GA based hybrid tier packing approach for three dimensional packing

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A GA Based Hybrid Tier Packing Approach For Three Dimensional Packing

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School of Electrical & Electronic Engineering

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SUMMARY

This thesis proposed the Hybrid Tier Packing Approach for solving three dimensional packing problems. HTPA uses both heuristic and GA to conduct its packing for each tier. Heuristic packing is used for solving simpler tier packing problems while GA packing is used for solving the tougher and more complex tier packing problems. By applying suitable packing methods for solving the two difficulty classes of tier packing problems, optimal packing results can be obtained in a time efficient manner.

Hybrid Tier Packing Approach uses two new features in optimising its packing performance for solving the three dimensional packing problems. First, a grouping function, formation of homogenous cargo blocks is proposed for improving the performance of Hybrid TierPacking Approach. The grouping function helps to simplify the packing problems by grouping similar cargos into block, making it easier and faster to solve the tier packing problem. Second, a predictive tool V_{exp} is proposed for optimising the overall packing efficiency that can be obtained from solving the three dimensional packing problems. By estimating the volume of cargos that will be packed in subsequent tiers, V_{exp} helps to choose the best current tier packing solution that is most likely to give the highest overall packed volume efficiency.

In the conduction of experiments, this thesis proposed Shape Heterogeneity as a common standard for creation of test cases for different three dimensional packing problems experiments. Shape Heterogeneity defines the heterogeneity of a test case according to the degree of shape variation in the packing consignment. By using shape variation in the packing consignment as a mean to classify packing problems, Shape Heterogeneity is able to make accurate interpretations for different packing situations as according to the changes made in the elements of the packing consignment.

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Comparison of Hybrid Tier Packing Approach with other methods on a series of packing problems has shown the superiority of the proposed packing method. Hybrid Tier Packing Approach is able to constantly produce packing results with higher packed volume efficiency than the other methods. However, Hybrid Tier Packing Approach shows a tendency of increasing processing time when more cargo types are involved in packing and is not suitable for usage in time critical packing applications that involve numerous cargo types.

Results also show that Shape Heterogeneity of a packing problem can affect how optimally it can be solved. Packing problems of substantial Shape Heterogeneity range of 0.65-1.35 can be solved more optimally as compared to packing problems of other SH values. Vice versa, solving packing problems that are either too homogenous ($SH \approx 0.25$) or too heterogeneous ($SH \geq 1.75$) will produce much poorer packing results.

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CHAPTER 1 INTRODUCTION

1 MOTIVATION

Three dimensional packing has always been a very popular research area due to its applicability to real-world problems and the complexity of such problems [1]. Packing and cutting stocks problems are very common in various industries, e.g. in steel, glass, paper and clothes manufacturing, cargo packing in shipping and logistic industries, warehouse storing, etc. All these problems are very closely related to three dimensional packing; hence the research on three dimensional packing is highly relevant to real-world industries' operations. Even though similar structure may exist to solve many of these packing problems, they often differ significantly with respect to specific goals or constraints. This justifies research into these problems. It is well known [1, 2] that three dimensional packing is an NP-hard combinatorial optimization problem. Therefore, development of new algorithms, which are superior to the existing ones, has always been an active research pursuit in this field.

In this thesis, the focus is on developing method based on Genetic Algorithms that is able to effectively solve the three-dimensional packing problems with realistic constraints. Some of the constraints such as weight factor of the cargos, stability of the packed cargos, are very important. Without taking into account of these constraints, the solution will most probably be infeasible in a real world situation. Some of the three-dimensional packing methods [3-5] either make use of aided support such as a hyper plane surface for each layer of packed cargos or assumed that there will be some supporting material to fill the gap between layers of packed cargos. It is a challenge to design an algorithm that does not require any aided support material and yet can ensure the stability of the packed cargos.

Genetic Algorithm (GA) is a search method based on the mechanics of evolution and natural genetics. GA makes use of survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search. In each generation, a new set of strings

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is created using bits and pieces of the fittest from the strings in earlier generations. GA is stochastic in nature, and it efficiently exploits historical information to speculate on new search points with expected improved performance [6]. Due to its robustness, GA has often been used for solving the complex NP hard problems such as the three dimensional packing problems.

Although many works has been proposed for solving three dimensional packing problems [3-5, 7-12], none has been able to propose a comprehensive experiment to validate the capabilities and bring out the strengths and weaknesses of their packing methods. Very often, customized tests cases are created by varying the various packing elements (e.g. cargo types, cargo number, cargo sizes) that are used in these experiments. Without a common standard in identifying the difference between each created test cases, many of the experiments that are conducted are usually skewed. Therefore, in order to test the true capabilities of the proposed methods, a standard for identifying the proposed test cases is required.

1.2 OBJECTIVES

There are two main objectives in this thesis:

- 1) To propose a robust packing algorithm that can effectively solve three dimensional packing problems
- 2) To conduct fair testing that can examine the true capabilities of the three dimensional packing methods

1.3 MAJOR CONTRIBUTIONS OF THESIS

The major contributions made in this thesis are:

- 1) Proposed a Genetic Algorithm based packing algorithm that solves the three dimensional packing problems and produces densely packed (Volumetric consideration) stable packing solutions.

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- 2) Proposed a predictive function for tier packing algorithms. It accurately forecast the volume of cargos that will be packed if the proposed packing solution for current tier is implemented.
- 3) Proposed a new standard in representing three dimensional packing problems with the shape heterogeneity of their packing consignments. By using a common standard in representing whatever changes made in the packing elements of a packing problem, more control is allowed in the creation of test cases. This will therefore lead to more credible tests for the three dimensional packing algorithms.

1.4 ORGANISATION OF THESIS

This thesis is divided into six chapters. Chapter two consists of literature review on the various types of packing methods that has been proposed for three dimensional packing. Chapter three introduces and discusses in details the proposed algorithm for three dimensional packing problems. Chapter four highlights the need of a common testing standard and the proposed scheme using shape heterogeneity to identify a packing problem for testing. Chapter five presents and analyzes the packing results obtained for both the Bischoff and Ratcliff's (B&R) experiment and the proposed experiment. Chapter six summarizes the conclusions from the findings made in this thesis and recommends probable future work.

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CHAPTER 2 LITERATURE REVIEW

Existing work on three dimensional packing problems can be divided to two approaches. The first approach uses heuristic rules based optimization techniques [8-11] to solve the container loading problems. Bischoff has done extensive work in this area. His work [8-10] includes discussion on popular issues such as stability, multipoint drop and weight distribution in development of packing methods for container loading.

The second approach uses AI (Artificial Intelligence) optimization techniques [3-5,7, 12] to solve the three dimensional packing problems. Commonly, the AI optimization techniques proposed are GA based. They are namely, Gehring's CBGAT, Khoo's Hybrid GA and Jin-Ling Lin's Hybrid SMILE system. Other type AI approaches have also been proposed, an example will be the tree based search technique proposed in Ely's work [12].

2.1 HEURISTIC RULES BASED APPROACHES

In this section, Bischoff work on heuristic approach for solving the three dimensional packing problems will be discussed.

2.1.1 BISCHOFF'S WORK

In his work on issues in development of approaches to three dimensional packing [8], Bischoff mentioned some of the practical requirements that are often lacking in the studies of constraint three dimensional packing problem. These requirements are orientation constraint, load bearing strength of items, handling constraints, load stability, multi drop situation and weight distribution within a container. Bischoff classified these considerations to packing constraints and objectives and discussed on their importance and the difficulty in implementing them.

AGA BASED HYBRID TIER PACKING APPROACH FOR THREEDIMENSIONAL PACKING**2.1.1.1 Packing Algorithm for stability consideration**

Bischoff then proposed two packing algorithms that dealt with not only volumetric considerations but also two others practical requirements during packing. The first algorithm Bischoff proposed catered stability as its consideration. The concept of the algorithm is based on the idea of packing bottom upward with every layer of up to two types of cargo packed. The choice of the type of cargo packed and their orientations are determined by the resulting utilization of the loading surface concerned.

Fig 2.1 Bischoff's algorithm for packing with stability requirement

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A simple flow chart of this algorithm is as shown in figure 2.1. The algorithm starts by setting up a table of unpacked cargos. The first loading surface considered is the pallet board. Potential loading patterns are generated for this surface from 'blocks' of cargos. 'Blocks' of cargos are defined as a single tier rectangular arrangement of identical cargos in the same orientation and their edges parallel to the sides of the pallet. Only single block and two adjacent blocks packing are considered. Out of the feasible patterns generated, the one with maximum area utilization will be chosen. When several patterns are generated in this aspect, patterns consist of one type of cargos will be preferred over those formed by two types. The second tie breaker rule look for large flat surface for next layer packing while the third tie breaker rule consider the unused surface. Figure 2.2a shows a good example for third tie breaker rule. Patterns with larger z values are assigned a higher rating with the rationale that the remaining surface might be easier to fill at later stage. Once the pattern for initial loading surface $L \times W$ is determined, table of unpacked cargos and potential loading surfaces can be updated and the packing for next loading surface will begin.

Fig 2.2 A two block arrangement

Bischoff has also applied this algorithm on multiple pallet packing problems using the sequential approach and has achieved relatively good results. This algorithm is characterized by layer packing of similar cargos. By disallowing cargos overhang and promoting interlocking between cargos, this algorithm will produce results that has better stability consideration.

A GA BASED HYBRID TIER PACKING APPROACH FOR THREE DIMENSIONAL PACKING**2.1.12 Packing Algorithm for multi drop situation consideration**

The second algorithm Bischoff mentioned, cater for multi drop situation (OW)). Multi drop situations usually require the creation of distinct sections in the container corresponding to the different destinations. Bischoff achieves this by processing the subsets in sequence, starting with that from the final destination, and packing each separate consignment with a view to maximize the space remaining for the rest. The algorithm starts with identifying potential loading surfaces where all flat, contiguous, rectangular surfaces are considered. Once the process of space identification is complete, all permissible unpacked cargos will go through the four tier selection ranking scheme to select the best alternative for packing.

Main Criterion: Largest potential space utilization, $U = k [xyz/XYZ]$

Tie Breaker 1: Smallest lengthwise protrusion, $p = a + x$

Tie Breaker 2: Largest box volume, $v = xyz$

Tie Breaker 3: Lowest value of b

a, b, c are reference points of the empty space

x, y, z are the dimensions for a cargo

X, Y, Z are the dimensions for the empty space

$k = \min([Z/z], m)$

m stands for the number of cargos of the candidate type yet to be packed in this stage

Both the main criterion and the tie breaker rule 1 involve parameters relating to the box, its orientation, and the space concerned. Tie breaker 2 relate only to box characteristic and is aimed at packing awkward cargos early. Tie breaker 3 relate to those of the packing space and serve to produce a definitive selection when the other rules give similar scores. The combination with the highest rank is selected and the selected cargo

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type will form a homogenous column with a corner coincide with the reference point of the packing space. It should be pointed out that although the value of U based on a feasible option for next packing scheme, subsequent steps do not automatically produce identical items, because higher ranking alternative may present themselves.

This algorithm has many characteristics in common with the wall building approaches. Its main advantage over these approaches is that it does not construct complete walls across the width but only columns. The main characteristic of this method is that it produces results with minimum protrusion, which is ideal for multi drops situation.

2.2 AI BASED APPROACHES

The AI based approaches for three dimensional packing to be discussed in this section are mainly GA based (Gehring's CBGAT, Khoo's hybrid GA, hybrid SMILE). Another type of AI approach, the tree based search technique is also discussed.

2.2.1 GEHRING'S WORK

Gehring proposed a hybrid algorithm [3] for solving the container loading problem. The first step of his algorithm generates a set of cargo-towers using a greedy algorithm and the second step will use GA to cover the container floor with the derived cargo towers.

In problem formulation, Gehring stated that only stable cargo arrangements are tolerated where stable means that cargos have a priori balanced positions and must not fall over. This will ensure that additional precautions for stability such as spacing material is not required. Three feasibility conditions for packing are stated as follow:

(F1) Each cargo lies on the container floor or is placed on the top of another cargo so that its center of gravity is supported by cargo(s) below.

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(F2) Each cargo is positioned parallel to the side walls of the container.

(F3) Each box lies completely within the container.

Fig 2.3 Two arrangements of boxes in a container

A tower is defined by an stack arrangement of cargos that meet the F1-3. Each tower is only allowed to have a single cargo as its base, called base cargo. Figure 2.3 shows a example on the feasible and not feasible tower formations. A disjunctive set of towers (with no overlapping cargos) will form a tower set. The detail of the formation of tower sets and tower is elaborated in Appendix B twin frame boxes 1 and 2.

At the second step, Gehring uses a general incremental GA for solving floor covering problem. The procedures for a general incremental GA is as shown in Appendix B twin frame box 3. Crossover and mutation is applied alternatively and is based on complimentary probabilities of $P_{\text{cross}} + P_{\text{mut}} = 1$

Two chromosomes are used to define the problem, vector chromosome(i) = 1,...,ntowers, which specify the sequence of the placements of the tower bases of a tower set. An element vector chromosome(i) contain the index of the tower bases and their rotation variant. Gehring also mentioned that he chosen these GA operators to achieve optimize effect

- Uniform order based crossover
- Partially mapped crossover

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- Cycle crossover
- Scramble sublist mutation
- Mutation by inversion
- Fitness scaling

Gehring did comprehensive studies on his proposed work and has shown much better results as compared to the others. However, it was observed that Gehring achieved these by trading off the overall stability of the solution obtained.

2.2.1.1 Packing with Overhang

Packing with overhang in the three dimensional packing problems is a popular way for improving the packing efficiency. Depending on the stability criteria and the amount of empty space left in between the packing spaces, packing with certain level of overhang can be allowed as shown in figure 2.4. Gehring proposed in his work that a maximum of 30% of overhang is allowable to improve the obtained packing results.

Fig 2.4 Allowable overhang for packing

2.2.2 KHOO'S WORK

In his thesis [7], Khoo proposed an ingenious encoding scheme for his Genetic Algorithm (GA) used for two dimensional (2D) packing, called *Slicing Tree Structure*. Slicing tree structure is an oriented rooted binary tree where each terminal node represents a cargo

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while an internal node represents the joint condition (vertical or horizontal) between the cargos.

For solving three dimensional (3D) packing problems, Khoo introduced a hybrid packing algorithm that combined a heuristic packing scheme with GA. The heuristic packing scheme is used for packing more common cargos while the GA is used to pack the remaining less common cargos. Packing is done from an extension of his 2D packing ideology whereby at any one time, only one layer is considered. Only when the current layer is packed, then the next layer (tier) of cargo packing will be considered. The GA used for 3D packing problems is similar to the one used in 2D packing with an additional consideration for flatness. Flatness consideration is used to ensure maximum packing space allowable for next layer. Khoo suggested a metric called Height Matrix for the evaluation of flatness for possible solutions. Height Matrix defines the height relationship of the solution. Solutions with cargos of similar height packed closed together will be preferred to solutions that failed to pack cargos with similar height closely.

Khoo defined two constraints for his derived solution. Firstly, derived packing solution must be within the given packing volume. Secondly, derived packing solution must have guaranteed mechanical stability. Khoo achieved constraint 2 by making sure that all cargo boxes have 100% of its base supported.

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Fig 2.5 Khoo's Hybrid Genetic Algorithm for container loading problems

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An overview of Khoo's hybrid algorithm is shown in figure 2.5. The algorithm starts by selecting a potential packingsurface from the list of packing spaces. Heuristic selection rules are applied to choose an optimal list of homogenous cargos for heuristic packing. Heuristic packing will be carried out by the best packing technique that can pack the most of the selected cargos into the given space. After heuristic packing is carried out, it then checks for any eligible unfilled area left on the packing space. These unfilled areas will be packed by GA and all eligible packing surfaces for next tier will be updated. The next packing area is selected and the cycle is repeated till the container is fully packed or when all cargos are packed.

2.2.2.1 Heuristic Selection Rules

One of the main features of Khoo's algorithm is his heuristic selection rules. Khoo uses heuristic selection rules for selecting cargos to be packed for both heuristic packing and GA packing. For heuristic packing, two important characteristics of the cargos are observed, the total area of modal cargos A_m and the area of the largest type of cargo A_L . Three cases are identified according to these two qualities.

Case 1: Total area of modal cargos, $A_m \geq k * \text{Packing Space Area}$

Case 2: Total area of modal cargos, $A_m < k * \text{Packing Space Area}$

*Case 3: Area of the largest type of cargo, $A_L > \text{Total area of modal cargos, } A_m$
& Area of the largest type of cargo, $A_L \leq \text{Packing Space Area}$*

The value of k is problem dependent and by default Khoo set it at 0.5.

For case 1 where the modal cargos are able to cover k portion of the packing space, modal cargos will be selected for packing. However, if total area of modal cargos is lesser or if the largest cargo covers a larger area, the largest cargo is selected for packing instead.

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Selection rules for GA are based on preference for more diverse types of cargos for packing. Two simple rules are set as below

- i) Exclude the type of cargos chosen earlier for heuristic packing and sort the remaining type of cargos into ascending order of their frequency
- ii) Choose maximum number of cargos that the packing space can hold going from the least frequent to the most frequent

2222 Heuristic Packing

Khoo proposed 8 different methods for heuristic packing and the best method will be chosen. The best method is chosen based on the following criteria

- i) Maximum number of cargo packed
- ii) Largest packing area available for next tier of packing
- iii) Large usable leftover area for GA packing

The characteristics of the eight different heuristic packing methods are as follow..

Method 1 and 2 pack from left to right in a horizontal orientation.

Method 3 and 4 pack from back to front in a vertical orientation.

Method 5 and 6 pack alternate pattern starting back to front then left to right in a diagonal orientation

Method 7 and 8 pack alternate pattern starting left to right then back to front in a diagonal orientation

All odd numbered methods pack cargo length wise while even numbered methods pack breadth wise.

After heuristic packing, the packing area for next tier and the unpacked area for the same tier are calculated. The general profiles for heuristic packing solution are as shown in figure 2.6.

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Fig 2.6 General profiles of heuristic packing solution

For a perfect rectangle profile, there will be only one packing space for next tier and two possible spaces for GA packing. As for a imperfect rectangle profile, there will be two packing spaces for next tier and three possible packing spaces for GA packing.

2.2.2.3 Genetic Algorithm Packing

GA packing is carried out based on Khoo's work on two-dimensional packing with an inclusion of flatness and contiguity considerations in objective function. With the optimal selected list of cargos for packing, the following GA processes are carried out.

Problem Representation

Khoo represented the packing problem with his proposed parse tree structure named slicing tree structure. This tree structure has the characteristics of an oriented binary rooted tree. Each terminal node represents a particular cargo included in the packing solution. Note that terminal nodes hold the identification number of the packed cargo and their values must be mutually exclusive which means no two terminal nodes should hold the same value. Each internal node holds the value of v or h corresponding to vertical

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joint/cut and horizontal joint/cut respectively. The ambiguity in the internal node representation lies with the different interpretation of the slicing tree structure. If it is interpreted from the very top to the bottom terminal nodes, it shows how a big rectangle is cut into smaller rectangles. However, if it is interpreted bottom to top, it indicates how small rectangles (cargos) are jointed to form the big rectangle (packing space required). Due to the nature (packing) of the problem, Khoo proposed the packing problem to be viewed bottom to top, left to right. At each internal node where two sub nodes (rectangles) are joined, a larger rectangle is formed by jointing (v or h) sub node A with sub node B as specified by the internal node's value.

Fig 2.7 A slicing tree structure for 4 cargo packing

Fig 2.7b shows a typical slicing tree structure for 5 cargos packing and Fig 2.7c the represented packing solution. Figure 2.7a shows the assortment of cargos packed. Using post-order polish notation, Fig 2.7d is the chromosome representation for Fig 2.7b.

AGA BASED HYBRID TIER PACKING APPROACH FOR THREE DIMENSIONAL PACKING***Objective Function***

An objective function is used to evaluate the fitness of the chromosome strings. Khoo defined his objective function as follows:

Fitness = Total area of cargo packed / total area required * C_r * F_r

$$\text{where } C_r = \begin{cases} 1/MC_v & \text{if } C_v = MC_v \\ (MC_v - C_v)/MC_v & \text{if otherwise} \end{cases} \quad 0 \leq C_v \leq MC_v$$

$$\text{and } F_r = \begin{cases} 1/MF_v & \text{if } F_v = MF_v \\ (MF_v - F_v)/MF_v & \text{if otherwise} \end{cases} \quad 0 \leq F_v \leq MF_v$$

Both C_r and F_r are penalty functions that ensure that the solution has a large and flat, contiguous area.

C_v is the contiguity value of the solution; MC_v is the maximum contiguity value of the solution. The higher the value of C_v means the solution has lesser contiguous area. F_v is the flatness value of the solution; MF_v is the maximum flatness value of the solution. The higher the value of F_v means the solution has lesser flat area. C_v and F_v are calculated based on a tool called height matrix that defined the height relationship between the packed cargos.

