OPTIMIZATION OF SHIP ROUTING USING HYBRID GENETIC ALGORITHM

ISMAIL

THESIS SUBMITTED IN FULLFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

FACULTY OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY UNIVERSITY OF MALAYA KUALA LUMPUR

2014

ABSTRACT

Vehicle Routing Problem (VRP) relates to the problem of providing optimum service with a fleet of vehicles to customers. It is a combinatorial optimization problem. The objective is usually to maximize the profit of the operation. However, for public transportation owned and operated by government, accessibility takes priority over profitability. Accessibility usually reduces profit, while increasing profit tends to reduce accessibility. In this research, we look at how accessibility can be increased without penalizing the profitability. This requires the determination of routes with minimum fuel consumption, maximum number of ports of call and maximum load factor satisfying a number of pre-determined constraints, i.e. hard and soft constraints. The hard constraints are travel time, travel distance and the restriction that a route must contain at least one fuel port. Soft constraints concerns with ship draft and load factor. To solve this problem, we propose a hybrid genetic algorithm (hybrid GA).

A chromosome in the proposed hybrid GA consists of some sub-chromosomes and each sub-chromosome consists of Q-arm, P-arm and two centromere. The initial population is generated randomly for the centromere while Q-arm and P-arm are generated by the nearest neighbor. An improvement procedure is proposed to increase the performance of the hybrid GA. The improvement procedure ensures a chromosome with the best fitness is carried forward into the next generation.

To evaluate the algorithm, three experiments are carried out. The first experiment is to investigate performance of the hybrid GA algorithm over 11 benchmarks. The results from this experiment show that the hybrid GA has better performance compared to the general GA, the PELNI method and the heuristic algorithm. The second experiment is to generate routes using three algorithms discussed in the research. The results shows that the best routes are generated by the hybrid GA followed by the general GA while the PELNI method shows the worst performance. The best and the worst fitness of the best solution in the second experiment were recorded. It is used to study the performance of the hybrid GA when compared to the general GA. The third experiment is to generate optimum routes when the number of vehicle used is minimized. The result of the experiments show that the hybrid GA performance better than the other algorithms.

ABSTRAK

Masalah perjalanan kendaraan berkaitan dengan masalah dalam menyediakan perkhidmatan yang optimum dengan armada kenderaan kepada pelanggan. Ini merupakan kombinasi masalah pengoptimuman. Objektif yang biasa adalah untuk memaksimumkan keuntungan operasi. Walau bagaimanapun, bagi pengangkutan awam yang dimiliki dan dikendalikan oleh kerajaan, kebolehcapaian merupakan keutamaan berbanding keuntungan. Kebolehcapaian biasanya mengurangkan keuntungan, manakala peningkatan keuntungan cenderung untuk mengurangkan kebolehcapaian. Dalam kajian ini, kita melihat bagaimana kemudahan boleh ditingkatkan tanpa mengurangkan keuntungan. Ini memerlukan penentuan laluan dengan penggunaan bahan api minimum, bilangan maksimum pelabuhan yang dilayani dan faktor beban maksimum yang boleh memenuhi beberapa kekangan yang telah ditetapkan; kekangan keras dan lembut. Kekangan keras meliputi masa perjalanan, jarak perjalanan dan sekatan bahawa laluan mesti mempunyai sekurang-kurangnya satu pelabuhan bahan api. Kekangan lembut pula berkait dengan draf kapal dan faktor muatan. Untuk menyelesaikan masalah ini, kami mencadangkan *hybrid genetic algorithm* (*hybrid GA*).

Sebuah kromosom dalam *hybrid GA* terdiri dari sejumlah sub-chromosome dan setiap sub-chromosome terdiri daripada Q-arm, P-arm dan dua centromere. Populasi awal dihasilkan secara rawak untuk *centromere* manakala Q-arm dan P-arm dihasilkan melalui kaedah *nearest neighbor*. Satu prosedur penambahbaikan dicadangkan untuk meningkatkan prestasi *hybrid GA*. Prosedur tersebut memastikan kromosom dengan kecergasan terbaik dibawa ke generasi seterusnya.

