build the smart engine for the bin packing for the case firm is stated as follows:

Maximize $$f(r,c,t) = \sum_{p=1}^{n} \sum_{q=1}^{2} (r_{pq} - c_{pq})\, t_{pq}$$

where

$f(r,c,t) =$ Total monthly profit earned the firm

$p = \{1, \dots, n\}$; Truck number

$q = \{1, 2\}$; truck types, where 1 refers to 14 ft trucks and 2 refers to 24 ft trucks

$r_{pq} =$ Monthly revenue gained for truck p of type q

$c_{pq} =$ Monthly operational cost for truck p of type q

$t_{pq} = \{1, 0\}$; Binary variable, denoting the existance of a particular truck p of type q

with the respective constraints

$$\sum_{p=1}^{n} \sum_{q=1}^{2} \frac{m \bullet a \bullet V_{pq} \bullet \mu}{V_s}\, t_{pq} \leq \delta$$
$$\sum_{p=1}^{n} \sum_{q=1}^{2} t_{pq} \leq s$$
$$t_{pq} = 0 \text{ or } 1; \quad r_{pq,} c_{pq} \geq 0 \; \& \; integer$$

where

$s =$ Maximum number of trucks as decided by management

$m =$ Number of working days in a month

$a =$ Average number of trips per day

$V_{pq} =$ Bin volume capacity

$V_s =$ Total monthly cargo volume carried

$\mu =$ Optimized fill rate

$\delta =$ Max possible volume for cargo

$\sigma =$ Cargo volume volatility based on historical cargo volume data

Using this model and implementing GA onto the case firm's platform, we were able to modify the sequence of the freight loading plan, as shown in Figure 1.

The GA model was coded on the GAMS platform using CPLEX 11.0, running on an i5 2.53 GHz dual core Intel processor with 4 GB RAM. CPLEX was allowed to run for 180 seconds to obtain the optimal packing results. The inputs used for the optimizer were the number of crates for the day's delivery, and the dimensions of each piece of cargo. From thereon, the outputs provided through the model and GA were the sequence of loading of the cargoes, the dimensions of the cargoes in their rotated positions. The last output attributes were similar to Wu et al. (2010).

A simulation was then built on Excel where a random sampling pick is taken in each of the various cargo base categories, namely long, rectangle, and square crates. This will create a representative selection of the case firm's cargoes within the data pool of 976 crates for an accurate test sample. In each sample, a list of n item sizes of crates are chosen uniformly and independently at random within each base category, upon which the sum of the crate volume is computed. Each randomised output is thus an assortment of cargo crates which will fill the total bin (truck) volume by a certain percentage. The *fill rate* is defined as the sum volume of each randomized assortment of cargo crates divided by the total bin volume. The results suggest that a 100% packing success rate can be achieved when the fill rate is less than or equal to 80%. The *packing success rate* is defined as the probability of being able to optimally pack a random assortment of cargo crates into a truck bin volume. In the simulation, the packing success rate for each fill rate range is calculated based on the cumulative results of 50 runs. Further, the packing success rate reduces rapidly between fill rates of 80% and 88%, upon which it reaches a packing success rate of zero. The packing success rate drops rapidly to zero, when the capacity utilization reaches a maximum and exceeds the capacity. Our results compared fairly well to Wu *et al.* (2010) who had reported an optimal fill rate with 100% packing success at a range of 82.7% – 85.1%, based on an arbitrary data set.

From a practical perspective, an 80% fill rate also allows for a reasonable 20% buffer to account for practical constraints which cannot be inserted into the algorithm, such as packing inefficiencies and odd shaped cartons.

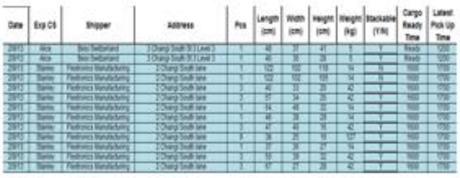
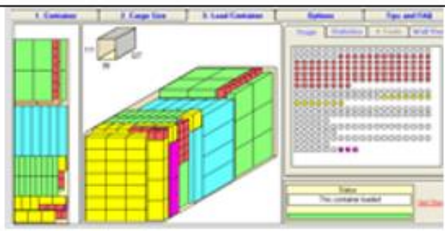
1		Scheduler receives and accepts the customer orders. Delivery and collection information is filled in the database of the system.
2		Import database into 3D BPP software. Key parameters include: a) Shipper – Customer name b) Quantity – Quantity of the cartons c) Length, Width, Height – Dimensions of the carton in centimeter (cm) d) Weight – Weight of the carton in kilogram (kg) e) Stackable (Y or N) – To determine whether the cargo is stackable.
3		Scheduler optimizes the truck capacity with loading planner. Then, sends out the 3D Packing Illustration Map to the Logistic Manager and notifies the Truck Driver.
4		Logistics Manager receives the delivery/ collection schedule, loading items and the 3D Packing Illustration Map. These information are printed and handed to the Truck Driver, who now has all the necessary information to perform the packing and delivery task.

Figure 1: Improved freight loading plan using GA and mathematical modelling

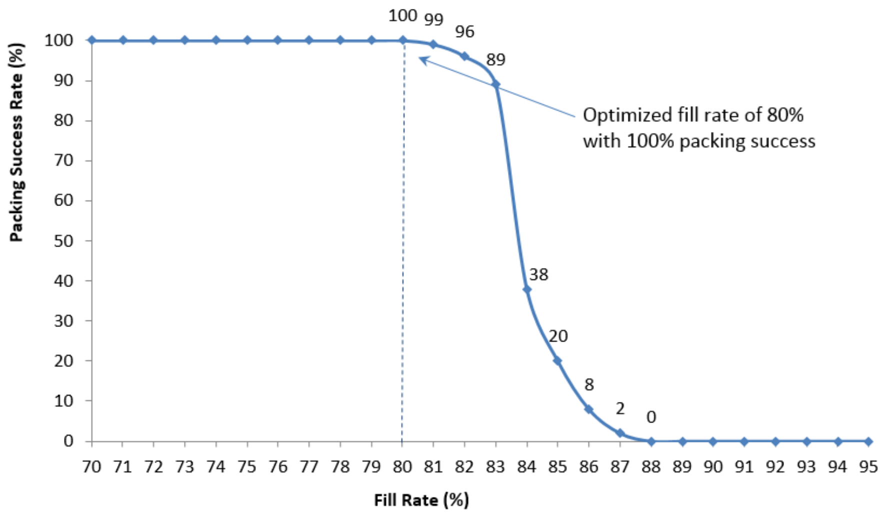


Figure 2: Packing success rate vs. fill rate

5. CONCLUSION

In this paper, we have applied mathematical modelling and GA to build a visually friendly user interface to help freight cargo schedulers responsively organise their cargo in three dimensions, in the most expedient manner, and pack the latter as optimally as possible to maximum capacity utilization. Our simulated results show that a fill rate of 80% is optimal to yield the best packing success under the existing set of operational constraints. This optimal value is obtained after factoring in the unloading demand on the cargo and other regulatory constraints. By using a simple GA and incorporating a visually appealing user interface, the case firm can improve her financial and operational efficiency, saving up to S$567K per annum. The practical scalability of the solution in the case firm suggests implementation applicability to fleet resource optimization across freight forwarding firms.

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