Reproduction

Stochastic Universal Sampling (SUS) selection scheme is used for the reproduction process of the GA. SUS, a form of fitness proportionate selection scheme, is very similar to the more popular roulette wheel selection scheme. However, SUS prevents premature convergence if the population size used is too small.

A GA BASED HYBRID TIER PACKING APPROACH FOR THREE DIMENSIONAL PACKING***Crossover***

Khoo's did not apply much crossover activities in his GA as it was argued that the tree structure of the chromosomes must not be disrupted by the operation. Khoo was afraid that normal crossover activities might affect the feasibility of the derived chromosomes and any corrective measures might be too complex. The crossover operator Khoo proposed chose a common terminal node between the trees and swapped their orientation symbol.

Mutation

For his GA, Khoo proposed three types of mutation operations: they are mutation of joint, orientation and interchange. Mutation of joint toggles the value of the inner nodes between 'v' and 'h' depending on their original value. P_j , probability of joint will determine the chance for this mutation to occur. Mutation of orientation toggles the orientation symbols of the terminal nodes. This operation is controlled by P_o , probability of orientation. Mutation of interchange swaps the position of any two random cargos in the string and is controlled by P_i , probability of interchange. These three operations implemented helped to provide diversity needed to search for a better solution.

Khoo's algorithm depended too much on heuristic packing and is more suitable for more homogenous cargos packing. Moreover, his heuristic packing rules are too simple as compared to those proposed by Bischoff and therefore do not perform as ideally when compared with Bischoff's works.

2.2.3 JIN-LING LIN AND BOOBIE FOOTE'S WORK

Lin and Foote proposed a hybrid SMILE algorithm [4] to solve the three dimensional packing problems. The hybrid SMILE algorithm is achieved by combining the multiple chromosomes GA with the SMILE to solve the three dimensional packing problems.

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First, Lin and Foote defined the three dimensional packing problem as a minimization problem. Lin and Foote expressed the objective function for a packing solution as given in equation 2.1. C is the objective cost function, N is the total number of boxes to be packed, L is the total number of layers, LEN is the length of the container, WID is the width of the container, VOL_i is the volume of cargo i and $MAXH^L$ is the height of packing when the job packing is done.

$$\min imise \ C = (MAXH^L * LEN * WID) - \sum_{i=1}^N VOL_i(1) \dots\dots\dots(2.1)$$

2.2.3.1 Heuristic Rules and the Performance Measures

Lin and Foote proposed using four performance indices to keep the free space between the packing cargos to be as compact as possible. The four performance indices are namely, the internal free space(IFS), the external free space(EFS), the vertical cross section penalty(VP) and the contiguity penalty(CP). These four performance indices are actively used in the decoder of the system to interpret the packing results from their represented chromosomes.

Internal Free Space(IFS)

For the placement of packing cargos, there is a tradeoff between placing the next packing cargo on a higher layer or placing it on the current layer. IFS helps to determine the placement by measuring the total amount of space buried among the layers and is no longer usable. Let $H'_{x,y}$ represent the height of location (x,y) from the base of the container and $BH'_{x,y}$ represents the height of the box that occupies location (x,y) after the 1st layer is packed. The equation representation of IFS^t is as given in equation 2.2

$$IFS^t = \sum_{x=1}^{LEN} \sum_{y=1}^{WID} \{H_{x,y}^t - H_{x,y}^{t-1} - BH_{x,y}^t\} \dots\dots\dots(2.2)$$

A GA BASED HYBRID TIER PACKING APPROACH FOR THREE DIMENSIONAL PACKING**External Free Space (EPS)**

EFS indicate the final height of current layer of packing cargos. It defines available free space under the roof of current packing plane. The equation representation of EFS is as given in equation 2.3.

$$EFS^t = \sum_{x=1}^{LEN} \sum_{y=1}^{WID} (MAXH^t - H_{x,y}^t) \dots\dots\dots(2.3)$$

Vertical Cross Section Penalty (VP)

VP is a penalty function that is used in the fitness function to penalize those packing configurations that allow cargos to be placed over empty space. The equation representation of VP is as given in equation 2.4.

$$VP^t = \sum_{x=1}^{LEN} \sum_{y=1}^{WID} \left\{ \left| H_{x,y}^t - H_{x,y+1}^t \right| + \left| H_{x,y}^t - H_{x+1,y}^t \right| \right\} + \sum_{x=1}^{LEN-1} \left| H_{x,WID}^t - H_{x+1,WID}^t \right| + \sum_{y=1}^{WID-1} \left| H_{LEN,y}^t - H_{LEN,y+1}^t \right| \dots\dots\dots(2.4)$$

Contiguous Penalty (CP)

To obtain optimum packing results, compactness of the packing solutions is essential. One way of measuring compactness is by computing the length of the line segment between the occupied space and the free space in the layer. This computation is only performed on a layer at a time and the smaller the CP the more compact is the packing for the layer. Let $L_{x,y}$ be a binary variable representing the logical occupancy status of the location (x,y) in the current layer of the container. If the location of (x,y) is occupied, then $L_{x,y} = 1$. The CP can then be computed by means of exclusive OR ($\oplus$) operation. The equation representation of CP is as given 2.5.

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$$CP = \sum_{x=1}^{LEN} \sum_{y=1}^{WID} \{L_{x,y} \oplus L_{x+1,y} + L_{x,y} \oplus L_{x,y+1}\} + \sum_{x=1}^{LEN-1} |L_{x,WID} \oplus L_{x+1,WID}| + \sum_{y=1}^{WID-1} |L_{LEN,y} \oplus L_{LEN,y+1}| \dots\dots\dots(2.5)$$

2.2.3.2 Hybrid Genetic Algorithm System

The hybrid GA system proposed by Lin and Foote is divided into five different components. They are namely, the chromosome representation, the creator, the interpretation and evaluation, the operators and the decoder.

Chromosome Representation

Lin and Boote proposed using a multiple chromosome representation for an individual packing solution. Each chromosome represent a layer of packing and a combination of related chromosomes will form a packing solution.

Creator

Creator is used to create the pool of initial population to be processed by the hybrid GA system. Three rules are applied in the creator. First, the boxes are sort out according to volume. The larger volume cargos will have priority over those that have smaller volume. Second, from the sorted list, construct the first feasible layout to be used as the first population. This is to guarantee that at least one feasible layout is found. Thirdly, mutation is done on respective chromosomes so that N feasible layouts are created.

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Operators

The basic operators used in Lin and Boote's hybrid GA are selection, crossover, mutation and reproduction. The selection scheme used in the hybrid GA is the popular roulette wheel selection. Since the packing problems are an ordering problem, PMX crossover scheme is used. For the mutation, the inversion technique is used on the local modification of the chromosomes. Both the Crossover and mutation schemes are performed within the relative chromosomes and no intra-chromosome exchanges are allowed. Elitism policy is used to carry out the reproduction scheme.

Decoder

Decoder is used to translate the ordering string into a feasible three dimensional layout. Heuristic rules will be used when generating the layout according to the order found in the related chromosomes. VP and CP are used in the computation of fitness for the derived individual packing solution while IFS and EFS are used for the construction of the solutions. The best individual with the minimum objective function through out the generations of evolution will form the final packing layout.

2.2.4 ELY'S WORK

Tree based search technique is another AI technique that has been applied on solving the three dimensional problems. Ely proposed in his work [12] a restricted breadth search strategy to optimally solve the three dimensional packing problems.

2.2.4.1 Usage of Homogenous Blocks

In his work, Ely proposed filling the packing space with homogenous blocks made up of identical items. All items within a block will take the same orientation. By packing with homogenous blocks, he states that there are several advantages for practical problems:

- Allow similar items to be closed together. Ease for sorting out.

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- Easier to arrange. Faster loading time
- By stacking similar items on top of each other, there will be lesser problems with load bearing strength issues.
- Items not easily slip within a block structure

2.2.4.2 The Algorithm

Ely proposed that the solving of the three dimensional packing problems to be divided into two parts. The first part uses greedy heuristic approach to formulate possible solutions for the packing problem. The second part of the algorithm applies the best based search on the formulated packing solutions so as to derive the optimal packing solution for the packing problem.

Greedy Heuristic

The greedy heuristic packing used by Ely is iteration based whereby each iteration added an additional item into the packing space. Starting with a empty container, the iteration greedy heuristic packing process is as elaborated.

- 1) Sorted the items according to volume with the larger items being chosen first.
- 2) Seek the empty spaces available for stowing the item.
- 3) Test the additional items in all orientations for all the empty spaces.
- 4) Evaluate the possible packing and take the one that achieved the highest evaluation.
- 5) The stowed item is removed from the list and the empty spaces are updated.
- 6) If there is no more item for stowing, terminate the packing process. Else, go back to step 1 and stow the next item in the list.

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Tree Based Search

With the initial solutions formulated, the tree based search technique is used to derive the optimal packing solution. For the tree representation, branching is not carried out for every different items, instead it is for different types of items involved in packing and their permitted orientations. The root node represents an empty container; each further node constitutes a (partially) filled container. If m is the number of different types, each of these partial solutions can be branched into $6 \cdot m$ number of new partial solutions.

For the search technique, a simple breadth search is not able to solve the three dimensional packing problems due to the enormous tree nodes that are required. For example, a three dimensional packing problem with 20 different types, each with six permitted orientations, has about 1.7 millions nodes after the third iterations. A depth first search is also seems inappropriate, as too much effort is concentrate on the lower levels of the tree where most of the container is already filled. As on the other hand, the decision as to whether a good solution can be located is seen in the upper half of the tree. Therefore, a best search strategy is adopted, which expand only those nodes that obtained the highest ranking from the evaluation function,

2.3 SUMMARY

Literature review looks into two popular approaches that are used for solving the three dimensional packing problems namely, the heuristic approach and the AI approach. The heuristic approach represents packing methods that uses heuristic rules to carry out the three dimensional packing. Bischoff has done a lot of work in this area. Two of his works, packing for stability condition and packing for multi drop condition are discussed. AI approach represents packing methods that uses AI technique to solve the three dimensional packing problems. Research shows that many of the AI techniques applied are GA based and some of these works are discussed [3,4,7]. Another type of AI based packing method, the tree based search technique, proposed by Ely[12] is also discussed.

CHAPTER 3 THE PROPOSED METHODOLOGY

In order to optimally solve the container packing problems, a systematic and structured packing methodology is required. The approaches discussed in chapter 2 treat the packing problem either as a sequential placement problem, a layer based packing problem or as a two dimensional block packing problem. In comparison, the layer based packing concept [4, 5, 7, 8] is the more popular choice. This is due to its ease in implementation and its ability in satisfying stability criteria without over simplifying the packing problem. In this thesis the layer packing called tier packing concept is used to formulate the proposed packing methodology.

The proposed algorithm based its search with the layer based packing concept. As both the heuristic packing and the GA packing alone can't optimally solve the three dimensional packing problems[7], the proposed algorithm uses a combination of both techniques to solve the layering packing problems. By using an innovative predictive function (V_{exp}) to accurately determine the optimal packing solution for each layer of packing, the best overall packing solution can therefore be derived.

GAs have a tendency of utilizing too much computing resources (eg time) in locating the optimal solution. Therefore a grouping function (Homogenous Cargo Blocks) is proposed to effectively reduce the processing time required for the proposed algorithm. By using V_{exp} and formation of homogenous cargo blocks, the proposed algorithm is able to effectively solve the three dimensional packing problems in a reasonable time.

3.1 TIER PACKING CONCEPT

Three dimensional tier packing is defined by its packing of the given flat contiguous cuboid packing space in a layering manner. Initially, packing is done on the floor of the given packing space, which is considered as the first tier. An arrangement of different cargos will be chosen to cover the given packing space. The resulted flat

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contiguous spaces from the cargos packed will be used as packing spaces for next tier. This process will be repeated for subsequent tiers till the container is fully packed, and none of the cargos available can be packed in anymore. In order to obtain good packing solutions, the packing of each tier must not only be optimized for its own prospect, consideration for optimum packing for subsequent tiers must also be considered. Fig 3.1 shows a typical tier packing result for a 6 cargos packing problem.

Fig 3.1 Packing of cargos for a single tier

Tier Packing can be split into three basic steps, namely Selection, Packing and Updating.

SELECTION

Selection is the initial step for conducting tier Packing and acts as a preparing stage prior to packing . Generally, selection process involves selecting the tier to be packed and selecting the intended packing cargos for the tier. Different approaches conduct their selection process differently. In [8] selection process is done by going through all possible packing arrangements for a tier before taking the best arrangement. Alternatively, [7] picks its packing tier according to size, giving higher priority to packing tier with larger packing space. Intended packing cargos are picked either as the largest single homogenous type of cargos or a mixed assortment of cargos that can fit into the packing space, depending on the packing method used.

PACKING

Packing is the crucial step in the tier packing process and proceeds after the selection process is done. Although many different types of packing methods are proposed in tier packing, most are similar in nature. Commonly, packing methods

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used in tier packing are heuristic in nature and usually limit the intended packing cargos to one or two cargo types. The reason behind this is that it is perceived that a single tier can be effectively packed with cargos belonging to one or two cargo types. And by limiting the packing choices, more computation resources can be saved in the process of solving the packing problem.

UPDATING

Updating is the final step of a tier packing process whereby the packing results for the packing tier is updated so as to prepare the packing for next tier. Updating is usually focus on renewing the information of new tiers created from the current packing and the remaining cargos available for packing.

3.1.1 A GENRIC TIER PACKING PROCESS

A generic tier packing process is an iterative packing procedure involving the three crucial steps, selecting, packing and updating. Fig 3.2 shows an eight cargos packing problem solved using tier packing approach. The eight cargos to be packed belong to 6 different cargo types.

To simplify the illustration of the packing process, it is assumed that no two cargos are packed along the container width. This assumption will make the side view adequate for interpreting the packing process.

Fig 3.2 Packing cargos for example on generic packing process

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Fig3.3a Example on generic packing process: Packing for tier1

Initially, the packing tier is automatically taken as the floor of the given packing space. C1 and C3 are selected and are packed as shown in figure 3.3a. The new tiers are identified as the space above C1 and the space above C3. C2, C4, C5, C6, C7 and C8 are left for further packing.

Fig3.3b Example on generic packing process: Packing for Tier 2

The next packing tier is then selected as the one which has the larger packing space, which is the space above C1. C5, C6, C7 and C8 are selected and packed on this tier. New created tiers are the space above C5 and the space above C6, C7 and C8. As the space above C5 is not large enough to accommodate packing for the remaining cargos, it is left out. The tiers that are available for packing are then identified as the space above C3 and the space above C6, C7 and C8. C2 and C4 are left for further packing.

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Fig3.3c Example on generic packing process: Packing for Tier 3

The next packing tier is selected as the space above C3. C2 is selected and packed on this tier. As the space above C2 can not accommodate further packing, there will be no new tier created. The tier available for packing is then identified as the space above C6, C7 and C8.

Fig3.3d Example on generic packing process: Packing for Tier 4

The next packing tier used for packing the remaining cargo is the space above C6, C7 and C8. Cargo 4 is packed on the packing tier. With all the packing cargos packed, the given packing problem is solved by the tier packing approach.

3.2 HYBRID TIER PACKING APPROACH, (HTPA)

The flow diagram of the proposed tier packing approach, namely Hybrid Tier Packing Approach (HTPA) is shown in Figure 3.4. Similar to the generic tier packing process, HTPA is an iterative three phases packing procedure. The three

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phases are preparation, packing and updating. At the start of the tier packing process, the preparation phase will select the packing tier, select the packing cargos, form the homogenous cargo blocks and determine the packing method to be used. With these crucial packing information determined, the packing process will derive the optimal packing solution for the packing tier. The updating process will then update on the new tiers that are created from the packing and the remaining cargos that are not yet packed. If there are tiers that are not packed yet, the tier packing process will repeat till all tiers are packed.

PREPARATION PHASE

Preparation phase is similar to the selection phase of the generic approach. The only difference will be the inclusion of a heuristic grouping function for the facilitation of packing.

Selection of current packing tier is based on the level of packability for the different potential packing spaces. Tiers that have less packing alternatives (awkward) will be given priority over tiers that have more (versatile). The list of tiers available for packing is named as Space_list. Space_list is arranged according to the selection criteria to facilitate the selection process.

During the packing phase, a predictive tool V_{exp} is used to guide the search for an optimal container packing solution. In order to conform closely to the predicted value, packing cargos are pre-assign for each probable next packing tier. Therefore, the list of packing cargos, Cargo_list can then be considered as a list of sets of packing cargos as shown in equation 3.1 for the corresponding tiers defined in the Space_list as shown in equation 3.2.

$$\text{Cargo_list} = [\text{Packing_Cargo}_{\text{Tier A}}, \text{Packing_Cargo}_{\text{Tier B}}, \dots, \text{Packing_Cargo}_{\text{Tier N}}]. \quad (3.1)$$

$$\text{Space_list} = [\text{Tier A}, \text{Tier B}, \dots, \text{Tier N}] \quad (3.2)$$

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Different from the generic approach that usually conducts heuristic packing, the proposed approach can conduct the tier packing process in either the heuristic method or the GA method. Choosing of the packing method depends on the nature of the tier packing problem. Simple packing problems that have few packing alternatives should be solved using heuristic packing while complex packing problems should be solved using the more sophisticated GA approach. By doing so, the tier packing problem can be solved effectively.

Before the actual packing of the tier can commence, a grouping function will form groups with the packing cargos according to their cargo type. The different groups of packing cargos formed are named as cargo blocks. These cargo blocks are later used by the respective packing method to solve the tier packing problem. The grouping function helps to simplify the packing problems, making it easier and faster to solve the tier packing problem. This is especially true for packing problems that have many similar cargos.

PACKING PHASE

Depending on the method chosen in the preparation phase, the packing phase performs either heuristic packing or GA packing. Heuristic packing uses the exhaustive search technique to obtain the optimal packing solution for the packing tier. All possible packing alternatives are examined and the one that can give the best packing result will be chosen.

GA is a powerful stochastic search technique that can effectively solve tough tier packing problems in a fraction of time that is actually required. Furthermore, with the usage of predictive tool V_{exp} , the derived packing solutions will not only give optimal packing efficiency for current tier, but will also ensure optimal packing for subsequent tiers. The tier packing problem is treated as an ordering problem and their packing order and orientations are represented by the chromosomes. These

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chromosomes then go through iterations of reproduction, crossover and mutation before evolving to the optimal packing solution.

UPDATING PHASE

Updating the Space_list and the Cargo_list is the crucial part of the updating phase. The updating process requires evaluation of the new tiers. Depending on their packability, the Space_list is updated in the order that the more awkward new tiers will be selected for packing first. The Cargo_list are then updated accordingly in correspond to the updated Space_list.

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Fig 3.4 Flowchart for HTPA

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3.2.1 THE PREPARATION PHASE

This is the first stage of HTPA's tier packing process, and in this phase the necessary information required for packing is acquired. The packing tier and the cargos to be packed must first be determined. The packing cargos are then formed into cargo blocks to facilitate packing. Lastly, with the derived packing information, the packing method that is more suitable for carrying out the packing will be chosen.

3.2.1.1 Preparation: Packing Tier

For every tier packing process, the first tier defined in Space_list is automatically selected as the packing tier. The selected packing tier is then taken out from the current Space_list, leaving the Space_list for next tier to be with one lesser element. Using predicate calculus representation[18], the relationship between packing tiers and Space_list is as defined in equation 3.3.

$$Space_list_{current} = [Packing_tier \mid Space_list_{next_tier}] \dots \dots \dots (3.3)$$

Where $\mid$ is the adjoining function that shows that the current space list consists of the packing tier and the remaining space list for packing of next tier.

Initially, there is only one legitimate packing tier and that is the given packing space. Only after the packing, the space_list will be updated with definition of the new tiers.

Each packing tier is defined by a 6 parameters array as shown below

$$[X_{tier_start}, Y_{tier_start}, Z_{tier_start}, X_{tier_limit}, Y_{tier_limit}, Z_{tier_limit}] \dots \dots \dots (3.4)$$

Start point of
packing tier

Limit of packing
tier

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X_{tier_start} , Y_{tier_start} and Z_{tier_start} are the starting point of the packing tier, which is the bottom, rear left corner of the packing space. X_{tier_limit} , Y_{tier_limit} and Z_{tier_limit} are the packing limits for each of the 3 dimensions (X, Y, Z).

The 1st packing tier, the container floor is defined as $[0 \ 0 \ 0 \ X_{container} \ Y_{container} \ Z_{container}]$ as shown in figure 3.5.