Untuk menilai algoritma, tiga eksperimen dijalankan. Eksperimen pertama adalah untuk mengkaji algoritma *hybrid GA* melalui 11 tanda aras. Hasil daripada eksperimen ini menunjukkan bahawa *hybrid GA* mempunyai prestasi yang lebih baik berbanding dengan *general GA*, kaedah PELNI dan algoritma heuristik. Eksperimen kedua adalah untuk menjana laluan menggunakan tiga algoritma yang telah dibincangkan dalam penyelidikan. Hasilnya menunjukkan bahawa laluan yang terbaik dihasilkan oleh *hybrid GA* diikuti oleh *general GA* manakala kaedah PELNI menunjukkan prestasi terburuk. Eksperimen ketiga ialah untuk menjana laluan optimum apabila jumlah kenderaan yang digunakan adalah minimum. Hasil daripada ekperimen menunjukkan bahwa prestasi *hybrid GA* adalah lebih baik dibandingkan dengan kaedah lain.

ACKNOWLEDGMENTS

I would like to thank Almighty Allah SWT Most Gracious, Most Merciful.

I would like to express my deepest appreciation to my supervisor, Prof. Dr. Mohd Sapiyan Baba, for giving me the opportunity to express my ideas via this project, providing constructive feedbacks, unfailing support and overall help in all aspects of this work. He contributed too many valuable insights into my research and he also directed the entire process and the writing of this project. Without his supervision, this project would not have been possible.

I highly appreciate the efforts of Dr. Effirul Ikhwan Ramlan, Dr. Barnabé Dorronsoro, Dr. Ayed Atallah Salman, Prof. Kenneth A. De Jong and Dr. Claudia Archetti who shared their practical experiences and ideas. Thanks are also extended to all of my friends in Artificial Intelligence Laboratory for their input and cooperation during my study.

For financial support, I gratefully acknowledge University of Malaya.

DEDICATION

To my beloved:

Mother, Hjh. Siti Rahmah Mother in Law, Pn. Rokiah bte Ahmad Father, Hj. Drs. Muh. Yusuf Wife, Rohana bte Abd. Hakim

Daughters, Andi Almeira Zocha and Andi Regina Acacia

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LIST OF NOTATIONS

- T^k_{ij} *Tij =* Travel time by ship *k* sailing from port *i* to port *j* and stays in port *i* added travel time for sailing from port *j* to port *i* and stays in port *j*
- T_r^k $=$ Total time travelled for route *r* served by ship *k*
- T^k \equiv Maximum allowed routing time for ship *k*
- *nP* = Number of ports
- P^k $=$ Engine power of ship k (HP)
- q^k $=$ Seat capacity of ship k
- v^k $=$ Speed of ship k
- *k r Y* = Number of ports of call of ship *k* when serving route *r*

CHAPTER 1 INTRODUCTION

Transportation is fundamental to the development of a nation's industry and economy (Japan International Corporation Agency, 2004). Transportation problems are complex and involve solving multiple objectives at the same time. Many research groups worldwide have studied transportation problems; and have often simplified the issues using real world cases. The effectiveness of transportation systems depends on the suitability of routes for the various types of vehicles available. Related studies are known as vehicle routing problems (Pertiwi, 2005).

Vehicle routing problems, which are some of the most important studies in the fields of transportation, involves routes that are designed for the benefit of passengers and operators, employing optimal routes to meet the objectives and interests of both parties. Problems often faced by transportation service providers include limited allocation of resources (e.g. financial and infrastructure). Determining optimal routes must take into account the allocation of resources for an efficient transport service (Japan International Corporation Agency, 2004).

The vehicle routing problem is a combination of optimization processes seeking to service a number of customers with a number of vehicles. As a generic name, it is given to a whole class of problems in which a set of routes, for a fleet of vehicles based at one or more depots must be determined for geographically dispersed cities and customers (Cordeau et. al., 1997).

There are many variations that depend on the characteristics of the vehicles, customers, and facilities (Cordeau et. al., 1997). For example, the vehicles may be either identical or different (with respect to size); they may be restricted to serve each customer depending on their suitability and the customers; and the problem may involve a single facility or multiple facilities. Many cases require a combination of two or more of these variants in order to solve a real world problem.