Fig 3.5 Definition for 1st packing tier

In order to produce legitimate packing result, for subsequent packing tiers, the dimensions defined must not exceed those set by the container as given by equation 3.5.

$$\begin{aligned} X_{tier_start} + X_{tier_limit} &\leq X_{container}, \\ Y_{tier_start} + Y_{tier_limit} &\leq Y_{container}, \\ Z_{tier_start} + Z_{tier_limit} &\leq Z_{container} \end{aligned} \dots\dots\dots (3.5)$$

Figure 3.6 shows an illustration of defining two different tiers, tier A and B. The spaces defined must not overlap and conform strictly to the rules set in equation 3.5.

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Figure 3.6 Definition of two different tiers that are available for packing.

3.2.1.2 Preparation: Packing Cargos

Packing cargos are cargos selected for packing on the current packing tier. As overhang is not allowed by the proposed approach, all cargos legitimate for selection must not exceed the given dimensions of the packing tier as shown in equation 3.6.

$$(x_{cargo} \leq X_{packing_tier}) \cap (y_{cargo} \leq Y_{packing_tier}) \cap (z_{cargo} \leq Z_{packing_tier}) \dots\dots\dots (3.6)$$

Not all legitimate cargos are used for packing and the packing cargos selection depends on the predictive element V_{exp} . V_{exp} predicts on the "further packing" potential of the proposed packing arrangements and plays an important role in determining the packing results. To conform closely to the predicted results derived from V_{exp} , packing cargos for new tiers are pre-assigned after the packing of the current packing tier.

The list of assigned cargos for the tiers is stored in the Cargo_list. The assigned packing cargos are arranged corresponding to the tiers ranked in the Space_list. During selection, the first set of assigned cargos is then taken out from the current Cargo_list, leaving the Cargo_list for next tier to be with one lesser element. Using predicate calculus representation[30], the relationship between assigned cargos for the packing tier and Cargo_list is defined in equation 3.7.

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$$Cargo_list_{current} = [Assigned_cargo_{Packing_tier} \mid Cargo_list_{next_tier}] \dots (3.7)$$

Where $\mid$ is the adjoining function that shows that the current cargo list consists of the assigned cargos for the packing tier and the remaining cargo list for packing of next tier.

The assigned cargos together with the legitimate miscellaneous cargos that are not selected for packing in any tiers will form the packing cargos for the packing tier as shown below.

$$Packing_cargo_{packing_tier} = Assigned_cargo_{packing_tier} + Cargo_{misc} \dots (3.8)$$

Where $+$ is the addition function that shows that the packing cargos for the packing tier are form by adding together the assigned cargos and the legitimate miscellaneous cargos

For a N types cargo packing problem, $packing_cargo_{packing_tier}$ is defined as a N parameters array set. Each entry represents the number of packing cargos belonging to the particular cargo type as shown below.

$$Packing_cargo_{packing_tier} = [C1_{packing_tier} \quad C2_{packing_tier} \quad \dots \quad CN_{packing_tier}] \dots (3.9)$$

3.2.1.3 Preparation: Grouping

Very often, three dimensional packing are used in industrial applications [1, 2, 4, 7] such as loading of container, packing of cargo plane or warehousing. These applications are usually time critical, making time saving a priority when designing for a three dimensional packing method. In reducing time required for solving the packing problems, the most direct way will be to simplify the packing problems.

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Grouping is a good way to simplify problems [16] and has been widely used in many different applications. In solving packing problems, cargos to be packed can form into groups [3, 4, 5, 7, 12] such that the packing needs only to consider for the groups of packing cargos instead of for all packing cargos.

a) Homogenous Cargo Blocks

In grouping of cargos, one of the more popular methods is to form homogenous cargo blocks. With no spaces trapped between the cargos, forming homogenous cargo blocks for packing will give maximum utilization of space with minimum resources used. Moreover, solutions built from homogenous cargo blocks usually looks neater, simpler and are easier to implement. Another added advantage for homogenous cargo blocks packing is the modularity of the derived solutions. This allows partial packing to be carried out even in the absence of certain type of cargos, which is important in the aspect of saving time for real life practical packing problems. Modularity also allows other considerations on a particular type of cargos to be taken into account while solving the packing problems.

Although using homogenous blocks packing has many advantages, it does come with a price. Homogenous cargo blocks formed come with a bulky shape with fixed dimensions. If this issue is not handled properly, the rigidly bonded cargos will limit the solution's search space and therefore hinder the capability of the algorithm to search for a overall better loading solution.

In this work, a mechanism is introduced to prevent loss of useful solution's search space while packing with homogenous cargo blocks. Each of the homogenous cargo blocks formed will be assigned with a permutation variable that will determine the permutation taken for the cargo block. Permutations are defined as the possible eligible arrangements of the homogenous cargos in forming the cargo block. Different permutations of a homogenous cargo block will yield a different arrangement of the cargos and therefore have different dimensions. By

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implementing this mechanism, the homogenous cargo blocks are allowed to take on different 'permutations' in the search of a possible better packing solution.

b) Formation of Homogeneous Cargo blocks

With the intended packing cargos, a grouping function is used to classify them into different groups of cargos called cargo blocks. The composition of a cargo block is defined as follows:

$$\bigcup b_n = B \quad b_i \cap b_j = \emptyset_{i \neq j} \quad b_i \in \{c_{i1}, \dots, c_{ik}\} \dots \dots \dots (3.10)$$

k stands for number of cargos of type I, and n stands for the number of cargo blocks

Pack list B is grouped into collectively disjoint subsets of cargo blocks, b_n . Each cargo block b_i is made out of cargos from cargo type I whereby no cargos are allowed to belong to more than one cargo type. Cargo block is then defined as an arrangement of its cargos taking the same orientation, packed closely such that no empty spaces are trapped in between. In order to optimize packing, each cargo block is allowed to take on different packing arrangement with its cargos, and each arrangement is termed as a permutation for the cargo block. The process for defining the permutations of a cargo block is as shown in Figure 3.7.

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Fig 3.7 Process of defining the permissible permutations for a cargo block

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The process of finding the list of permissible permutations starts with determining the orientation the cargos are taking. The cargos can take up to a maximum of 6 different orientations as shown in Figure 3.8, depending on the intended orientation and dimensional constraints. In the experiment conducted, only dimensional constraints due to the intended packing space are considered. Orientation constraints are omitted as it is perceived that satisfactory stability can still be obtained from the derived densely packed solutions.

Fig 3.8 Six different orientations of a cargo

After choosing the orientation of the cargo, the $stack_count$ of the cargo block is calculated. $Stack_count$ defined the packing height of the cargo block for orientation N . It can take on the value as the maximum cargos allowed for stack or as the number of cargos in the block, depending on whichever value is lower. $stack_count_N$.

With $stack_count$ derived, the next step will be to determine the $base_count$. $Base_count$ defined the packing area of the cargo block for orientation N . It is calculated as the rounding down value of number of cargos in the block divide by

With both $base_count_N$ and $stack_count_N$ derived, the next step will be to determine the list of permissible permutations ($Perm_list_N$) for the cargo block under orientation N . $Perm_list_N$ is represented in the form of $[N \ L_t \ B_t \ Stack_count_N]$. N and $stack_count_N$ holds static value, with N representing the orientation of the cargos and $stack_count_N$ representing the number of cargos allowed for stacking for orientation N . L_t and B_t are the pair of values that define a permissible permutation. L_t represents the number of cargos that can be placed lengthwise for the cargo block

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while B_t represents the number of cargos that can placed breadth wise. B_t can take on the value of 1 to $\text{Base_count}_N - 1$, while the corresponding $L_t = \text{Base_count}_N / B_t$. To prevent the inclusion of any unwanted permutations, three rules are implemented for the selection for permissible permutations. Rule 1 defines that B_t should not hold the same value as any of the previous L . This prevents a duplication of representation for the same cargo block formed. Rule 2 defines that the cargo block formed must be within the boundaries of the given packing space and any permutation that define a cargo block that exceed the boundaries will be discarded. Rule 2 prevents any infeasible permutations to be included for the consideration in perm_list . Rule 3 defines that the permutation should only be taken account if Base_count_N is totally divisible by B_t . Rule 3 limits only permutations that can form a perfect cube to be considered for perm_list . This prevents excessive empty spaces to be created during blocks formation. However, for special cases when Base_count_N is a prime number, the number of permissible permutations might be too limited ($\text{length}(\text{perm_list}_N) = 1$, $\text{perm_list}_N = [N \text{ Base_count}_N 1 \text{ stack_count}_N]$) to encourage effective searching of the global optimal. In this case, the cargo block is allowed to take on the next best set of permutations. Figure 3.9 shows two examples of permutation representation in perm_list .

Fig 3.9 Two possible permutations for cargos taking orientation 1

The derived Perm_list_N is then joined to the list of permissible permutations that are derived earlier as the total list of permissible permutations for the cargo block. The permutations finding process will repeat for cargos taking another orientation till all six orientations are used.

A GA BASED HYBRID TIER PACKING APPROACH FOR THREE DIMENSIONAL PACKING**3.2.1.4 Selection of Packing Method, Heuristic or GA?**

After forming the homogenous cargo blocks, the next step will be to determine the packing method that can effectively solves the tier packing problem. The heuristic method will be used to solve simple tier packing problems while GA will be used to solve the more complex tier packing problems. To choose between these two packing methods, a method chooser is required.

An ideal method chooser will be to use a threshold to detect whether a packing tier problem is complex enough for the use of GA as shown in equation 3.11. Given that the number of possible packing arrangements for a packing tier problem is $Count_{possible_packing_solution}$

$$\begin{aligned}
 Count_{possible_packing_solution} \leq Threshold_{method_chooser} &\Rightarrow Heuristic\ Packing \\
 Count_{possible_packing_solution} > Threshold_{method_chooser} &\Rightarrow GAPacking
 \end{aligned}
 \dots\dots\dots(3.11)$$

Proposed approach estimates its $Count_{possible_packing_solution}$ through two simple steps shown below.

1) Determine the ideal number of packing blocks

Although there can be quite a few of cargo blocks formed for packing, in most cases not all will be used for packing. The number of packing blocks required usually depends on the size of the packing space and the dimensions of the various selected cargo blocks. A way to estimate the ideal number of packing blocks required is by estimating the area covered.

Equation 3.12 shows the approach to estimate for the ideal number of packing blocks. B_n stands for the minimum covering area of the n^{th} cargo block. B is ranked in a hierarchical order as that B_n will have a larger value than B_{n+1} . The ideal number

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of packing block is derived when the sum of B_1 to $B_{ideal_num_packing_block}$ exceed the value of $Area_{packing_tier} * Packing_factor$. $Packing_factor$ is a parameter used to give allowance for possible partial packing to take place and usually takes a value of > 1 .

$$Area_{packing_tier} * Packing_factor \geq B_1 + B_2 + B_3 \dots B_{ideal_num_packing_block} \dots (3.12)$$

2) Derive the estimated value for $Count_{possible_packing_solution}$

After obtaining the ideal number of packing blocks, the estimated value for $Count_{possible_packing_solution}$ can be derived. I_N is the estimated number of packing alternatives for the N^{th} packing block used in the packing process. It is determined by multiplying the number of possible packing blocks that can take in the position with the number of possible orientations (vertical or horizontal) and the average number of permutations for a packing block as shown in equation 3.13. By multiplying the value of I_1 to $I_{Ideal_num_packing_blocks}$, the estimated $Count_{possible_packing_solution}$ can be obtained as shown by equation 3.14. $Threshold_{method_chooser}$ is conveniently chosen to take a value of 1000 for all simulations and tests done for this report.

$$I_N = (Number_{selected_packing_block} - N + 1) * 2 * Perm_count_{average} \dots (3.13)$$

$$Count_{possible_packing_solution} \approx I_1 * I_2 * I_3 * \dots I_{Ideal_num_packing_block} \dots (3.14)$$

3.2.2 THE PACKING PHASE

With the necessary information gathered in the preparation phase, the packing phase will pack the packing tier with the selected method.

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3.2.2.1 Heuristic Method

In solving simple tier packing problems, the best way of obtaining optimal packing results will be to use the exhaustive search (ES) technique. This heuristic search technique is conducted in a simplistic two steps manner.

STEP 1- From the selected cargo blocks, derive all possible packing arrangements for the packing tier.

STEP 2 - Calculate the packing efficiency for the derived packing arrangements. The packing arrangement with the highest packing efficiency will be chosen for actual packing.

Due to the nature of the search technique, it will take exponential computing resources for ES to solve tougher packing problems that have a lot of packing possibilities. Therefore, a much more powerful search technique (Genetic Algorithm) is proposed for solving tough tier packing problems.

3.2.2.2 Genetic Algorithm Method

GA is a stochastic search technique that has been used in solving different type of optimization problems. In HTPA, GA is used to solve for the tier packing problems that cannot be effectively solved using the Heuristic approach. The applied GA packing method can be segmented in three main parts: the problem representation for the packing problems, the fitness function used for evaluation of probable solutions and last but not least the GA operators used.

a) Problem Representation

The permutable cargo blocks derived from the homogenous cargo grouping are used by HTPA to solve for an optimal packing solution for the packing tier. The problem representation used is similar to the one proposed by Gehring[3]. Firstly, while all

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the cargo blocks are represented in the tier packing solution, only part of them will be used in the actual packing. Secondly, placement of the cargo blocks is done in a sequential back to front, left to right manner. The origin for placement is taken as the left rear corner of the packing tier. Potential points for placement, named by Gehring as "Placement corners", are identified and ranked according to their proximity to the origin. The placement corner that is nearest to the placement origin and has the width to place the cargo in will be selected for packing.

The tier packing solution is represented by a chromosome with a length of $N+3*N$ genes. N represents the number of cargo blocks available for packing. The chromosome can be divided into two parts, the status genes and the operational genes as shown in Figure 3.10.

The status genes (S_N) show the packing status for the cargo blocks. S_N can take a value of '0', '1' or '2'. A value of '0' for S_N means that CB_N is not included for the actual packing. Vice versa, a value of '1' means CB_N is completely packed into the packing space. If S_N has a value of '2', CB_N is considered partially packed whereby only part of the cargos from the cargo block is included for packing.

The operational genes show how the chromosome solves the current tier packing problem. Operational genes are made up of $3*N$ genes, whereby every 3 genes are used to represent for a cargo block that is sequence for packing. CB_I identifies the I_{th} cargo block that is sequence for packing while PM_I shows the permutation taken by the cargo block. RT_I shows the orientation taken by the I_{th} cargo block. A value of '0' will have the larger dimension of the cargo block to be parallel to the X axis of the packing space (Horizontal). Vice-versa, a value of '1' for RT_I will have the larger dimension of the cargo block to be parallel to the Y axis (Vertical).

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Fig 3.10 Chromosome representation for tier packing problem

In tier packing, the cargo blocks can get three different packing status namely completely packed, partial packed or not packed as shown in figure 3.11. The definition for a completely packed condition will be that both the X and Y dimensions of the packing block must not exceed the boundaries of the packing tier. Equation 3.15 shows the condition for completely packed to occur, with X_p and Y_p as the packing corner chosen for the packed cargo block

$$(X_{Tier_Limit} \geq X_P + X_{block}) \cap (Y_{Tier_Limit} \geq Y_P + Y_{block}) \dots \dots \dots (3.15)$$

When the packing tier cannot pack the whole cargo block, but can pack a portion of it, this situation is classified as partially packed. The condition for partially packed as shown in Equation 3.16 will be that at least a column of cargos can be totally packed in the packing tier. The cargos that are totally supported by the packing tier will be left for packing while the rest of the cargos in the cargo block will be removed for subsequent packing.

$$(X_{Tier_Limit} \geq X_P + x_{cargo}) \cap (Y_{Tier_Limit} \geq Y_P + y_{cargo}) \dots \dots \dots (3.16)$$

The condition for not packed to occur will be when the packing tier cannot support even one column of the cargos from the cargo block. This is check by the violation in either the X or Y dimension limit of the packing tier when only a column of cargos are packed as shown in equation 3.17.

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$$(X_{Tier_Limit} < X_P + X_{cargo}) \cup (Y_{Tier_Limit} < Y_P + Y_{cargo}) \dots \dots \dots (3.17)$$

Fig 3.11 Illustrations for different packing situations

To further elaborate on the proposed chromosome representation, Figure 3.12 shows a chromosome and its corresponding packing solution for solving a 5 types cargo tier packing problem.

Figure 3.12a shows the 5 different cargo blocks, in their respective permutation taken as indicated by the solution chromosome. The interpretation of the solution chromosome is in a triplet genes manner from the operation genes, with the first gene indicating which cargo block to pack, 2nd indicating the permutation taken and the 3rd indicating its orientation.

The example shows that cargo block type 4 is sequence as the first to be packed and is placed at P1, the origin for packing. The 5th permutation {L_t=3, B_t=3} from its perm_list is chosen for the cargo block. As R₁ has a value of '0', the cargo block will be packed lengthwise parallel to the X-axis of the tier. Cargo block type 5 is sequence as the next cargo block to be packed. As P2 is the current nearest eligible packing corner to the origin after packing of cargo block type 4, CB₂ is chosen to be

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pack from that point. The 2nd permutation $\{L_t=3, B_t=1\}$ is chosen for the cargo block. With R_2 set at '0', cargo block type 5 is packed length wise parallel to X-axis. Cargo block type 1 is a singular column cargo block which can only take on a sole permutation of $\{L_t=1, B_t=1\}$. Cargo block type 1 is sequence to be placed at P3 as it is the current closest eligible placement comer to the origin. As $R_3 = '1'$ the cargo block is packed length wise parallel to the Y-axis of the tier. The next cargo block sequence for packing is cargo block type 4. However, for cargo block type 4, with its chosen permutation cannot entirely rest within the tier. Since part of the cargo block can still be used in the packing, partial packing is carried out. Status gene S_4 is updated as '2'. Another singular column cargo block, cargo block type 2 is sequence as the last cargo block to be packed. Since full and partial packing is not possible, cargo block type 2 is not included in the actual packing solution and S_5 is set as '0'.

Fig 3.12a Example for a 5 types cargo tier packing problem: Information on the 5 packing cargo blocks

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Fig 3.12b Example for a 5 types cargos tier packing problem: Chromosome representation

Fig 3.12c Example for a 5 types cargos tier packing problem: Plan View of the implemented solution

b) Fitness Function & Evaluation

Fitness function is the tool for GA to evaluate on its progress in searching for the optimal solution. After every GA operation, it is essential to check and update the fitness of the affected chromosome in the population. Therefore, an accurate and efficient fitness function is essential for the successful implementation of GA.

i) Definition of Fitness Function

The evaluation of a tier packing solution depends on its packing efficiency. In previous work [4,5, 7, 8], tier packing efficiency is commonly regarded as the actual packing done on the packing tier and nothing is done to check on the effect of the current tier packing on subsequent tiers. In the proposed HTPA proposed that a tier packing solution is evaluated not only by the efficient packing for current packing tier, but also on its facilitation for efficient packing in subsequent tiers. Therefore,

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tier packing efficiency is determined in two parts, the volume of cargo packed on the packing tier and the volume of cargos expected to be packed for subsequent tiers as shown in equation 3.18.

$$\text{Tier Packing Efficiency} = \text{Packed Efficiency} + \text{Expected Further Packing Efficiency} \dots\dots\dots(3.18)$$

Packed efficiency is defined as the ratio of the total volume of packed cargos divided by the volume of the current packing space as shown in equation 3.19. The actual packed volume for a represented GA solution is determined by the packing status of the cargo blocks (S_i) and the actual volume of the cargo blocks packed (Packed_Vol_{CBi}) within the packing tier. For n packing blocks involved in the packing, if packing status = 1 or 2, the packed cargo volume will be considered. Else, the cargo block will be considered as not packed and will be ignored in the calculation. The summation of the volume of packed cargo blocks is then divided by the total volume of the packing tier for the derivation of the packed efficiency.

$$\text{Packed Efficiency} = \frac{\sum_{i=1}^n ((S_i \oplus 0) * \text{Packed_Vol}_{CBi})}{(X_{tier_limit} * Y_{tier_limit} * Z_{tier_limit})}$$

n is the total number of packing cargo blocks
(3.19)

where $\oplus$ is the exor operation used for excluding the unpacked ($S_i = 0$) cargo blocks from the calculation of packed cargo volume

Expected further packing efficiency estimates on the probable packing that can take place for subsequent tiers if the current tier packing is implemented. The estimation on further packing depends on the predictive function V_{exp} that predicts on the possible volume of cargos that will be packed for subsequent tiers. Equation 3.20 shows the derivation of expected further packing efficiency, which is the ratio of expected packed volume of cargos for subsequent tiers over the volume of the current packing space.

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$$\text{Expected Further Packing Efficiency} = V_{\text{exp}} / (X_{\text{tier_limit}} * Y_{\text{tier_limit}} * Z_{\text{tier_limit}}) \dots (3.20)$$

ii) Prediction Function, V_{exp}

The function of V_{exp} is to estimate the volume of cargos that can still be packed if the proposed packing solution is adopted.

The derivation of V_{exp} goes through several steps, beginning with defining NT_factor. NT_factor is a M*N matrix as shown in equation 3.21. M represents the number of new tiers that are available for packing and N represents the number of different types of cargos available for packing. The entries in NT_factor define the packing relationship between the new tiers that are created from the packing with the available cargos. The entries in NT_factor are determined by equation 3.22 where the dimensional constraints of the new tiers are checked for the different types of cargos. A value of '0' means that cargo type j cannot be packed into new tiers i. Vice-versa, a value of '1' will mean that cargo type j can be packed into new tiers i.

$$NT_factor = \begin{bmatrix} Tf_{11} & Tf_{12} & \dots & Tf_{1N} \\ Tf_{21} & Tf_{22} & \dots & Tf_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ Tf_{M1} & Tf_{M2} & \dots & Tf_{MN} \end{bmatrix} \dots (3.21)$$

$$\text{The value for entry, } Tf_{ij} = (x_j \leq X_i) \wedge (y_j \leq Y_i) \wedge (z_j \leq Z_i) \dots (3.22)$$

After defining NT_factor, the next step will be to prioritize the packing cargos and the packing blocks. Cargo Awkwardness (CA) and Tier Awkwardness (TA) are used for determining the priority order for the packing cargos and the new tiers respectively. CA_j is determined by adding the Tf values of NT_factor along the

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column j while TA_i is determined by adding the Tf values of NT_factor along the row i .

$$CA = [CA_1 \quad \dots \quad CA_N]$$

$$\text{Whereby } CA_j = \sum_{i=1}^M Tf_{ij} \dots \dots \dots (3.23)$$

$$TA = [Ta_1 \quad \dots \quad Ta_M]$$

$$\text{Whereby } Ta_i = \sum_{j=1}^N Tf_{ij} \dots \dots \dots (3.24)$$

The CA values are used to set up a packing priority list (CL) for the packing cargo types. The lower the CA value of a cargo type, the higher the priority to pack the cargo type. Vice-versa, the higher the CA value of a cargo type, the lower the priority for packing the specify cargo type. Likewise, TA values are used to set up a packing priority list (TL) for the new tiers. The logic behind setting up of priority list is to prevent "skew" packing whereby more awkward cargos are left unpacked and less favorable next packing tiers scarcely packed. Priority list "smooth" up the packing process by giving priority for packing the more awkward cargos and the less favorable next packing tiers. By "smoothing" up the packing process, a more even packing can be obtained for all the new tiers and a better overall packing solution can more likely be obtained.

To obtain V_{exp} for a proposed packing solution, the packing order must first be derived. Similar to NT_factor , Packing order is an $M \times N$ matrix as shown in equation 3.25. Its entries define the allocation of cargos for the different new tiers.

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$$Packing_Order = \begin{bmatrix} P_{11} & P_{12} & & P_{1N} \\ P_{21} & P_{22} & & P_{2N} \\ \vdots & \vdots & & \vdots \\ P_{M1} & P_{M2} & & P_{MN} \end{bmatrix} \dots\dots\dots(3.25)$$

The entries for Packing order are derived from an iterative procedure, using TL, CL, cargo volume (Cargo-vol), packing space volume (Space-vol), number of cargos available for different cargo types(Cargo_Num). The following pseudo codes described how the entries for the Pack Order matrix are determined.

For i = 1 : length of CL

For j = 1 : length of TL^{i*}

$$P_{TL^{i*}(j) \ CL(i)} = \left\lfloor Space_vol_{TL^{i*}(j)} / Cargo_vol(CL(i)) \right\rfloor$$

$$Cargo_Num_{CL(i)} = Cargo_Num_{CL(i)} - P_{TL^{i*}(j) \ CL(i)}$$

$$Space_vol_{TL^{i*}(j)} = Space_vol_{TL^{i*}(j)} - \left(P_{TL^{i*}(j) \ CL(i)} * Cargo_vol(CL(i)) \right)$$

If Cargo_Num_{CL(i)} ≤ 0

Exit current j loop

End

End

End

TL^{i*} ∈ TL, whereby TL^{i*} represents the sub list of priority for new tiers that can pack for cargo i.

Initially, cargo type i defined in CL will be chosen. For all new tiers that can pack cargo type i, they would be ranked accordingly to awkwardness for packing with the new tier that has the high rating given the priority. With the selected tier j, the number of cargos from type i that will be assigned to this tier is estimated by

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dividing Space_vol j with Cargo_vol of type i. The number of cargos in type i that can be used in allocation for packing will be reduced accordingly. The Space_vol of the selected tier j will also be reduced according to the Cargo_vol of the assigned cargos. If all the cargos in type i are allocated for packing, the assigning process will proceed to the next cargo type ranked in CL, else the next eligible new tier for cargo type i will be chosen for assigning. The process of determining the allocation of cargos to the respective new tiers will be completed when all the cargo types are tested.

After obtaining the packing order matrix, V_{exp} can be derived by summing up the total volume of cargos that are allocated to the new tiers. The total number of type i cargos that are allocated to the new tiers can be calculated by summing the P entries along the column i of the packing order matrix. Then, the total volume of type i cargos that are allocated can be determined by multiplying the obtained number with the individual cargo volume. By summing the volume of cargos that are allocated for the different cargo types, V_{exp} for the proposed packing solution can be obtained as shown below.

$$V_{exp} = \sum_{i=1}^N \left(\sum_{j=1}^M P_{ij} * cargo_vol(i) \right) \dots\dots\dots (3.26)$$

c) GA Operators

The choosing of operators is an important step in designing the GA search technique, as the prowess of the GA depends a lot on the capability of its operators. The three main GA operations are namely Reproduction, Crossover and Mutation.

i) Reproduction

Reproduction, commonly known as the selection operation chooses the offspring of the GA process that will be kept for further operations. The main purpose of

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reproduction is to retain or increase the number of useful chromosomes, and discard those that are perceived as weak or less useful.

In most cases, reproduction process is fitness driven [6, 13-15] and the fitter chromosomes usually can have more offspring while the weaker ones either shrink in population or extinct. This is analogue to the evolution theory for survival of the fittest.

The common approach in conducting the reproduction process will be Roulette Wheel selection (RWS), Stochastic Universal Selection (SUS) and Elitism Selection (ES). RWS bases its search on a controlled randomized selection of offspring where the probability of selection depends on the fitness of the chromosomes. For a population of 10 offspring, RWS will conduct its selection 10 times. SUS is an improvement of RWS as it only conducts the selection once, and all offspring will be selected. By conducting the selection once only, it prevents the probability of skew selection, especially for chromosomes with small population size.

Elitism is another popular selection scheme as the top N% fittest chromosomes of the last iteration process are used to replace the bottom N% fittest chromosomes of the current iteration. Elitism is a popular approach for directly eliminating weaker chromosomes, filling the population with stronger chromosomes. By doing so, it is able to speed up the GA process in obtaining optimal solution. However, elitism does have its shortcoming. An over high replacement rate will usually result in early extinction of high potential chromosomes that has low initial fitness value, causing a premature convergence to a local optimal.

In the implemented GA, reproduction process is done in two steps as shown in figure 3.13. Firstly, elitism is used to preserve the top 20% fittest chromosomes of the old populations and replaced the bottom 20% fittest chromosomes of the new population. The SUS reproduction scheme is then applied on this new pool of parents to produce offspring for GA operations. The relatively small percentage of

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replacement implemented by elitism will allow knowledge from previous generations to be carried down without fear of causing premature convergence.

By combining two different selection schemes together, it is hoped that the reproduction scheme can harness the strengths from both methods.

Fig 3.13 The proposed Reproduction process

ii) Crossover

Crossover [6, 15, 36,37] is the GA operation that promotes data exchange between two different chromosomes. The information from two different parent chromosomes is selectively taken to form the offspring chromosomes. Crossover is important, as data exchange is crucial in passing down useful information and to form better and stronger chromosomes.

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Popular crossover schemes include; Single point crossover, two points crossover, uniform crossover and PMX crossover. Single point crossover is one of the most common and widely used crossover schemes in GA. A cutting point is first chosen at the parent chromosomes. For the 1st offspring chromosome, its first part will be directly inherited from the 1st parent chromosome, while the second part of the offspring chromosome is inherited from the 2nd parent chromosome. For the 2nd offspring chromosome, the roles of the parent chromosomes are swapped. For two points crossover scheme, 2 cutting points is used instead of 1 as used in single point crossover. The 1st offspring chromosome will have its first and third part inherited from the 1st parent chromosome, while its second part is inherited from the 2nd parent chromosome. Similarly, the 2nd offspring chromosome is produced with the role of the parent chromosomes swapped.

Uniform crossover is another popular crossover scheme commonly used in GA. Instead of interchanging random length of the parent chromosomes to form the offspring, the offspring is formed by randomly inheriting the allele value from the parent chromosomes. Each allele of the offspring randomly chooses to either take the value from the 1st parent chromosome or to take it from the 2nd parent chromosome.

Due to the nature of the implemented GA, common approaches such as single point crossover, two points crossover and uniform crossover cannot be easily applied. Instead, the Partially-Matched Crossover (PMX) crossover scheme is used to solve for the ordering GA packing problems. PMX is an operator proposed by Goldberg and Lingle [6] for solving ordering problems. It is designed to preserve many absolute positions from both parents and to avoid duplicate allele values after crossover. Crossover will begin by randomly select two cut points for the parents. The elements between the cut points will be selected and swapped between the parents. In the process of swapping, if any element is lost in the exchange, it is to replace a duplication element that occurs outside the cut points and has close proximity to its old position prior to swapping. An example of the crossover operation is as shown in figure 3.14.

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Fig 3.14a The proposed Crossover process: Chromosome representation for parent I and II

Fig 3.14b The proposed Crossover process: PMX Crossover operation

iii) Mutation

Mutation [6, 15, 17], usually the last of the three GA operations to be applied, provides the randomized minor changes in the chromosomes to keep up the effort in exploiting for hidden highly potential packing solutions. With mutation, the population can be insured against permanent fixation at any particular locus. For example, suppose all the strings in the population have converged to a 0 at a given position, and the optimal solution is a 1. With their limitations, neither crossover nor

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reproduction can generate a 1 at that position. However, if a mutation operation is applied at that position, the optimal solution can be obtained.

There are two main ways in conducting mutations, inversion and interchanging of allele. Inversion [6,15] selects a random position in any string and then changes the allele in that position to other possible values. Interchange [17], also known as switch or swap, is to select and two random positions in the same string and interchange the alleles in these two positions.

In the implemented GA, two types of mutation are implemented. They are mutation of permutation and mutation of rotation. Mutation of permutation inverts the permutation of the chosen cargo block N to another permissible permutation in $perm_list_N$. Definition of the mutation of permutation is as shown below.

$$\begin{aligned}
 PM_{N_{OLD}} &\Rightarrow MUTATION \Rightarrow PM_{N_{NEW}} , \\
 (PM_{N_{OLD}} \in Perm_list_N) &\cap (PM_{N_{NEW}} \in Perm_list_N), \\
 PM_{N_{OLD}} &\neq PM_{N_{NEW}} \\
 &\dots\dots\dots(3.27)
 \end{aligned}$$

In the implementation of mutation of rotation, the orientation of the selected cargo block N will take a 90 degrees change. RT_N with an original value of '0' will take a value of '1'. Vice versa, if RT_N has an original value of '1', it will take a value of '0'. Definition of the mutation of rotation is as given in equation 3.28.

$$RT_{N_{NEW}} = RT_{N_{OLD}} \oplus 1 \dots\dots\dots(3.28)$$

where $\oplus$ is the exor operation used for toggling the value of RT_N

A GA BASED HYBRID TIER PACKING APPROACH FOR THREE DIMENSIONAL PACKING**3.2.3 THE UPDATING PHASE**

The updating process requires to update on both the new tiers and their allocated packing cargos. New tiers are defined as the legitimate packing spaces created from the current tier packing. The packing cargos are allocated to the respective new tiers as defined by the derived Packing_Order matrix for the implemented tier packing solution.

3.2.3.1 UPDATE SPACE_LIST & CARGO_LIST

In the updating process, the two important metrics that need to be attended are the Space_list and the Cargo_list. As mentioned earlier, Space_list contains the list of tiers that is to be packed later, while Cargo_list contains the allocated packing cargos for the corresponding tiers in the space_list.

After every tier packing, the new tiers will be updated to space_list and the packing cargos allocated for them will also be updated to the cargo_list. As mentioned earlier, tier packing gives priority to packability of the tiers. Tiers that are more awkward will be packed first while tiers that are more versatile will be packed later. To facilitate the selection process, the updating of space_list and its corresponding cargo_list will be as according to the tiers' packability.

To define the packability of the new tiers, the packing relationship between the allocated cargos and the tiers must first be defined. This is done so by deriving the packability matrix. Packability matrix can be derived with a mapping from the pack order matrix as given in equation 3.29. The mapping is carried out by first, checking the value of the entry (P_{ij}) in the pack order matrix. If the value is greater than '0', the corresponding entry (PR_{ij}) in packability matrix will take a value of '1'. Else, the corresponding entry (PR_{ij}) in packability matrix will take a value of '0'.

$$Pack_Order_matrix \xrightarrow[\substack{\text{mapping} \\ (P>0)}]{} Packability_matrix \dots\dots\dots (3.29)$$

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The packability of the new tiers is then defined by summing the packability relationship with all the different types of packing cargos. Definition of tier packability relationship is as shown in equation 3.30.

$$TP_i = \sum_{j=1}^N PR_{ij} \dots\dots\dots (3.30)$$

The new tier packability relationship can then be represented as shown in equation 3.31.

$$New_Tier_Packability = \begin{bmatrix} TP_1 \\ TP_2 \\ \vdots \\ TP_M \end{bmatrix} \dots\dots\dots (3.31)$$

The updating process depends on the new tier packability relationship. Tiers with higher TP will be updated first, while tiers that have lower TP will be updated later. Tiers with lower TP are updated last as they will be selected for packing first. If two tiers have the same TP value, the packing space volume will be used to decide on the packing sequence. The pseudo codes for describing the updating process is as shown below.

While Number of New Tiers not updated $\neq 0$

$V_tier = \max(New_Tier_packability)$

If $length(V_tier) > 1$

% If there is more than 1 tiers that has the highest packability rating

While $length(V_tier) \neq \phi$

$Update_Tier = \min(V_tier_{volume})$

$Update_Cargo = Pack_Order_{ROW_{Update_Tier}}$

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```

        Space_list = [Update_Tier Space_listOLD]
        Cargo_list = [Update_Cargo Cargo_listOLD]
        New_Tier_packabilityUpdate_Tier = 0

    End

Else
    % If there is only 1 tiers that has the highest packability rating

    Update_Tier = V_tier
    Update_Cargo = Pack_OrderROWUpdate_Tier
    Space_list = [Update_Tier Space_listOLD]
    Cargo_list = [Update_Cargo Cargo_list]
    New_Tier_packabilityUpdate_Tier = 0