1.1 Problem Statement

In public transportation owned and operated by the government the most important factors to consider are accessibility and profitability. Accessibility consists of how to maximise the number of ports of call and profitability consists of how to minimise fuel consumption whilst maximising the load factor by satisfying a number of predetermined constraints (PELNI, 2010).

Accessibility usually reduces profit; an increasing profit tends to reduce accessibility. To increase profit, fuel consumption may have to be reduced, but this may affect the number of ports of call. However, increasing profits by decreasing the number of ports of call will decrease accessibility. The goal of increasing profit can conflict with the aim of increasing accessibility. To overcome these problems, an operational strategy is required to minimise conflicts of interest between accessibility and profitability.

In this research, PELNI's routing was chosen as the case study. PELNI is a transportation company owned and operated by the Indonesian government. PELNI lost Rp . 1,427,610,866,209 in 2007 and Rp. 1,561,235,420,278 in 2008 (PELNI, 2008).

A way to reduce losses in existing available resources (i.e., ships and their crews) is the optimization of routes. There are two important things to consider in the optimum routes of our case study; namely accessibility and profitability. In this research, we used computational intelligence to help create a route that met both of these conditions.

PELNI operates ships of different sizes, types and capacities. Hence, the problem is deemed to be a Heterogeneous fleet Vehicle Routing Problem (HVRP). Table 1.1 shows the sizes, types, and capacities of the ships used.

N _o	SHIP	Capacity (Seats)	Engine Power (HP)	Speed (Knot)
1	KM. A W U	1,312	2,176	11
$\overline{2}$	KM. BINAIYA	1,325	2,176	12
$\overline{3}$	KM. BUKIT RAYA	1,518	2,176	13
4	KM. BUKIT SIGUNTANG	2,513	8,700	16
5	KM. CIREMAI	2,612	8,700	17
6	KM. DOBONSOLO	2,602	8,700	17
7	KM. DORO LONDA	3,204	11,587	17
8	KM. GUNUNG DEMPO	1,583	8,160	18
9	KM. KELIMUTU	1,198	2,176	10
10	KM. KELUD	2,404	11,587	18
11	KM. KERINCI	2,126	8,500	16
12	KM. LABOBAR	3,018	11,421	19
13	KM. LAMBELU	2,513	8,700	16.5
14	KM. LAWIT	1,198	2,176	11
15	KM. LEUSER	1,325	2,176	11
16	KM. NGGAPULU	3,410	11,587	18
17	KM. PANGRANGO	594	1,632	9
18	KM. SANGIANG	593	1,632	10
19	KM. SINABUNG	2,402	11,587	19
20	KM. SIRIMAU	1,312	2,176	11
21	KM. TATAMAILAU	1,312	2,176	11
22	KM. TIDAR	2,554	8,700	17
23	KM. TILONGKABILA	1,518	2,176	11
24	KM. UMSINI	1,518	8,500	16
25	KM. WILIS	595	1,632	10

Table 1.1 Sizes, types, and capacities of the ships owned by PT. PELNI (2010)

The sea depth of each port may be different and since PELNI uses a heterogeneous fleet, the ship's drafts would also be different. A ship may only visit a port if ship's draft is not equal to or greater than the sea's depth at that port. Hence, the routing is deemed to be a Site Dependent Capacitated Vehicle Routing Problem (SDCVRP). Table 1.2 shows the ship's draft of the ships used and the sea depths of each port shown in Appendix A.3.

No.	Ship	Ship Draft (meter)
1	KM. A W U	4.2
$\overline{2}$	KM. BINAIYA	4.2
3	KM. BUKIT RAYA	4.2
$\overline{4}$	KM. BUKIT SIGUNTANG	5.9
5	KM. CIREMAI	5.9
6	KM. DOBONSOLO	5.9
7	KM. DORO LONDA	5.9
8	KM. GUNUNG DEMPO	5.9
9	KM. KELIMUTU	4.2
10	KM. KELUD	5.9
11	KM. KERINCI	5.9
12	KM. LABOBAR	5.9
13	KM. LAMBELU	5.9
14	KM. LAWIT	4.2
15	KM. LEUSER	4.2
16	KM. NGGAPULU	5.9
17	KM. PANGRANGO	4.2
18	KM. SANGIANG	4.2
19	KM. SINABUNG	5.9
20	KM. SIRIMAU	4.2
21	KM. TATAMAILAU	4.2
22	KM. TIDAR	5.7
23	KM. TILONGKABILA	4.2
24	KM. UMSINI	5.9
25	KM. WILIS	4.2