End

End

```

3.2.3.2 DEFINITION OF A NEW TIER

After every tier packing, new tiers are created for subsequent packing. These new tiers are derived as the empty spaces above each of the packed cargo blocks.

A new tier can be defined as a six parameters array given in equation 3.32.

$$[X_{Ntier_start} \ Y_{Ntier_start} \ Z_{Ntier_start} \ X_{Ntier_limit} \ Y_{Ntier_limit} \ Z_{Ntier_limit}] \dots \dots \dots (3.32)$$

During the updating process, the definition of a new tier can be divided into two portions namely, definition of the start point and definition of limit.

a) Definition for Start Point of New Tier

X_{Ntier_start} , Y_{Ntier_start} and Z_{Ntier_start} define the start point of the new tier as given in equation 3.33. The X_{Ntier_start} and Y_{Ntier_start} are both directly affected by the packing position of the packed cargo block A. The exact distance from the origin is derived

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as the addition of the distance from block position to packing tier start point and the distance from the packing tier start point to origin. Z_{Ntier_start} can be calculated by literally adding the block's height with the height of the packing tier.

$$\begin{aligned} X_{Ntier_start} &= X_{Ptier_start} + X_{blockA_pos}, \\ Y_{Ntier_start} &= Y_{Ptier_start} + Y_{blockA_pos}, \\ Z_{Ntier_start} &= Z_{Ptier_start} + Z_{blockA} \\ &\dots\dots\dots(3.33) \end{aligned}$$

b) Definition for limits of New Tier

The dimensions of the packed cargo block determine the packing limits of the new tier. The Z axis limit of the new tier is determined by the deduction of the packing block's height from the Z axis limit of the packing tier. The definition for limits of new tier is as given in equation 3.34.

$$\begin{aligned} X_{Ntier_limit} &= X_{blockA}, \\ Y_{Ntier_limit} &= Y_{blockA}, \\ Z_{Ntier_limit} &= Z_{Ptier_limit} - Z_{blockA} \\ &\dots\dots\dots(3.34) \end{aligned}$$

Figure 3.15 shows the definitions of starting point and dimension limits for a new tier after packing, the new tier is defined on top of packed cargo block A.

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Fig 3.15 Defining a new tier

3.2.3.3 REALLOCATION OF CARGOS LEFT AFTER PACKING

After every tier packing, there are always packing cargos that are left out from the packing. Since most of the cargos are allocated for packing at other tiers, these leftover cargos will be added to the group of miscellaneous cargos and will be used in packing of other tiers when required. Update on the group of miscellaneous cargos is as shown in equation 3.3 5.

$$Cargo_{misc} = Cargo_{misc_{old}} + Cargo_{Leftover} \dots \dots \dots (3.35)$$

Where + is the addition function that shows that the miscellaneous cargos are updated with the addition of the left over cargos

3.3 SUMMARY

This chapter gives a detail description on the proposed methodology for three dimensional packing. The proposed three dimensional packing method, HTPA is conducted through Preparation, Tier Packing and Updating. Preparation involves in the selection of packing tier, its corresponding packing cargos, grouping of homogenous cargo blocks and selection of packing methods. Selection of packing

tier depends on the packability of the tier. A tier with few packing alternatives will be given priority over those that have more. A grouping function, formation of homogenous cargo blocks is used for improving the performance of the system. The grouping function helps to simplify the packing problems by grouping similar cargos into block, making it easier and faster to solve for the tier packing problem.

The tier packing process can be conducted either in the heuristic method or by the GA method. Simple packing problems that have few packing alternatives should be solved using heuristic packing while complex packing problems should be solved using the more sophisticated GA packing. By doing so, the tier packing problem can be both effectively and efficiently solved. GA is a powerful randomized search technique that can effectively solve tough tier packing problems in a fraction of time that is actually required. Furthermore, with the usage of predictive tool V_{exp} , the derived packing solutions will not only give optimal packing efficiency for current tier, but will also ensure optimal packing for subsequent tiers. In GA, the tier packing problem is treated as an ordering problem and their packing order and orientations are represented by the chromosomes. These chromosomes will then go through iterations of reproduction, crossover and mutation process before evolving to the optimal packingsolution.

Updating is the final step of a tier packing process whereby the packing results for the packing tier is updated so as to prepare for the packing for next tier. Updating usually involves on the information of new tiers created from the current packing and the remaining cargos available for next packing.

The proposed algorithm uses the two powerful tools, V_{exp} and formation of homogenous cargo blocks to form an efficient packing method that is capable of optimally solving the three dimensional packing problems in a reasonable time

CHAPTER 4 EXPERIMENTAL DETAILS

In order to evaluate the capability of the proposed three dimensional packing approach, a robust experimental design is required. Observation on work done for three dimensional packing [3-5, 7-12] shows that there are several different approaches in conducting the experiment.

4.1 PAST EXPERIMENTS DONE ON THREE DIMENSIONAL PACKING PROBLEMS

Numerous methods have been presented for three dimensional packing and different experiments are proposed to validate the capability of the packing methods. Three different experiments are being discussed here, namely the experiment proposed by C.Pimpawat and N.Chaiyaratana[5], experiment proposed by Jin-Lin Lin and Bobbie Foote[4] and experiment proposed by EE Bischoff and MSW Ratcliff[3].

4.1.1 EXPERIMENT BY PIMPAWAT AND CHAIYARATANA[5]

In their experiment, Pimpawat and Chaiyaratana used only a single customized packing problem to evaluate their method. The details of the cargo dimensions for their packing problem are given in Table 4.1.

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Group	Type	Dimension (unit:mm)			Quantity
		Width	Length	Height	
L	1	295	420	613	15
L	2	380	417	242	20
L	3	360	465	238	30
L	4	350	415	227	10
M	5	290	437	220	15
M	6	285	440	215	10
M	7	295	535	215	25
M	8	370	475	202	15
S	9	315	530	201	20
S	10	360	510	177	15
S	11	300	435	175	25
S	12	523	645	80	5

Table 4.1 Cargo consignment for C.Pimpawat and N.Chaiyaratana's Customize Packing problem

The cargo consignment specified in table 4.1 is packed into containers of 1,170 x 2,960 x 1,190 mm. The packing efficiency is evaluated as the number of containers required for packing and the amount of empty volume left in the last container as shown in equation 4.1.

$$Packing_Efficiency = w_1 \left[\frac{C_{\max} - C_i}{C_{\max} - C_{\min}} \right] + w_2 \left[\frac{V_i - V_{\min}}{V_{\max} - V_{\min}} \right] \dots\dots\dots (4.1)$$

$C_{\max}$ is the maximum possible number of containers

$C_{\min}$ is the minimum possible number of containers

C_i is the number of containers required

$V_{\max}$ is the maximum volume of empty space in the last container

$V_{\min}$ is the minimum volume of empty space in the last container

V_i is the resulted empty volume in the last container

w_1 and w_2 are the weighting factors

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Characteristics of the Experiment

Few people had used this experiment to benchmark their packing method [5,7].

The experiment proposed by C.Pimpawat and N.Chaiyaratana is considered to be inadequate in deciding on the capability of a packing method. Using only the result from a typical multi containers packing problem, it is unconvincing to conclude that a packing method that perform well in this experiment can perform equally well in solving other types of packing problems. Moreover, the lack of comparisons between packing method and test cases makes it difficult to understand the real prowess of the packing method.

However, C.Pimpawat and N.Chaiyaratana did proposed an innovative way of representing packing efficiency. Eqn 4.1 can accurately reflect packing efficiency for different type of three dimensional constrained packing problems [5, 7] etc Single container packing problems, Multi container packing problems.

4.1.2 EXPERIMENT BY JIN-LIN LIN AND BOBBIE POOTE [4]

Jin-Lin Lin and Bobbie Foote proposed conducting the experiment with 200 different test cases of packing problems. Each test case is created from the following five rules:

- 1) Number of packing boxes ranged from 10-40
- 2) Container size varies from 5x5, 6x6, 7x7, 8x8, 9x9,
- 3) 5 cases of differentsize boxes
- 4) Less than 20% of the boxes have the same size
- 5) No boxes having the same shape

For evaluation, each test case was repeated ten times for the objective function value of the best, the average and the worst result obtained.

Characteristics of the Experiment

The experiment proposed by Jin-Lin Lin and Bobbie Foote is more robust than the one proposed by C.Pimpawat and N.Chaiyaratana. Firstly, a reasonable size of 200 test cases is used. Secondly, a wide variation between packing problems is ensured through varying the size of the container and of the packing cargos.

However, this experiment structure does have its shortcoming. Although the scale of the experiment is large (200 test cases), no classification is proposed for the test cases. This inevitably will encourage duplication of similar test cases in the experiment, which will cause the experimental results to be skewed.

4.1.3 EXPERIMENT BY BISCHOFF AND RATCLIFF[8]

Bischoff and Ratcliff (B&R) define their experiment with a series of test data sets. A test data set compromise of 100 similar tests cases for the specified problem type. Problem type determines the heterogeneity of the packing problem and is defined by the number of types of cargo to be packed. Each test case is a unique packing problem for an ISO 20ft (587x233x220) container and is differ by their cargo composition and cargos' dimensions. Target volume T_c is set as the volume of a container so that the total cargo volume C for each test case will be as close as possible to the intended packing volume. The limits on the cargo boxes' dimensions are kept constant at $a_1 = 30$, $b_1 = 120$, $a_2 = 25$, $b_2 = 100$, $a_3 = 20$, $b_3 = 80$

In promoting ease of replication, B&R emphasize on three main aspects in generating the test cases. Firstly, usage of a standard random generator that is capable of reproducing the same number string over a wide range of platforms. B&R achieved this by designing his random generator based on the multiplicative congruential method [18, 19]. Secondly, only non-random seed numbers are used in generating the test cases and the seed for test case p is defined by $s = 2502505 + 100(p-1)$. Thirdly, ensure that the process of generating the test cases are strictly

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followed by providing a detail step by step breakdown of the procedure [8] as shown in figure 4.1.

For each test data set, the intended packing method will solve for all 100 test cases and the volume utilization for each test case is calculated as shown in equation 4.2. The average of the volume utilization obtained (equation 4.3) and its standard deviation (equation 4.4) will determine the overall capability of the packing method in solving packing problems for the specified problem type N.

$$VU_p^N = \frac{\text{Volume of cargo boxes packed}}{\text{Volume of pallet}} \dots\dots\dots(4.2)$$

$$\overline{VU}^N = \frac{\sum_{p=1}^{100} VU_p^N}{100} \dots\dots\dots(4.3)$$

$$SD^N = \left(\frac{1}{100} \sum_{p=1}^{100} (VU_p^N - \overline{VU}^N)^2 \right) \dots\dots\dots(4.4)$$

In their work, a total of 7 test data sets (N=3,5,8,10,12,15 and 20) are used to test the algorithms' capability to solve for a range of container loading problems, from highly homogenous cargo packing (3 types) to more heterogeneous (20 types) cargo packing problems.

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Figure 4.1 Procedure for generating a single Bischoff & Ratcliff test case

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Characteristics of the Experiment

Due to its robustness and ease in replication, the experiment proposed by B&R has been the one of the most popular benchmark used for three dimensional packing methods. Since a universal size is adopted for the packing container, the three dimensional packing problems are classified by the composition of the packing consignment. If the packing consignment consists of only 3 types of packing cargo, the packing problem is considered as a highly homogenous packing problem. However, if the packing consignment consists of 20 or more type of packing cargo, it is consider as a highly heterogeneous packing problem. By defining 7 different data sets for testing, the packing method can be evaluated for solving packing problems of different heterogeneity.

4.2 WEAKNESSES OF CURRENT EXPERIMENT STRUCTURES

Observations on the previously discussed experiment set up show two main areas of weakness: lack of systematic approach in conducting the experiment and lack of in-depth studies in the characteristics of the studied packing method. These are described below.

4.2.1 LACK OF SYSTEMATIC APPROACH IN CONDUCTING EXPERIMENT

Very often, the proposed experiments for three dimensional packing are custom designed and show a lack of consistency in the conduction of tests. Some proposed using sparse and specific application problems for testing [5, 7] while others use quantitative testing with self-created test cases [3, 4, 8-10]. Even among the self-created test cases, different elements are used for the creation of the test cases. The elements that are used include the packing container's size, packing cargos's size, number of packing cargos or number of different types of packing cargo.

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The main reason for the diversified experimental structures used in three dimensional packing is due to the lack of a common standard in classifying the test cases. As mentioned earlier, elements such as cargo's size or number of different types of packing cargo can be used as a mean to create different classes of test cases. However, these elements are usually independent, and it is usually tough to find the correlation between them. The lack of a common standard in classifying the test cases have made it difficult to compare the experimental results from different experiments. A good example for the correlation problem will be to find the replacement for the effect of packing a large cargo with the packing of several smaller cargos.

4.2.2 LACK OF IN DEPTH STUDIES IN THE CHARACTERISTICS OF THE PACKING METHODS

Most proposed experiments are only interested in obtaining the final outcome from the studied packing method and little analysis was applied on the behavior of the packing method. Experiments seldom highlight the strength and weaknesses of the studied packing method or situations that may be favorable or not favorable for the packing method.

The experiment proposed by Bischoff and Ratcliff does attempt to further analyze the packing method by introducing heterogeneity into their tests. Their work uses the number of different types of packing cargo as a mean to control the heterogeneity of the test cases. By varying the number of types of packing cargo involved in the test case, the packing method can be evaluated for solving packing problems of different heterogeneity.

Although B&R approach of defining heterogeneity is clear and straightforward, it might not be able to accurately translate the actual packing situation in some cases. For example, in the packing of 5 cargo types packing problems, figure 4.2a shows a set of five different cargos of similar sizes for packing while figure 4.2b shows a set of five different cargos of varying sizes for packing. Although both are classified as

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the same class of packing problems, it is almost certain that the packing with cargos defined in 4.2a will be much easier than the packing with cargos defined in 4.2b. This is because the packing of similar cargos has always been perceived to be easier as compared to packing of cargos of varying sizes, and B&R's approach of heterogeneity does not identify this situation.

Fig 4.2a Comparison between 2 different 5 cargo types packing problems:
Five cargos of similar sizes

Fig 4.2b Comparison between 2 different 5 cargo types packing problems:
Five cargos of varying sizes

4.3 INTRODUCTION TO SHAPE HETEROGENEITY

The thesis has discussed on the need for a new experimental standard that can effectively classify the test cases and also facilitate in depth studies on the packing method. The new experimental standard must be able to solve the correlation problem by accurately represents any changes in the elements of the test cases etc size of cargos, number of cargos. It must also be robust so that a broad and detailed experiment can be carried out on the packing method.

In this thesis, new experimental standard named shape heterogeneity (SH) is introduced. SH defines the heterogeneity of a test case to be according to the degree of shape variation in the packing consignment. A test case of similar cargos will have a low shape heterogeneity rating while a test case of packing cargos of varying sizes and shapes will be rated with a much higher shape heterogeneity rating.

By establishing dimensions' variation of the packing consignment as a metric in measuring the heterogeneity of a test case, SH is able to represent different packing situations with any changes made in the elements of the packing consignment. Furthermore, SH is capable of representing a wide range of packing problems, making it an attractive standard to be used in experiment.

4.3.1 DEFINITION OF SHAPE HETEROGENEITY

To measure the shape variation in the packing consignment of a test case, all three dimensions of the cargos must be considered. First, consider the largest dimension of the packing cargos as X axis, the 2nd largest dimension of the packing cargos as Y axis and the smallest dimension of the packing cargos as Z axis.

Fig 4.3 Alignment of axes for a packing consignment consisting of five different cargos

After aligning the axes of the packing cargos, the next step will be to calculate the cargo length variation at each of the axis. The cargo length variation which defined the heterogeneity at each of the axis is calculated as the ratio of the standard deviation of the cargo length for that axis over the average value of cargo length for the axis as shown in equation 4.3.

$$\begin{aligned}
 \text{Axis_Heterogeneity} &= \delta_{\text{axis}} / \overline{\text{axis}} \\
 &= \left(\frac{1}{N} \sum_{i=1}^N \left(\text{axis}_{ci} - \frac{1}{N} \sum_{j=1}^N \text{axis}_{cj} \right)^2 \right)^{1/2} / \left(\frac{1}{N} \sum_{k=1}^N \text{axis}_{ck} \right) \dots\dots\dots(4.3)
 \end{aligned}$$

Where δ_{axis} is the standard deviation cargo length for that axis while $\overline{\text{axis}}$ is the mean cargo length for that axis.

The SH is then calculated by adding the heterogeneity value for all three axes as shown in equation 4.4.

$$\text{Shape_Heterogeneity} = \text{Axis_Heterogeneity}_x + \text{Axis_Heterogeneity}_y + \text{Axis_Heterogeneity}_z \dots\dots\dots(4.4)$$

4.3.2 SHAPE HETEROGENEITY FOR BISCHOFF & RATCLIFF'S TEST CASES

After defining SH, the next step will be to test whether the current experiment is able to provide a broad range of tests with regard to SH. Due to its wide recognition as benchmark test for three dimensional packing, B&R's experiment is selected to check its SH.

In table 4.2, the distribution of SH for the 700 test cases proposed by B&R is shown. It can be observed that for most of the B&R's test cases, their SH fall within the range of 0.25 – 1.25. In fact, for test data sets of 8 and above cargo types, most of the test cases' SH are within the range of 0.75-1.25. The lack of test cases for other SH values makes B&R's experiment inadequate in concluding the performance of packing methods. Instead, a more robust experiment will be one that has each test data set to include test cases from a wide range of SH.

SH Types	0.00- 0.25	0.25- 0.50	0.75- 1.00	1.00- 1.25	1.25- 1.50	1.50- 1.75	1.75- 2.00
3	1	36	37	25	1	0	0
5	0	14	45	38	3	0	0
8	0	4	47	45	4	0	0
10	0	3	39	55	3	0	0
12	0	0	37	61	2	0	0
15	0	0	32	65	3	0	0
20	0	0	27	72	1	0	0

Table 4.2 Shape Heterogeneity value for B&R's test cases

4.3.3 APPLICATIONS FOR SHAPE HETEROGENEITY

Shape heterogeneity is a versatile way of representing packing problems. Its robustness allows it to excel in two main areas of three dimensional packing.

Analysis for Effects of Packing Consignment

SH can be used to detect for conditions of the packing consignment that will produce optimal packing result. SH can also help solving multi containers packing problems by selecting cargos to be packed together as according to the optimal SH value. Vice versa, low packing efficiency can also be avoided by avoiding packing consignment with less favorable SH rating.

Analysis of the Behavior for the Methods Studied

The other area where SH can be used is for studying the packing method's behaviors. There may be conditions where a packing method will excel, and also conditions whereby the method performed poorly. With the robustness of SH, these conditions of the studied method can be identified with ease. By understanding the studied packing method's behavior, optimal packing results can be assured.

4.4 SUMMARY

Numerous works have been done on three dimensional packing and different experiments are proposed to validate on the capability of the packing methods. Experiments by C.Pimpawat and N.Chaiyaratana, by Jin-Lin Lin and Bobbie Foote and by EE Bischoff and MSW Ratcliff are discussed. However, these experiments lack systematic approach in conducting and do little in studies on the characteristics of the packing method.

The thesis proposed SH as a common standard for conducting experiment. SH defines the heterogeneity of a test case according to the degree of shape variation in the packing consignment. By using shape variation in the packing consignment as a mean to classify packing problems, SH is able to make accurate interpretations for different packing situations as according to the changes made in the elements of the packing consignment.

As a popular benchmark for three dimensional packing, B&R's experiment is selected to check on its SH for their proposed test cases. Results shown that B&R's experiment is inadequate and a more robust and distinguish experiment is required.

Shape heterogeneity can be used in two main areas of three Qmensional packing. Firstly, it can be used to detect for ideal composition of the packing consignment that will produce optimal packing result. Secondly, it can be used for studying the behavior of the packing method.

CHAPTER 5 EXPERIMENTAL RESULTS & DISCUSSIONS

In this section, the results from two conducted experiments are exhibited and discussed. The first experiment is based on the popular benchmark test proposed in B&R whereby seven different classes namely 3, 5, 8, 10, 12, 15 and 20 cargo types packing problems are used for analyzing the observed methods.

As mentioned earlier in section 4.3.2, the test cases proposed in B&R are too similar in nature and may not be able to provide a complete analysis on the performance of the observed methods. Therefore, in the second experiment, it is proposed that for each class of packing problems to be examined, tests cases from a wide range of SH (0.25 – 2.00) are to be used. The proposed test cases are divided to eight categories (SHR1, 2, 3, 4, 5, 6, 7 and 8) as according to their SH value, 0.25, 0.5, 0.75, 1.00, 1.25, 1.50, 1.75, 2.00. To maintain consistency in the conducted tests, each category of SH will have an equal number of test cases involved in the testing.

OBSERVED METHODS

Three different packing methods will be studied in the experiments, namely Bischoff & Ratcliff's Multi Drop (MD) heuristic method, Gehring's GA based CBGAT and the proposed HTPA.

As discussed earlier, MD based its packing process with a set of heuristic sequential packing rules. In the conducted experiments, MD is chosen as a representation for the heuristic three dimensional packing approaches.

CBGAT is carried out first by heuristically forming blocks of cargos, GA is then used to pack the formed blocks of cargos into the constraint space. As both CBGAT and the proposed HTPA based their search in GA, CBGAT will be an ideal comparison for HTPA in solving the three dimensional packing problems. Gehring

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state that the three dimensional packing done in his work [3] is with overhang condition permitted. He prompted that by allowing overhanging during packing, it helps the packing method to obtain better packing results. To verify the effectiveness of overhanging in three dimensional packing, CBGAT is tested for both conditions (with overhang and without overhanging) in the conducted experiments.

EVALUATION TOOLS

In solving the three dimensional packing problems, the thesis will look into two main areas of performance (packed cargos' volume, processing time) to evaluate the capabilities of the observed methods. Like most works that are done on three dimensional packing, the volume of cargos that are packed into the constraint packing space is used as a gauge for the performance of the observed method. It is commonly express in the ratio of volume of cargos packed divided by the volume of the packing space as shown in equation 5.1. In this thesis, it is termed as the packed volume efficiency.

To monitor the packed volume efficiency for the test cases, the thesis calculates the average and the standard deviation of the packed volume efficiency for the test cases. Average packed volume efficiency (Efficiency_{packed-volume}) measures the overall volume packing efficiency while the standard deviation checks the spread of the obtained packed volume efficiency for the test cases as shown in equation 5.2 and 5.3.

$$Efficiency_{packed_volume}^p = \frac{\text{Volume of cargos packed for test case P}}{\text{Volume of packing pallet}} \dots\dots\dots(5.1)$$

$$Efficiency_{packed_volume} = \frac{\sum_{p=1}^{number_of_test_cases} Efficiency_{packed_volume}^p}{number_of_test_cases} \dots\dots\dots(5.2)$$

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$$SD_{packed_volume} = \left(\frac{1}{number_of_test_cases} \sum_{p=1}^{number_of_test_cases} \left(Efficiency_{packed_volume}^p - \overline{Efficiency_{packed_volume}} \right)^2 \right) \dots\dots\dots (5.3)$$

The other area of performance to evaluate the capabilities of the observed packing methods will be the processing time taken to solve the packing problem. A good packing method should not only be able to produce densely packed results, but also to produce them in a time efficient manner. To monitor the processing time efficiency of the test cases, the average and the standard deviation of the processing time taken for solving the test cases are measured as shown in equation 5.4 and 5.5.

$$\overline{time_taken} = \frac{\sum_{p=1}^{number_of_test_cases} time_taken}{number_of_test_cases} \dots\dots\dots (5.4)$$

$$SD_{proceesin g_time} = \left(\frac{1}{number_of_test_cases} \sum_{p=1}^{number_of_test_cases} \left(time_taken^p - \overline{time_taken} \right)^2 \right) \dots\dots\dots (5.5)$$

COMPUTATIONAL PLATFORM & SETTINGS

To ensure fair testing, a common computational platform is used for the conduction of the experiments. The configuration for the computer system used is as given below

Hardware configuration: Intel Pentium IV
512MRAM
Software Simulation tools: MatLab 6.5

Settings for HTPA: $\text{Threshold}_{\text{method_chooser}} = 1000$, Elitism=Top 20%, Probability of Mutation of Inversion $p_i = 0.1$, Probability of Mutation of Orientation $p_o = 0.1$, Probability of Mutation of Joint $p_j = 0.16$, Probability of Mutation of permutation $p_p = 0.1$.

5.1 BISCHOFF & RATCLIFF EXPERIMENT

The experimental setup carried out for this experiment is as discussed in section 4.1.3.

5.1.1 SIMULATION RESULTS

The 7 different classes of data sets are applied on the observed methods. The obtained simulation results will be discussed for both packed volume efficiency and processing time efficiency.

5.1.1.1 Packed Volume Efficiency

For evaluation on packed volume efficiency, the average packed volume efficiency per test case for the 7 data sets are as shown in figure 5.1. The standard deviation in the packed volume efficiency ($\text{SD}_{\text{packed volume}}$) for the test data sets is as shown in figure 5.2.

Fig 5.1 Average packing volume efficiency for the 7 tested data sets

Fig 5.2 $SD_{\text{packed volume}}$ for the 7 tested data sets

Analyzing on average packed volume efficiency

Analyzing figure 5.1 shows that HTPA gives the highest average packed volume efficiency for all tested data sets as compared to the other methods. Consistently, HTPA is able to obtain over 85% of average packed volume efficiency for all the

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tested data sets. It performs best for solving the 15 cargos type data set with 87.8% average packed volume efficiency.

The MD packing method performs reasonably well and outperformed CBGAT (with/without overhang) in average packed volume efficiency for all 7 data sets. For the experiment, MD is able to obtain over 83% average packed volume efficiency for all the tested data set. It performed best for solving the 10 cargos type data set with 84.3% average packed volume efficiency.

Gehring's CBGAT(with overhang) and CBGAT(w/o overhang) have the weakest performance in the experiment as compared to the other two packing methods. This is a strong contrast to the excellent results obtained from the similar experiment conducted in Gehring's work[3]. Similarly, big discrepancies in results by CBGAT is also observed in Bischoff's work[10]. These prompt that the actual performance of CBGAT might be weaker than as stated in [3].

Both CBGAT(with overhang) and CBGAT(w/o overhang) can only achieve around 75% average packed volume efficiency for all 7 tested data sets. They performed best for solving the 3 cargo types test date set with 78% and 77.6% average packed volume efficiency respectively.

Analyzing on $SD_{\text{packed_volume}}$

$SD_{\text{packed_volume}}$ is used to measure the capability of the observed methods in achieving consistent packing results. A low $SD_{\text{packed_volume}}$ means that the observed method regularly solves test cases close to the average packed volume efficiency. Vice-versa, a high $SD_{\text{packed_volume}}$ means that the observed method perform inconsistently, solving test cases with big deviation from the average packed volume efficiency. In order to be an effective packing method, the observed packing method must not only have high average packed volume efficiency, but also a relatively low $SD_{\text{packed_volume}}$ for solving the data sets.

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Analyzing figure 5.2 shows that HTPA has the lowest $SD_{\text{packd_volme}}$ for most of the tested data sets except for the 20 cargos type. It is able to obtain below 4 % of $SD_{\text{packed_volume}}$ for all the tested data sets. It performs best solving the 10 cargos types data Set with $SD_{\text{packed_volume}}$ of 2.15%.

MD performs reasonably well and outperformed CBGAT (with/without overhang) in $SD_{\text{packed_volme}}$ for all 7 data sets. It also obtained the lowest $SD_{\text{packed-volme}}$ for the 20 cargos type data sets. For the experiment, MD is able to obtain below 5% $SD_{\text{packed_volume}}$ for all the tested data sets. It performed best solving the 20 cargos type data set with 2.03% for $SD_{\text{packed_volume}}$

Similarly, CBGAT(with overhang) and CBGAT(w/o overhang) have the weakest performance in the experiment as compared to the other two packing methods. Both CBGAT(with overhang) and CBGAT(w/o overhang) can only achieve below 8% $SD_{\text{packed_volume}}$ for all 7 tested data sets. They performed best for solving the 20 cargos type test date set with 3.60% and 3.87% $SD_{\text{packed_volume}}$ respectively.

5.1.1.2 Processing Time Efficiency

For evaluation on processing time efficiency, the average packing time per test case for the 7 data sets are as shown in figure 5.3. The standard deviation in the packing time ($SD_{\text{packing time}}$) for the test data sets is as shown in figure 5.4.

Fig 5.3 Average processing time per test case (seconds) for the 7 tested data sets

Fig 5.4 $SD_{\text{packing time}}$ (seconds) for the 7 tested data sets

Analyzing on average processing time

As expected, analyzing figure 5.3 shows that MD takes the shortest processing time to solve a test case for all tested data sets. This is because MD is heuristic in nature and usually takes much shorter processing time to solve problems than the GA based

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approaches (CBGAT and HTPA). On average, MD requires less than 100 seconds to solve a test case for all the tested data sets. It performed best when solving the 12 cargos type data set, taking only an average of 40.3 seconds to solve a test case.

HTPA performed reasonably well in term of processing time efficiency. It uses the shortest processing time for solving the 3 cargos type data set (36.09 seconds per test case) and in average, takes shorter time for solving the test cases in the data sets as compared to CBGAT. However, it is observed that the processing time taken by HTPA to solve the packing problems is directly proportional to the number of cargo types involved in the packing. The higher the number of types of packing cargos is involved in the packing, the longer it'll take to solve the packing problems. This drawback of HTPA makes it inappropriate for solving packing problems that involve many different types of packing cargos.

CBGAT(with overhang) and CBGAT(w/o overhang) have similar performance in the experiment, taking roughly the same amount of processing time for solving the tested data sets. Both CBGAT(with overhang) and CBGAT(w/o overhang) need more than 700 seconds per test case for solving most of the tested data sets. CBGAT(with overhang) performed best in solving the 8 cargo types data set, taking in average 534.6 seconds to solve a test case. Meanwhile, CBGAT(w/o overhang) performed best in solving the 20 cargo types data set, taking in average 716.4 seconds to solve a test case.

Analyzing on $SD_{processing_time}$

In the earlier section, Standard deviation is used as a gauge for measuring the consistency of the packing result (SD_{packed_volume}), and is used for comparison between the observed methods. However, the same usage might not be applied for measuring processing time efficiency. This is due to the fact that unlike packed volume efficiency, the processing time taken for the different observed methods defers in a much wider range. Therefore, instead of being used as a comparison tool

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between the observed methods, $SD_{\text{processing_time}}$ is used for studying the variance of the observed method in processing time for solving the different data sets.

Generally, it is observed that $SD_{\text{processing_time}}$ decreases as the number of cargo types involved in packing increases. This is especially true for B&R method, which shows a trend of significant decreases in $SD_{\text{processing_time}}$ for data sets that has more cargo types. The same applies to CBGAT(with overhang) and (without overhang), which also show a moderate decrease in $SD_{\text{processing_time}}$ for data sets that has more cargo types. The only exception will be HTPA, which is observed to show significant increase in $SD_{\text{processing_time}}$ for data sets that has more cargo types. However, this can be explained by the sharp increase in processing time for HTPA as the cargo types involved in packing increase. With longer processing time, the $SD_{\text{processing_time}}$ for the corresponding data sets is expected to increase accordingly.

5.1.2 CONCLUSION ON RESULTS

In the first experiment, the interpretation on results of the observed methods for average packed volume efficiency is easy and straightforward. There is little variation in the performance of the observed methods for the different tested data sets. Therefore, it can be concluded that the performance of the observed methods for average packed volume efficiency is as ranked:

- 1st HTPA
- 2nd MD
- 3rd CBGAT(with Overhang)
- 4th CBGAT(w/o Overhang)

In the results on $SD_{\text{packed volume}}$, it is observed that there is a general trend of declining $SD_{\text{packed volume}}$ for data sets of more cargo types as shown in figure 5.5. This observed phenomenon prompts that by increasing the number of cargos involved in packing,

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more consistent packing results can be obtained. However, this might not be true as will be explained in the second experiment.

Fig 5.5 Observed trend in $SD_{\text{packed volume}}$ of the studied methods for the tested data sets

For processing time efficiency, the performance of the observed methods is as ranked:

- 1st MD
- 2nd HTPA
- 3rd CBGAT(with overhang)
- 4th CBGAT(w/o overhang)

Due to its application of simplistic heuristic rules for solving the packing problems, MD is a more time efficient method as compared to the more sophisticated GA based HTPA and CBGAT. It takes only a fraction of the processing time required by HTPA or CBGAT to solve the three dimensional packing problems.

In this experiment, HTPA performs better in term of processing time efficiency as compared to both CBGAT(wth overhang) and CBGAT(w/o overhang). However, it is observed that HTPA shows a steep increase in processing time for data sets with

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more cargo types as shown in figure 5.6. This undesirable characteristic of HTPA suggested situations where HTPA will take much longer processing time as compared to MD or even CBGAT in solving numerous(eg 50, 100) cargo types packing problems. Therefore, HTPA will not be suitable for time critical packing applications that involve packing numerous cargo types.

Fig 5.6 Observed trend of increasing processing time (seconds) required by HTPA for solving the tested data sets

To measure on the effect of three dimensional packing with overhang allowed, both CBGAT(with overhang) and CBGAT(w/o overhang) are tested in the experiment. The overall average packed volume efficiency for both conditions is shown in figure 5.7 while the overall average processing time required is shown in figure 5.8. Overall average packed volume efficiency is derived through averaging the packed volume efficiency obtained from all the test cases used in the experiment. Similarly, overall average processing time is derived through averaging the processing time obtained from all the test cases used in the experiment. As can be observed from figure 5.7, the application of overhang provides only a mild improvement of 0.5% in term of packed volume efficiency. On the other hand, the application of overhang brings a significant decrease($\approx 10\%$) in processing time for CBGAT.

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The significant decrease in processing time for CBGAT(with overhang) can be explained by the speeding up of the tower formation process due to overhanging allowed. From the experiment, it shows that overhang condition bring minimal improvement in terms of packed volume efficiency, but may reduces the processing time required due to more ease in packing.

Fig 5.7 Overall average packed volume efficiency of CBGAT(with overhang) and CBGAT(w/o overhang) for the experiment

Fig 5.8 Overall average processing time of CBGAT(with overhang) and CBGAT(w/o overhang) for the experiment

A GA BASED HYBRID TIER PACKING APPROACH FOR THREE DIMENSIONAL PACKING**5.2 PROPOSED EXPERIMENT**

In section 4.3, this thesis proposed SH as the new experimental standard for effective classification of test cases and facilitate in depth studies on the observed methods. In this second experiment, SH is applied to create the test cases for the five classes (3,5,8, 10 and 12 cargo types) of packing problems.

5.2.1 TEST SETUP

Similar to the first experiment, the constraint packing space is taken as the ISO 20ft (587x233x220) container. For each of the five classes of packing problems discussed, the experiment proposes using sets of test cases from eight different ranges of SH (SHR1-8) to examine the observed methods. For each set of test cases, there will be 30 test cases of similar SH values. The criteria for creating the test cases are as stated in table 5.1.

	SHR1	SHR2	SHR3	SHR4	SHR5	SHR6	SHR7	SHR8
SH value	0.15- 0.35	0.40- 0.60	0.65- 0.85	0.90- 1.10	1.15- 1.35	1.40- 1.60	1.65- 1.85	1.90- 2.10
Number of packing cargos	60- 120	60- 120	60- 120	60- 120	60- 120	50- 100	50- 100	30-40

Table 5.1 Criteria for creating test cases for SHR1-8

Note that for SHR6-8, the number of packing cargos for a test case is generally lesser than one from SHR1-5. This is because for test cases with higher SH, there are larger variations in the packing consignment in terms of cargo shapes and sizes. Therefore, there is a tendency that lesser packing cargos will be needed to fill up the given packing space.

A GA BASED HYBRID TIER PACKING APPROACH FOR THREE DIMENSIONAL PACKING**5.2.2 SIMULATION RESULTS**

The proposed SH sets(SHR1-8) of test cases for the five classes of packing problems are applied on the observed methods. The obtained simulation results will be discussed for both packed volume efficiency and processing time efficiency.

5.2.2.1 3 CARGO TYPES PACKING PROBLEMS

This section discusses the simulation results obtained from the SH tests(SHR1-8) conducted for the 3 cargo types packing problems.

Packed Volume Efficiency

For evaluation on packed volume efficiency for 3 cargo types packing problems, the average packed volume efficiency per test case for SHR1-8 are as shown in figure 5.9. $SD_{\text{packed volume}}$ for SHR1-8 is as shown in figure 5.10.

Fig 5.9 Average packing volume efficiency obtained by the observed methods for solving SHR1-8 3 cargo types packing problems

Fig 5.10 $SD_{\text{packed volume}}$ obtained by the observed method for solving SHR1-8 3 cargo types packing problems

Analyzing on average packed volume efficiency

Analyzing figure 5.9 shows that for 3 cargo types packing problems, HTPA gives the highest average packed volume efficiency in SHR1, 2, 3, 5, 7 and 8. HTPA is able to consistently obtain over 78% of average packed volume efficiency for all tested SH sets. It performs best for solving SHR2 with an average packed volume efficiency of 83.06%. Vice-versa, it performs least satisfactorily for solving SHR6 with an average packed volume efficiency of 78.69%.

CBGAT performs reasonably well in solving the 3 cargo types packing problems for SHR1-8. CBGAT(with Overhang) gives the highest average packed volume efficiency for SHR4 and SHR6. Both CBGAT (with Overhang) and CBGAT (w/o Overhang) are able to obtain over 75% of average packed volume efficiency for most of the tested sets except for the most heterogeneous SHR8. They perform best solving SHR4 with 81.23% and 80.42% packed volume efficiency respectively. Vice-versa, they perform least satisfactorily for solving SHR8 with an average packed volume efficiency of 71.1% and 71.9 respectively.

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MD packing method has the weakest performance for solving the 3 cargo types packing problems as compared to the other two packing methods. It can only achieve around 75% average packed volume efficiency for all tested sets. MD performs best for solving the SHR2 with 78.05% average packed volume efficiency. Vice-versa, they performed least satisfactorily for solving SHR5 with 72.77% average packed volume efficiency.

Analyzing on SD_{packed_volume}

Analyzing figure 5.10 shows that HTPA has the best performance and is able to obtain around 5 % of SD_{packed_volume} for all tested SH sets. It performs best for solving SHR8 with SD_{packed_volume} of 3.9%. Vice-versa, it performs least satisfactorily for solving SHR1 with SD_{packed_volume} of 6.28%.

CBGAT performs reasonably well in solving the 3 cargo types packing problems for low SD_{packed_volume} . Both CBGAT(with Overhang) and CBGAT(w/o Overhang) are able to obtain around 6% SD_{packed_volume} for the tested SH sets. CBGAT(with Overhang) performs best solving SHR5 with 5.32% SD_{packed_volume} while CBGAT(w/o Overhang) performs best solving SHR3 with SD_{packed_volume} of 5.02%. Vice-versa, they perform least satisfactorily for solving SHR8 with SD_{packed_volume} of 8.8% and 8.7 respectively.

MD packing method shows the highest SD_{packed_volume} for SHR1, 3, 4, 5, 6, and 7. For the tested SH sets, MD needs more than 6% of SD_{packed_volume} in solving them. MD performs best for solving the SHR8 with 5.05% SD_{packed_volume} Vice-versa, They performed least satisfactorily for solving SHR7 with 11.5% SD_{packed_volume} .

Processing Time Efficiency

For evaluation on processing time efficiency for 3 cargo types packing problems, the average processing time per test case for SHR1-8 is as shown in figure 5.11. The $SD_{processing_time}$ for SHR1-8 is as shown in figure 5.12.

Fig 5.11 Average processing time (seconds) per test case obtained by the observed methods for solving SHR1-8 3 cargo types packing problems

Fig 5.12 $SD_{processing_time}$ (seconds) obtained by the observed methods for solving SHR1-8 3 cargo types packing problems

Analyzing on average processing time

Similar to the first experiment, MD takes the shortest processing time to solve a test case for all tested SH sets of 3 cargo types packing problems as shown in figure

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5.11. On average, MD requires less than 15 seconds to solve a test case for all the tested SH sets. It performed best when solving SHR8, taking only an average of 9.6 seconds to solve a test case.

In processing time efficiency, HTPA performed marginally better than CBGAT. In average, HTPA requires less than 100 seconds to solve a test case for all tested SH sets. It performed best when solving SHR4, taking only an average of 62.88 seconds to solve a test case.

CBGAT takes the longest processing time for solving the SH sets of 3 cargo types packing problems. In average, both CBGAT(with overhang) and CBGAT(w/o overhang) need more than 100 seconds per test case for solving most of the tested SH sets. They performed best in solving SHR8, taking in average 88.82 seconds and 83.72 seconds respectively to solve a test case.

Analyzing on ***SD_{processing_time}***

It is observed that for MD packing method, ***SD_{processing_time}*** is relatively constant for all the tested SH sets. HTPA and CBGAT does show a trend of reducing ***SD_{processing_time}*** for higher SH(SHR6-8) sets. However, this trend is not created by the changes in SH. Instead, it is caused by the corresponding significant decrease in processing time required per test case that is due to the decrease in the number of packing cargos involved for packing in SHR6-8.

5.2.2.2 5 CARGO TYPES PACKING PROBLEMS

This section discusses the simulation results obtained from the SH tests(SHR1-8) conducted for the 5 cargo types packing problems.

Packed Volume Efficiency

For evaluation on packed volume efficiency for 5 cargo types packing problems, the average packed volume efficiency per test case for SHR1-8 is as shown in figure 5.13. ***SD_{packed volume}*** for SHR1-8 is as shown in figure 5.14.

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Fig 5.13 Average packing volume efficiency obtained by the observed methods for solving SHR1-8 5 cargo types packing problems

Fig 5.14 $SD_{\text{packed volume}}$ obtained by the observed methods for solving SHR1-8 5 cargo types packing problems

Analyzing on average packed volume efficiency

Analyzing figure 5.13 shows that for 5 cargo types packing problems, HTPA gives the highest average packed volume efficiency for all the tested SH sets. HTPA is

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able to consistently obtain over 79% of average packed volume efficiency for all the tested SH sets. It performs best for solving SHR4 with an average packed volume efficiency of 84.03%. Vice-versa, it performs least satisfactorily for solving SHR1 with an average packed volume efficiency of 79.43%.

CBGAT has mediocre performance in solving the 5 cargo types packing problems for average packed volume efficiency. Both CBGAT(with Overhang) and CBGAT(w/o Overhang) are able to obtain over 76% of average packed volume efficiency for most of the tested sets except for the most heterogeneous SHR7 and SHR8. They perform best solving SHR4 with 79.42% and 79.12% packed volume efficiency respectively. Vice-versa, they perform least satisfactorily for solving SHR8 with an average packed volume efficiency of 71.795% and 70.09% respectively.

MD packing method also gives ordinary performance in solving the 5 cargo types packing problems for average packed volume efficiency. It can only achieve over 75% average packed volume efficiency for most of the tested SH sets except for SHR7 and SHR8. MD performs best for solving the SHR6 with 81.31% average packed volume efficiency. Vice-versa, they performed least satisfactorily for solving SHR8 with 72.33% average packed volume efficiency.

Analyzing on SD_{packed_volume}

Analyzing figure 5.14 shows that HTPA has the best performance and is able to obtain around 5 % of SD_{packed_volume} for the tested SH sets. It performs best for solving SHR3 with SD_{packed_volume} of 2.66%. Vice-versa, it performs least satisfactorily for solving SHR1 with SD_{packed_volume} of 6.5%.

Both CBGAT(with Overhang) and CBGAT(w/o Overhang) are able to obtain around 6% SD_{packed_volume} for the tested SH sets. They perform best solving SHR3 with 4.7% and 4.34% SD_{packed_volume} respectively. Vice-versa, they perform least satisfactorily for solving SHR1 with SD_{packed_volume} of 7.97% and 8.17 respectively.

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MD packing method shows the highest SD_{packed_volume} for SHR1, 2, 3, and 5. However, It also gives the best result for solving SHR6 with SD_{packed_volume} of 4.26%. Vice-versa, MD performed least satisfactorily for solving SHR1 with 10.22% SD_{packed_volume} .

Processing Time Efficiency

For evaluation on processing time efficiency for 5 cargo types packing problems, the average processing time per test case for SHR1-8 is as shown in figure 5.15.

$SD_{processing_time}$ for SHR1-8 is as shown in figure 5.16.

Fig 5.15 Average processing time (seconds) per test case obtained by the observed methods for solving SHR1-8 5 cargo types packing problems

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Fig 5.16 $SD_{processing_time}$ (seconds) obtained by the observed method for solving SHR1-8 5 cargo types packing problems

Analyzing on average processing time

As usual, MD takes the shortest processing time to solve a test case for all tested SH sets in solving 5 cargo types packing problems as shown in figure 5.15. In average, MD requires less than 12 seconds to solve a test case for all the tested SH sets. It performed best when solving SHR8, taking only an average of 8.27 seconds to solve a test case.

In processing time efficiency for solving 5 cargo types problems, HTPA performed marginally better than CBGAT. In average, HTPA requires less than 100 seconds to solve a test case for all the tested SH sets. It performed best when solving SHR8, taking only an average of 48.81 seconds to solve a test case.

CBGAT takes the longest processing time for solving the SH sets of 5 cargo types packing problems. In average, both CBGAT(with overhang) and CBGAT(w/o overhang) need more than 100 seconds per test case for solving most of the tested SH sets except for SHR8. They performed best in solving SHR8, taking in average 72.34seconds and 65.63 seconds respectively to solve a test case.

Analyzing on $SD_{processing_time}$

Similar to the results for 3 cargo types packing problems, it is observed that for MD packing method, $SD_{processing_time}$ is relatively constant for all the tested SH sets. A trend of reducing $SD_{processing_time}$ for heterogeneity(SHR6-8) sets of test cases is observed for HTPA and CBGAT.

5.2.2.3 8 Cargo Types Packing Problems

This section discusses the simulation results obtained from the SH tests(SHR1-8) conducted for the 8 cargo types packing problems.

Packed Volume Efficiency

For evaluation on packed volume efficiency for solving 8 cargo types packing problems, the average packed volume efficiency per test case for SHR1-8 is as shown in figure 5.17. $SD_{packed\ volume}$ for SHR1-8 is as shown in figure 5.18.

Fig 5.17 Average packing volume efficiency obtained by the observed methods for solving SHR1-8 8 cargo types packing problems

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Fig 5.18 $SD_{\text{packed volume}}$ obtained by the observed methods for solving SHR1-8 8 cargo types packing problems

Analyzing on average packed volume efficiency

Analyzing figure 5.17 shows that for 8 cargo types packing problems, HTPA gives the highest average packed volume efficiency for all the tested SH sets except for SHR1. HTPA is able to consistently obtain over 78% of average packed volume efficiency for all the tested SH sets except for SHR1. It performs best for solving SHR7 with an average packed volume efficiency of 83.7%. Vice-versa, it performs least satisfactorily for solving SHR1 with an average packed volume efficiency of 76.68%.

CBGAT performs reasonably well in solving the 8 cargo types packing problems. CBGAT(with Overhang) gives the highest average packed volume efficiency for SHR1. Both CBGAT(with Overhang) and CBGAT(w/o Overhang) are able to obtain around 75% of average packed volume efficiency for most of the tested SH sets. They perform best solving SHR1 with 77.69% and 76.85% average packed volume efficiency respectively. Vice-versa, CBGAT(with Overhang) performs least satisfactorily solving SHR8 with 72.7% average packed volume efficiency while

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CBGAT(w/o Overhang) performs least satisfactorily solving SHR7 with 71.99% average packed volume efficiency.

MD packing method can only achieve over 75% average packed volume efficiency for SHR3 and SHR6. MD performs best for solving the SHR3 with 77.13% average packed volume efficiency. Vice-versa, They performed least satisfactorily for solving SHR1 with 70.1% average packed volume efficiency.

Analyzing on SD_{packed_volume}

Analyzing figure 5.18 shows that HTPA has the best performance for most of the tested SH sets. It performs best for solving SHR5 with SD_{packed_volume} of 2.75%. Vice-versa, it performs least satisfactorily for solving SHR8 with SD_{packed_volume} of 7.1%.

CBGAT(with Overhang) performs best solving SHR4 with 3.29% SD_{packed_volume} while CBGAT(w/o Overhang) performs best solving SHR5 with 3.29% SD_{packed_volume} . Vice-versa, they perform least satisfactorily for solving SHR8 with SD_{packed_volume} of 9.15% and 7.61% respectively.

MD packing method shows the highest SD_{packed_volume} for SHR1, 2, 4, and 5. However, MD performance improves when used for solving the higher SH sets (SHR6-8) as shown in figure 5.18. MD performs best solving SHR7 with 4.07% SD_{packed_volume} . Vice-versa, MD performed least satisfactorily for solving SHR1 with 7.56% SD_{packed_volume} .

Processing Time Efficiency

For evaluation on processing time efficiency for solving 8 cargo types packing problems, the average processing time per test case for SHR1-8 is as shown in figure 5.19. $SD_{processing_time}$ for SHR1-8 is as shown in figure 5.20.

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Fig 5.19 Average processing time (seconds) per test case obtained by the observed methods for solving SHR1-8 8 cargo types packing problems

Fig 5.20 $SD_{processing_time}$ (seconds) obtained by the observed methods for solving SHR1-8 8 cargo types packing problems

Analyzing on average processing time

MD takes the shortest processing time to solve a test case for all tested SH sets in solving 8 cargo types packing problems as shown in figure 5.19. In average, MD requires less than 10 seconds to solve a test case for all the tested SH sets. It

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performed best when solving SHR8, taking only an average of 7.71 seconds to solve a test case.

For solving the SH sets of 8 cargo types packing problems, CBGAT performs marginally better than HTPA. In average, both CBGAT(with overhang) and CBGAT(w/o overhang) need around 100 seconds to solve a test case from the tested SH sets. They performed best in solving SHR8, taking in average 67.84 seconds and 100.02 seconds respectively to solve a test case.

HTPA has the weakest performance in processing time efficiency for 8 cargo types packing problems. It takes the longest processing time to solve a test case in SHR 5-8. For SHR4-8, HTPA needs more than 200 seconds to solve a test case. HTPA performs best when solving SHR1, taking only an average of 81.84 seconds to solve a test case.

Analyzing on $SD_{processing_time}$

It is observed that for MD packing method, $SD_{processing_time}$ is relatively constant for all the tested SH sets. A trend of reducing $SD_{processing_time}$ for higher SH(SHR6-8) sets can still be observed for CBGAT.

5.2.2.4 10 Cargo Types Packing Problems

This section discusses the simulation results obtained from the tests(SHR1-8) conducted for the 10 cargo types packing problems.

Packed Volume Efficiency

For evaluation on packed volume efficiency for solving 10 cargo types packing problems, the average packed volume efficiency per test case for SHR1-8 is as shown in figure 5.21. SD_{packed_volume} for SHR1-8 is as shown in figure 5.22.

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Fig 5.21 Average packing volume efficiency obtained by the observed methods for solving SHR1-8 10 cargo types packing problems

Fig 5.22 $SD_{\text{packed volume}}$ obtained by the observed methods for solving SHR1-8 10 cargo types packing problems

Analyzing on average packed volume efficiency

Analyzing figure 5.21 shows that for 10 cargo types packing problems, HTPA gives the highest average packed volume efficiency for all the tested SH sets. HTPA is

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able to consistently obtain over 80% of average packed volume efficiency for all the tested SH sets except for SHR1 and SHR8. It performs best for solving SHR3 with an average packed volume efficiency of 84.19%. Vice-versa, it performs least satisfactorily for solving SHR8 with an average packed volume efficiency of 74.02%.

Both CBGAT(with Overhang) and CBGAT(w/o Overhang) are able to obtain around 75% of average packed volume efficiency for most of the tested SH sets except for SHR8, CBGAT(with Overhang) perform best solving SHR6 with 78.04% while CBGAT(w/o Overhang) perform best solving SHR1 with 77.09% average packed volume efficiency. Commonly, they perform least satisfactorily solving SHR8 with 67.09% and 67.98% average packed volume efficiency respectively.

MD packing method has the weakest performance in term of average packed volume efficiency for solving the 10 cargo types packing problems. For SHR1,2,5,6,7 and 8, MD is not able to achieve over 75% average packed volume efficiency. MD performs best for solving the SHR3 with 76.8% average packed volume efficiency. Vice-versa, they perform least satisfactorily for solving SHR8 with 67.7% average packed volume efficiency.

Analyzing on SD_{packed_volume}

Analyzing figure 5.22 shows that HTPA has the best performance for most of the tested SH sets. It performs best for solving SHR5 with SD_{packed_volume} of 2.61%. Vice-versa, it performs least satisfactorily for solving SHR8 with SD_{packed_volume} of 7.51%.

CBGAT(with Overhang) performs best solving SHR5 with 3.22% SD_{packed_volume} while CBGAT(w/o Overhang) performs best solving SHR5 with 3.87% SD_{packed_volume} . Vice-versa, they perform least satisfactorily for solving SHR8 with SD_{packed_volume} of 10.57% and 12.11 % respectively.

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MD packing method is able to obtain below 7.5% SD_{packed_volume} for all the tested SH sets. MD performs best solving SHR3 with 3.33% SD_{packed_volume} . Vice-versa, MD performs least satisfactorily for solving SHR8 with 7.2% SD_{packed_volume} .

Processing Time Efficiency

For evaluation on processing time efficiency for solving 10 cargo types packing problems, the average processing time per test case for SHR1-8 is as shown in figure 5.23. $SD_{processing_time}$ for SHR1-8 is as shown in figure 5.24.

Fig 5.23 Average processing time (seconds) per test case obtained by the observed methods for solving SHR1-8 10 cargo types packing problems

Fig 5.24 $SD_{processing_time}$ (seconds) obtained by the observed methods for solving SHR1-8 10 cargo types packing problems

Analyzing on average processing time

Similar to earlier experimental results, MD takes the shortest processing time to solve a test case for all tested SH sets in solving 10 cargo types packing problems as shown in figure 5.23. In average, MD requires less than 15 seconds to solve a test case for all the tested SH sets. It performed best when solving SHR8, taking only an average of 8.07 seconds to solve a test case.

For solving the SH sets of 10 cargo types packing problems in term of processing time efficiency, CBGAT performs better than HTPA. The performance varies little from the earlier results for 3, 5 and 8 cargo types packing problems. Both CBGAT(with Overhang) and CBGAT(w/o Overhang) perform best in solving SHR8, taking in average 111.61 seconds and 76.93 seconds respectively to solve a test case.

The increase in processing time for higher cargo types packing problems causes HTPA to have the weakest performance in processing time efficiency for solving 10 cargo types packing problems. It takes the longest processing time(>400 seconds) to

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solve a test case for all the tested SH sets. HTPA performs best when solving SHR7, taking only an average of 417.76 seconds to solve a test case.

Analyzing on $SD_{processing_time}$

There is little variation in the trends observed in $SD_{processing_time}$ as compared to the earlier results obtained for 3, 5, 8 cargo types packing problems. MD packing's $SD_{processing_time}$ is unaffected by the changing of SH while a trend of reducing $SD_{processing_time}$ for higher SH(SHR6-8) is observed for CBGAT.

5.2.2.5 12 Cargo Types Packing Problems

The last sets of simulation results to be discussed are on the 12 cargo types packing problems.

Packed Volume Efficiency

The average packed volume efficiency per test case for SHR1-8 is as shown in figure 5.25. $SD_{packed\ volume}$ for SHR1-8 is as shown in figure 5.26.

Fig 5.25 Average packing volume efficiency obtained by the observed methods for solving SHR1-8 12 cargo types packing problems

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Fig 5.26 $SD_{\text{packed volume}}$ obtained by the observed methods for solving SHR1-8 12 cargo types packing problems

Analyzing on average packed volume efficiency

Analyzing figure 5.25 shows that for 12 cargo types packing problems, HTPA gives the highest average packed volume efficiency for all the tested SH sets. HTPA is able to consistently obtain over 80% of average packed volume efficiency for all the tested SH sets except for SHR1 and SHR8. It performs best for solving SHR4 with an average packed volume efficiency of 83.48%. Vice-versa, it performs least satisfactorily for solving SHR8 with an average packed volume efficiency of 72.18%.

Both CBGAT(with Overhang) and CBGAT(w/o Overhang) are able to obtain around 75% of average packed volume efficiency for most of the tested SH sets except for SHR8. They perform best solving SHR6 with 79.24% and 78.90% average packed volume efficiency respectively. Commonly, they perform least satisfactorily solving SHR8 with 67.04% and 65.97% average packed volume efficiency respectively.

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MD packing method has the weakest performance in term of average packed volume efficiency for solving the 12 cargo types packing problems. It has the lowest average packed volume efficiency for all the tested SH sets except for SHR7. MD performs best for solving the SHR6 with 76.76% average packed volume efficiency. Vice-versa, it performs least satisfactorily for solving SHR8 with 64.81% average packed volume efficiency.

Analyzing on SD_{packed_volume}

Analyzing figure 5.26 shows that HTPA has the best performance for SHR3, 4, 5 and 8. It is able to obtain around 6% SD_{packed_volume} for most of the tested SH sets. HTPA performs best solving SHR3 with 2.18% SD_{packed_volume} . Vice-versa, it performs least satisfactorily for solving SHR8 with SD_{packed_volume} of 8.18%.

CBGAT performs relatively well as it has the best performance for SHR1,2 and 6. CBGAT(with Overhang) performs best solving SHR3 with 3.76% SD_{packed_volume} while CBGAT(w/o Overhang) performs best solving SHR4 with 3.65% SD_{packed_volume} . Vice-versa, they perform least satisfactorily for solving SHR8 with SD_{packed_volume} of 12.39% and 11.58% respectively.

MD packing method is able to obtain below 9% SD_{packed_volume} for all the tested SH sets. MD performs best solving SHR4 with 4.12% SD_{packed_volume} . Vice-versa, MD performs least satisfactorily for solving SHR8 with 8.77% SD_{packed_volume} .

Processing Time Efficiency

For evaluation on processing time efficiency for solving 12 cargo types packing problems, the average processing time per test case for SHR1-8 is as shown in figure 5.27. $SD_{processing_time}$ for SHR1-8 is as shown in figure 5.28.

Fig 5.27 Average processing time (seconds) per test case obtained by the observe methods for solving SHR1-8 12 cargo types packing problems

Fig 5.28 $SD_{processing_time}$ (seconds) obtained by the observed methods for solving SHR1-8 in solving 12 cargo types packing problems

Analyzing on average processing time

As usual MD takes the shortest processing time to solve a test case for all tested SH sets in solving 12 cargo types packing problems as shown in figure 5.27. In average,

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MD requires less than 15 seconds to solve a test case for all the tested SH sets. It performed best when solving SHR8, taking only an average of 9.43 seconds to solve a test case.

For solving the SH sets of 12 cargo types packing problems in term of processing time efficiency, CBGAT out performs HTPA. The performance varies little from the earlier results. Both CBGAT(with Overhang) and CBGAT(w/o Overhang) performed best in solving SHR8, taking in average 69.33 seconds and 55.65 seconds respectively to solve a test case.

Following the earlier trend, HTPA has the weakest performance in processing time efficiency for solving 12 cargo types packing problems. It takes the longest processing time(>400 seconds) to solve a test case for all the tested SH sets. HTPA performs best when solving SHR7, taking only an average of 471.74 seconds to solve a test case.

Analyzing on $SD_{processing_time}$

There is little variation in the trends observed in $SD_{processing_time}$ as compared to the earlier results. MD packing's $SD_{processing_time}$ is unaffected by the changing of SH while a trend of reducing $SD_{processing_time}$ for higher SH(SHR6-8) is observed for CBGAT. HTPA only shows randomize changes in $SD_{processing_time}$ with the variation in SH.

5.2.3 CONCLUSION ON RESULTS

For the second experiment, the effects of SH on solving the 3, 5, 8, 10 and 12 cargo types packing problems are examined. For each class of packing problems, eight sets of test cases (SHR1-8) are proposed to represent packing problems from a wide range of SH (0.25-2.00).

A GA BASED HYBRID TIER PACKING APPROACH FOR THREE DIMENSIONAL PACKING**5.2.3.1 Effect of SH on Packed Volume Efficiency**

To analyze the quantitative simulation results obtained from the experiment, a systematic approach is required. The thesis proposed using performance bands to facilitate the process of result analysis. Performance bands are preset ranges in the packed volume efficiency, used to identify SH sets that produce distinguish results when solved by the observed packing methods. In this thesis, two performance bands are proposed namely, the high performance band and the low performance band.

High performance band is used to identify SH sets where the observed method produces optimal or near optimal average packed volume efficiency. These SH sets are classified as the high performance group. Vice-versa, the low performance band is used to identify SH sets where the observed method produces relatively poor average packed volume efficiency. These SH sets are classified as the low performance group. High performance band is defined by a tolerance range below the highest average packed volume efficiency obtained from the SH sets, while low performance band is defined by a tolerance range above the lowest average packed volume efficiency obtained from the SH sets as shown in figure 5.29.

Fig 5.29 Identification of the high performance and low performance groups of SH sets in average packed volume efficiency for an observed method using the performance bands

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The high performance and low performance groups for the observed methods in average packed volume efficiency solving the 5 different classes of packing problems are identified as shown in table 5.2 and 5.3. The tolerance for both high performance band and the low performance band is set at 2 percents. By obtaining the high performance and low performance groups for the observed methods, the analysis with the effect of SH on average packed volume efficiency can then be carried out.

Classes of Packing problems	3	5	8	10	12
HTPA	SHR2-4	SHR2-5,7	SHR4-7	SHR3,4,6,7	SHR2-7
CBGAT(w/o Overhang)	SHR4-6	SHR1,2,4-6	SHR1,3,5,6	SHR1-3,5,6	SHR1,6
CBGAT(with Overhang)	SHR4,6	SHR1,2,4-6	SHR1,3,6	SHR1,6	SHR1,6
MD	SHR1,2,4,6	SHR4-6	SHR3-6	SHR3,4,6	SHR2,6,7

Table 5.2 High performance groups of the observed methods in average packed volume efficiency for solving the different classes of packing problems

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Classes of Packing problems	3	5	8	10	12
HTPA	SHR5,6,8	SHR1,8	SHR1	SHR8	SHR8
CBGAT(w/o Overhang)	SHR8	SHR7	SHR7,8	SHR8	SHR8
CBGAT(with Overhang)	SHR8	SHR7,8	SHR2,5,7,8	SHR8	SHR8
MD	SHR3,5,8	SHR7,8	SHR1,8	SHR8	SHR8

Table 5.3 Low performance groups of the observed methods in average packed volume efficiency for solving the different classes of packing problems

a) Optimal SHRs in Average Packed Volume Efficiency for Solving the different Classes of Packing Problems

From table 5.2, the optimal SHRs in average packed volume efficiency for solving the different classes of packing problems can be derived. Being the optimal SHR for solving the particular class of packing problems, the SHR must be included in the high performance groups for all or most of the observed methods.

Observing the information in table 5.2 shows that for 3 cargo types packing problems, only SHR4 is in the high performance group for all the observed methods. This shows that all four of the observed methods perform optimally for solving 3 cargo types packing problems with SH of approximately 1.

Next, for 5 cargo types packing problems, both SHR4 and SHR5 is in the high performance group for all the observed methods. This shows that all four of the observed methods perform optimally for solving 5 cargo types packing problems with SH of approximately 1 and 1.25.

The process of determining the optimal SHR is repeated for the other classes of packing problems and the optimal SHRs for solving the different classes of packing problems are as given in table 5.4.

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Classes of packing problems	3 types	5 types	8 types	10 types	12 types
Optimal SHR	4	4,5	6	6	6
SH	0.90-1.10	0.90-1.10, 1.15-1.35	1.40-1.60	1.40-1.60	1.40-1.60

Table 5.4 Optimal SHRs in average packed volume efficiency for solving the different classes of packing problems

b) Optimal SHRs in average packed volume efficiency for the observed methods

From table 5.2, the optimal SHR in average packed volume efficiency for the observed methods can be derived. Being the optimal SHR for the observed method, the SHR must be included in the high performance groups for solving all or most of the different classes of packing problems.

Observing the information in table 5.2 shows that for HTPA, SHR4 is in the high performance group for solving all the five classes of packing problems. This shows that HTPA is able to perform optimally for solving the 3, 5, 8, 10 and 12 cargo types packing problems with SH of approximately 1.

Next, for CBGAT(w/o Overhang), SHR6 is in the high performance group for solving all the five classes of packing problems. This shows that CBGAT(w/o Overhang) is able to perform optimally for solving the 3, 5, 8, 10 and 12 cargo types packing problems with SH of approximately 1.5.

The process of determining the optimal SHR is repeated for CBGAT(with Overhang) and MD, the optimal SHRs for the observed methods are then as given in table 5.5.

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Packing Methods	HTPA	CBGAT(w/o Overhang)	CBGAT(with Overhang)	MD
Optimal SHR	4	6	6	6
SH	0.90-1.10	1.40-1.60	1.40-1.60	1.40-1.60

Table 5.5 Optimal SHRs in average packed volume efficiency for the observed methods

c) Worst SHRs in average packed volume efficiency for solving the different classes of packing problems

From table 5.3, the worst SHRs in average packed volume efficiency for solving the different classes of packing problems can be derived. Worst SHR is the SH set of packing problems that has obtained the poorest packing result. Being the worst SHR in average packed volume efficiency for solving the different classes of packing problems, the SHR must be included in the low performance groups for all or most of the observed methods.

Observing the information in table 5.3 shows that for 3 cargo types packing problems, SHR8 is in the low performance group for all the observed methods. This shows that all four of the observed methods perform poorly for solving 3 cargo types packing problems with SH of approximately 2.

Next, for 5 cargo types packing problems, both SHR7 and SHR8 is in the low performance group for three out of four of the observed methods. However, the packing results for SHR8 is relatively poorer as compared to those obtained for SHR7. Therefore, SHR8 is identified as the worst SHR for 5 cargo types packing problems. This means that all four of the observed methods perform poorly for solving 5 cargo types packing problems with SH of approximately 2.

The process of determining the worst SHR in average packed volume efficiency is repeated for the other classes of packing problems and the worst SHRs for solving the different classes of packing problems are as given in table 5.6.

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Classes of packing problems	3 types	5 types	8 types	10 types	12 types
Worst SHR	8	8	8	8	8
SH	1.90-2.10	1.90-2.10	1.90-2.10	1.90-2.10	1.90-2.10

Table 5.6 Worst SHRs for solving the different classes of packing problems

*d) Worst **SHRs** in average packed volume efficiency for the observed methods*

From table 5.3, the worst SHRs in average packed volume efficiency for the observed methods to solve the different classes of packing problems can be derived. Being the worst SHR for the packing method, the SHR must be included in the low performance groups for solving all or most of the different classes of packing problems.

Observing the information in table 5.3 shows that for HTPA, SHR8 is in the low performance group for solving all the five classes of packing problems except for the 8 cargo types packing problems. However, even for the 8 cargo types packing problems, SHR8 obtained the second lowest packed volume efficiency when solved by HTPA. Therefore, SHR8 is concluded to be the worst SHR in average packed volume efficiency for HTPA. This shows that HTPA performs poorly for solving the 3, 5, 8, 10 and 12 cargo types packing problems with SH of approximately 2.

Next, for CBGAT(w/o Overhang), SHR8 is in the low performance group for solving all the five classes of packing problems. This shows that CBGAT(w/o Overhang) performs poorly for solving the 3, 5, 8, 10 and 12 cargo types packing problems with SH of approximately 2.

The process of determining the worst SHR is repeated for CBGAT(with Overhang) and MD, the worst SHRs for the observed methods are then as given in table 5.7.

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Packing Methods	HTPA	CBGAT(w/o Overhang)	CBGAT(with Overhang)	MD
Optimal SHR	8	8	8	8
SH	1.90-2.10	1.90-2.10	1.90-2.10	1.90-2.10

Table 5.7 Worst SHRs in average packed volume efficiency for the different packing methods

From the analysis on the effect of SH on packed volume efficiency, it shows that SH does not affect the packed volume efficiency as commonly perceived. Generally, it is deemed that higher variation in shapes and sizes of the packing consignment will cause poorer packing result. However, from table 5.4 and 5.5, it is observed that none of the optimal SH sets derived for both the packing methods and the classes of packing problems are of the more homogeneous set of SHR1. Instead, all of the optimal SH sets fall between the more heterogeneous sets of SHR4-6. This shows that a certain level of variation in shapes and sizes ($1 \leq SH \leq 1.5$) of the packing consignment is required in order to obtain optimal packing results. However, if the packing consignment is too heterogeneous (SHR8), the packing result obtained will be much poorer as shown in table 5.6 and 5.7.

In the first experiment, the average packed volume efficiency of the packing methods for solving the different classes of packing problems is discussed. However, it was mentioned earlier that the test cases used are not holistic, with too many similar test cases involved in the experiment. In this experiment, the packing methods are tested with test cases from a wide range of SH (0.15 – 2.10) for solving the different classes of packing problems. By involving a greater variety of test cases in the experiment, more credible packing results can be obtained from the experiment. For this experiment, the average packed volume efficiency of the observed methods for solving the different classes of packing problems is as shown in figure 5.30. The average packed volume efficiency obtained by the observed methods is derived from averaging the results obtained in SHR1-8.

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Fig 5.30 The average packed volume efficiency of the packing methods for solving the different classes of packing problems (from the second experiment)

Similar to the first experiment, results from the second experiment shows that HTPA has the highest packed volume efficiency for solving the different classes of packing problems. By performing well in both experiments, it proves the robustness of HTPA in solving the 3, 5, 8, 10 and 12 cargo types packing problems.

Another phenomenon observed from figure 5.30 is the improvement in performance from CBGAT. In the first experiment, CBGAT performance in solving the different classes of packing problems is inferior when compared with MD's. However, in the second experiment, both CBGAT(w/o Overhang) and CBGAT(with Overhang) show an improvement in performance and produce better packing results when compared to MD's. This phenomenon shows that on the whole, the GA based CBGAT is still able to obtain better packing results as compared to the heuristic rules based MD packing method.

5.2.3.2 Effect of SH on $SD_{\text{packed-volume}}$

Similar to the earlier section, for the analysis on the effect of SH on $SD_{\text{packed-volume}}$, both the high performance and low performance groups of SH must be defined. For

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the definition of these two performance groups, the performance bands (high performance band, low performance band) must be used.

High performance band is used to identify SH sets where the observed method achieves minimum or near minimum $SD_{\text{packed_volume}}$. These SH sets are classified as the high performance group. Vice-versa, the low performance band is used to identify SH sets where the observed method achieves the maximum or near maximum $SD_{\text{packed_volume}}$. These SH sets are classified as the low performance group. High performance band is defined by a tolerance range above the minimum $SD_{\text{packed_volume}}$ obtained, while low performance band is defined by a tolerance range below the maximum $SD_{\text{packed_volume}}$ obtained as shown in figure 5.31.

Fig 5.31 Identification of the high performance and low performance groups of SH sets in $SD_{\text{packed_volume}}$ for an observed method in $SD_{\text{packed_volume}}$ using the performance bands

The high performance and low performance groups for the observed methods are identified for the 5 different classes of packing problems as shown in table 5.8 and 5.9. The tolerance for both high performance band and the low performance band is set at 1 percents. By obtaining the information on the high performance and low performance groups for the observed methods, the analysis with the effect of SH on $SD_{\text{packed_volume}}$ can then be carried out.

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Classes of Packing problems	3	5	8	10	12
HTPA	SHR3,6-8	SHR2-5,8	SHR4-6	SHR3-5	SHR3-4
CBGAT(w/o Overhang)	SHR3-5	SHR3,5,6	SHR4,5	SHR2-5	SHR1,3,4
CBGAT(with Overhang)	SHR3-6	SHR3-5	SHR4,5	SHR4,5	SHR1,3-6
MD	SHR2,8	SHR4-6	SHR3,5-7	SHR3,5	SHR3-5

Table 5.8 High performance groups of the observed methods in SD_{packed_volume} for solving the different classes of packing problems

Classes of Packing problems	3	5	8	10	12
HTPA	SHR1	SHR1,6	SHR8	SHR8	SHR8
CBGAT(w/o Overhang)	SHR7	SHR1,7	SHR7,8	SHR8	SHR8
CBGAT(with Overhang)	SHR7	SHR1	SHR8	SHR8	SHR8
MD	SHR7	SHR1	SHR1, 2, 8	SHR2, 8	SHR8

Table 5.9 Low performance groups of the observed methods in SD_{packed_volume} for solving the different classes of packing problems

a) Optimal SHRs in SD_{packed_volume} for solving the different classes of packing problem

From table 5.8, the optimal SHRs for obtaining low $SD_{packing_volume}$ in solving the different classes of packing problems can be derived. Being the optimal SHR for solving the particular class of packing problems, the SHR must be included in the high performance groups for all or most of the observed methods.

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Observing the information in table 5.8 shows that for 3 cargo types packing problems, SHR3 is in the high performance group for most of the observed methods. This shows that the observed methods perform optimally for solving 3 cargo types packing problems with SH of approximately 0.75.

Next, for 5 cargo types packing problems, SHR5 is in the high performance group for all the observed methods. This shows that all four of the observed methods perform optimally for solving 5 cargo types packing problems with SH of approximately 1.25.

The process of determining the optimal SHR in $SD_{\text{packed_volume}}$ repeated for the other classes of packing problems and the optimal SHRs in $SD_{\text{packed_volume}}$ for solving the different classes of packing problems are as given in table 5.10.

Classes of packing problems	3 types	5 types	8 types	10 types	12 types
Optimal SHR	3	5	5	5	3-4
SH	0.65-0.85	1.15-1.35	1.15-1.35	1.15-1.35	0.65-0.85, 0.90-1.10

Table 5.10 Optimal SHRs in $SD_{\text{packed_volume}}$ for solving the Qfferent classes of packing problems

b) Optimal SHRs in $SD_{\text{packed_volume}}$ for the observed methods

From table 5.8, the optimal SHR in $SD_{\text{packed_volume}}$ for the observed methods in solving the different classes of packing problems can be derived. Being the optimal SHR for the packing method, the SHR must be included in the high performance groups for solving all or most of the different classes of packing problems.

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Observing the information in table 5.2 shows that for HTPA, both SHR3 and SHR4 are in the high performance group for solving most of the five classes of packing problems. This shows that HTPA is able to perform optimally for solving the packing problems with SH of approximately 0.75 and 1.0.

Next, for CBGAT(w/o Overhang), SHR3, SHR4 and SHR5 are in the high performance group for solving four of the five classes of packing problems. This shows that CBGAT(w/o Overhang) is able to perform optimally for solving the packing problems with SH of approximately 0.75, 1.0 and 1.25.

The process of determining the optimal SHR is repeated for CBGAT(with Overhang) and MD, the optimal SHRs for the observed methods are then as given in table 5.11.

Packing Methods	HTPA	CBGAT(w/o Overhang)	CBGAT(with Overhang)	MD
Optimal SHR	3,4	3,4,5	4,5	5
SH	0.65-0.85, 0.90-1.10	0.65-0.85, 0.90-1.10, 1.15-1.35	0.90-1.10, 1.15-1.35	1.15-1.35

Table 5.11 Optimal SHRs for the different packing methods

From the above analysis, it shows that SHR3,4 and 5 are the popular SH range that can produce consistent packing results regardless of packing method used or the class of packing problems to be solved. Packing problems belonging to these 3 SH sets can get relatively lower $SD_{\text{packed_volume}}$ as compared to packing problems from other SH sets.

c) Worst SHRs in $SD_{\text{packed_volume}}$ for solving the different classes of packing problems

From table 5.9, the worst SHRs in $SD_{\text{packed_volume}}$ for solving the different classes of packing problems can be derived. Worst SHR in $SD_{\text{packed_volume}}$ is the SH set that has obtained the highest $SD_{\text{packed_volume}}$. Being the worst SHR for solving the different

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classes of packing problems, the SHR must be included in the low performance groups for all or most of the observed methods.

Observing the information in table 5.9 shows that for 3 cargo types packing problems, SHR7 is in the low performance group for most of the observed methods. This shows that the observed methods perform poorly for solving 3 cargo types packing problems with SH of approximately 1.75.

Next, for 5 cargo types packing problems, SHR1 is in the low performance group for all the observed methods. This shows that all four of the observed methods perform poorly for solving 5 cargo types packing problems with SH of approximately 0.25.

The process of determining the worst SHR in $SD_{\text{packed_volume}}$ is repeated for the other classes of packing problems and the worst SHRs for solving the different classes of packing problems are as given in table 5.12.

Classes of packing problems	3 types	5 types	8 types	10 types	12 types
Worst SHR	7	1	8	8	8
SH	1.65-1.85	0.15-0.35	1.90-2.10	1.90-2.10	1.90-2.10

Table 5.12 Worst SHRs in $SD_{\text{packed-volume}}$ for solving the different classes of packing problems

It is noted that initially the worst SHR in $SD_{\text{packed-volume}}$ for solving the lesser(3 types, 5 types) cargo types packing problems is SHR7 and SHR1 respectively. However, when solving for higher(8, 10, 12) cargo types packing problems, the worst SHR is constantly SHR8.

d) Worst SHRs in $SD_{\text{packed-volume}}$ for the observed methods

From table 5.9, the worst SHR in $SD_{\text{packed-volume}}$ for the observed methods to solve the different classes of packing problems can be derived. Being the worst SHR in consistency for the packing method, the SHR must be included in the low

performance groups for solving all or most of the different classes of packing problems.

Observing the information in table 5.9 shows that for HTPA, SHR8 is in the low performance group for solving three of the five classes of packing problems. Since SHR8 is in the low performance group more than any of the other SH sets, it is considered the worst SHR for HTPA to obtain consistency in packing results.

Next, for CBGAT(w/o Overhang), SHR7 and SHR8 are in the low performance group for solving three of the five classes of packing problems. SHR7 appears in the low performance group when solving for 3, 5 and 8 types cargo packing problems while SHR8 is in the low performance group for 8, 10 and 12 cargo types packing problems. Both are considered to be the worst SHR in consistency for CBGAT(w/o Overhang) in solving the packing problems.

The process of determining the worst SHR in $SD_{\text{packed_volume}}$ is repeated for CBGAT(with Overhang) and MD, the worst SHRs for the observed methods are then as given in table 5.13.

Packing Methods	HTPA	CBGAT(w/o Overhang)	CBGAT(with Overhang)	MD
Optimal SHR	8	7,8	8	8
SH	1.90-2.10	1.65-1.85, 1.90-2.10	1.90-2.10	1.90-2.10

Table 5.13 Worst SHRs in $SD_{\text{packed_volume}}$ for the different packing methods

From the analysis on the effect of $SD_{\text{packed_volume}}$, it shows that packing problems with SH of 0.75-1.25 (SHR3,4 and 5) can obtain more consistent packing results as compared to packing problems from other SH values. For SH sets that produce the most inconsistent packing results, SHR1 and SHR7 show high inconsistency when solving the 3 cargo types and the 5 cargo types packing problems respectively.

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However, for the higher(8, 10 and 12) cargo types packing problems, SHR8 shows the highest inconsistency in packing results regardless of the packing method used.

e) Explanation for the Trend of Reducing $SD_{\text{packed-volume}}$ obtained from the first Experiment

In the first experiment, it is observed that $SD_{\text{packed_volume}}$ reduces as the number of cargo types involved in packing increase. However, analyzing results from the second experiment proves this trend to be misleading. From section 4.3.2, it is known that test cases used in first experiment are skewed. Most of the test cases used have SH between 0.25-1.25. However, for the higher cargo types(8, 10, 12, 15, 20) packing problems, most test cases are instead from SH of 0.75-1.25 which coincide with the optimum SHRs in $SD_{\text{packed_volume}}$ (SHR3, 4 and 5) as shown in table 5.14. As more test cases are chosen from the optimal SHRs in $SD_{\text{packed_volume}}$, lower $SD_{\text{packed-volume}}$ will be obtained for solving the tested data sets. Therefore, it can be concluded that the improvement in $SD_{\text{packed_volume}}$ obtained in the first experiment is instead due to the skewed selection of test cases.

Data sets	3 types	5 types	8 types	10 types	12 types	15 types	20 types
Number of test cases with SH between 0.75-1.25	72	83	92	94	98	97	99

Table 5.14 Number of test cases in the data sets of the first experiment with SH between 0.75-1.25

5.2.3.3 Effect of SH on Processing Time

From the results obtained from the second experiment, it is observed that SH does not have any significant impact on the processing time required for a test case. This means that the processing time required for solving a test case with high SH is about

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the same as solving a test case with low SH. Although in earlier section, some minor variation in processing time is observed for the different SH sets, this variation is concluded to be due to the number of packing cargos involved instead of the SH of the test cases.

5.3 SUMMARY

In this chapter, two experiments are conducted and analyzed. The first experiment is based on the popular benchmark test proposed in Bischoff work[3] while the second experiment is proposed by the thesis in examining the effect of SH on packing results. It is proposed in the second experiment to use test cases from a wide range of SH from 0.25 to 2.00.

Three Different packing methods are studied in the experiments, namely Bischoff & Ratcliffs MD heuristic method, Gehring's GA based CBGAT and the proposed HTPA. For evaluation on the performance of the observed methods, the thesis looks into two main areas of performance. They are, the volume of cargos that are packed into the constraint packing space(packed volume efficiency) and the time taken to solve the packing problem (processing time efficiency). A good packing method should not only be able to produce densely packed results, but also to produce them in a time efficient manner.

In the first experiment, the experimental results show HTPA excel in the packed volume efficiency aspect. It gives the highest packed volume efficiency for all tested data sets as compared to the other observed methods. For processing time efficiency aspect, MD performs better and is a more time efficient method as compared to the more sophisticated GA based HTPA and CBGAT. MD takes only a fraction of the processing time required by HTPA or CBGAT to solve the packing problems. HTPA also shows a tendency of increasing processing time when more cargo types are involved in packing. This makes HTPA inappropriate to be used in time critical packing applications that involve numerous cargo types.

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For the overhang condition in CBGAT, the first experiment shows minimal improvement is obtained for packed volume efficiency. However, a significant($\approx 10\%$) decrease is observed in processing time required for packing. The significant decrease in processing time for CBGAT(with overhang) can be explained by the speeding up of the tower formation process due to overhanging allowed.

For the second experiment, to process the vast information obtained from the experimental results, performance bands are used. Performance bands are preset ranges used to identify SH sets that produce distinguish results when solved by the observed packing methods. In this thesis, two performance bands are proposed namely, the high performance band and the low performance band. The SH sets that fall in the high performance band is classified as the high performance group while the SH sets that fall in the low performance band is classified as the low performance group.

With the definition of the high performance groups, the optimal range of SH is identified for the different classes(3, 5, 8, 10 and 12 cargo types) of packing problems and for the different observed methods. Similarly, with the definition of low performance groups, the unfavorable range of SH for the different classes of packing problems and for the observed methods can be identified too. The overall results from the second experiment shows that HTPA has the highest packed volume efficiency for solving the different classes of packing problems as compared to the other observed methods. It typically outperformed the other three benchmark methods by 5-10% for each class of packing problems tested. By performing well in both the experiments, it proves the robustness of HTPA in solving the 3, 5, 8, 10 and 12 cargo types packing problems. HTPA also shows sign of shorter processing time for solving small cargo types packing problem but this advantage diminish as the number of cargo types involve in the packing problem increased. An enhancement on HTPA will be required for making the processing time less prompt to the number of cargo types involve in the three dimensional packing problems.

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The results from the second experiment also shows that the improvement in $SD_{\text{packed_volume}}$ obtained in the first experiment is due to the skewed selection of test cases instead of the class of packing problems being solved.

As for the analysis on the effect of SH on processing time, it is observed that SH does not have any significant impact on the processing time required for a test case. This means that the processing time required for solving a test case with high SH is about the same as one taken for solving a test case with low SH.

CHAPTER 6 CONCLUSION AND RECOMMENDATION

HTPA is proposed for optimal solving of the three dimensional packing problems. It is GA based and solves three dimensional packing problems in a tier packing manner. Unlike other conventional approaches that pack in similar manner, HTPA can choose between heuristic packing rules and GA to conduct its packing for each tier. Heuristic packing rules are used for solving less complex tier packing problems while GA packing is used for solving more complicated tier packing problems. By using appropriate packing methods for solving different packing problems, better packing results can be obtained in a time efficient manner.

HTPA proposes two new features in improving its packing capabilities for solving the three dimensional packing problems. Firstly, a grouping function is introduced. The grouping function named formation of homogenous cargo blocks is proposed for improving the performance of HTPA. Grouping of homogenous cargo blocks helps to simplify the packing problems as it groups similar cargos into a block, making it more effective to solve the three dimensional packing problem. Secondly, a predictive tool V_{exp} is introduced. V_{exp} is proposed for improving the overall packing efficiency that can be obtained from solving the three dimensional packing problems. It estimates the volume of cargos that will be packed in subsequent tiers, helping to choose the best current tier packing solution that will most likely to give the optimal overall packed volume efficiency.

For conducting experiments, SH is proposed as a common standard for creation of test cases for three dimensional packing problems experiments. SH classifies the heterogeneity of a test case according to the degree of shape variation in the packing consignment. By using shape variation in the packing consignment as a mean to define packing problems, SH is enable to make accurate interpretation for different packing conditions as according to the changes made in the elements of the packing consignment.

Two experiments are conducted in this thesis, the first one is the popular B&R experiment where the observed methods are require to solve seven different classes of

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packing problems. The second experiment proposed solving five different classes of packing problems with their test cases created from a wide range of SH. Four different packing methods are being examined in the experiments namely, Bischoff's MD, Gehring's CBGAT(with Overhang), Gehring's CBGAT(w/o Overhang) and the proposed HTPA. The experimental results are compared for packed volume efficiency and processing time taken for solving each test cases.

In packed volume efficiency, HTPA performs much better than the other three observed methods for both experiments. By performing well in both the experiments, it proves the robustness of HTPA in solving the three dimensional packing problems for packed volume efficiency. Both CBGAT(with Overhang) and CBGAT(w/o Overhang) perform relatively well in solving three dimensional packing problems for packed volume efficiency. Although they perform less ideal in the B&R experiment, they outperform MD in the second experiment. This shows that overall, the GA based CBGAT is still capable to produce better packing results as compared to the heuristic rules based MD packing method.

As for observation on effect of SH on packed volume efficiency, it is noticed from the second experiment that solving packing problems of SH values between 0.65 – 1.35 can usually get much better packing results than packing problems from other SH ranges. Vice-versa, solving packing problems of higher heterogeneity with SH of 1.65-2.10 usually obtains lousier packing results as compared to solving packing problems from other SH ranges.

For processing time efficiency aspect, MD performs better and is a more time efficient method as compared to the more sophisticated GA based HTPA and CBGAT. MD takes only a fraction of the processing time required by HTPA or CBGAT to solve the packing problems. HTPA also shows a tendency of increasing processing time when more cargo types are involved in packing. This makes HTPA inappropriate to be used in time critical packing applications that involve numerous cargo types. As for the analysis on the effect of SH on processing time, it is observed that SH does not have any significant impact on the processing time required for solving a packing problem. This means that the processing time required for solving a

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packing problem with high SH is about the same as one taken for solving a packing problem with low SH.

For the effectiveness of packing with overhang condition, the experiments show minimal improvement is obtained for packed volume efficiency. However, a significant decrease is observed in processing time required for packing. The significant decrease in processing time can be explained by the ease of packing with overhang condition allowed.

From the experiment, it can be observed that HTPA is capable to produce excellent packing results for the different classes of three dimensional packing problems. However, if the processing time taken for solving the packing problems is crucial and the packing problems are less complicated, heuristic rules based approaches such as the MD method will be a better choice.

Two recommendations are made for future work on this project. The first recommendation will be to remove tendency of increasing processing time for HTPA when more cargo types are involved in packing. This can be achieved by implementing a selection scheme to limit the number of cargo types to be considered for packing of each tier. By making this improvement, HTPA will be a more robust three dimensional packing method and the processing time taken for solving a packing problem will not fluctuate so drastically.

The second recommendation will be to implement HTPA for solving multi containers packing problems. Although many of the packing problems that are discussed in research work are single container packing problems, searching for a packing method to optimally solve multi container problems is of great importance too. This is especially true for real world applications (eg store packing, aircraft packing) that may need to pack the given cargos in more than one given packing area.

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