Table 1.2 Ship drafts of the ships owned by PT. PELNI (2010)

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Each ship serves only one route, and that route must include at least one fuel port. If the number of fuel ports is more than one, the problem is then deemed to be a Multi Depot Vehicle Routing Problem (MDVRP). There are 12 fuel ports in Indonesia; namely

Ambon, Balikpapan, Belawan, Benoa, Bitung, Kupang, Makassar, Pontianak, Semarang, Surabaya, Tanjung Priok and Ternate (PELNI, 2010).

The distance travelled from port *i* to port *j* may not be the same as that of port *j* to port *i*. This results in an Asymmetric Vehicle Routing Problem (AVRP). The distances between two ports are shown in Appendix A.4.

By satisfying a number of predetermined constraints, we propose to determine a combination of routes that will have minimum fuel consumption, maximum number of ports of call, and maximum load factor. These constraints consist of two soft constraints and three hard constraints. The soft constraints are ship draft and load factor, and the hard constraints are travel time, travel distance, and that a route must include at least one fuel port.

A vehicle has to deliver to *n* different ports, and then have *n!* possible route solutions. If the number of ports is 10 then we have 3,628,800 possible route solutions and if the number of ships is 10 then we have 36,288,000 possible route solutions for a single objective. To demonstrate how difficult this problem can be; imagine that the number of ports is 65, and the number of ships is 25 with three objectives.

This research proposes the use of a population search algorithm (Liu et al., 2004) to solve the problem. Such algorithms operate on several generations of solution populations and are able to generate several solutions together in a single iteration. The population search algorithm is a branch of the meta-heuristic method and can be applied to multi-objective optimisation problems (Liu et al., 2004).

1.2 Aims and Objectives

This research aims to develop an algorithm that will find the optimal route for four different variants of vehicle routing problems i.e., the Heterogeneous fleet Vehicle Routing Problem (HVRP), Site Dependent Capacitated Vehicle Routing Problem (SDCVRP), Multi Depot Vehicle Routing Problem (MDVRP), and Asymmetric Vehicle Routing Problem (AVRP) with multiple goals. This problem arises from the real situation faced by PT. PELNI (an Indonesian state-owned ship company). Two important factors of this state-owned ship company are accessibility and profitability. The proposed algorithm is meant to:

- 1. Maximise the number of ports of call
- 2. Maximise the number of load factor
- 3. Minimise fuel consumption.

The objectives of this research are as follows:

i. Objective 1: To investigate a variety of vehicle routing problems with similarities to the ship routing problem in our case study.

The vehicle routing problem has many variations that depend on the characteristics of the vehicles, the customers, and the facilities. In many cases, a combination of two or more of these variants for solving a real world problem was needed. Therefore, we need determine the variant of the vehicle routing problem that has similarities with the ship routing problem in our case study.

ii. Objective 2: To identify the objective function and constraints of the ship routing problem in our case study.

In our case study, the two important factors to consider in the ship routing problem in our case study are accessibility and profitability. Accessibility and profitability will be used to analyse the performance of the routes. Therefore, we need to determine which suitable objective function can be used to analyse the performance of the routes in our case study.

Since the ships in PT. PELNI are of different sizes, this may restrict these vehicles from serving each port; depending on their suitability to the port. This will lead to both soft and hard constraints. Therefore, we need to determine the soft and hard constraints in our case study's ship routing problem.

iii. Objective 3: To develop an algorithm based on a population search algorithm

The proposed algorithm will be used to solve the problem of suitable objective functions by satisfying a number of predetermined constraints. Therefore, we need to determine how to represent the objective function and satisfy a number of predetermined constraints into a mathematical model.

This research proposes using a population search algorithm to solve the vehicle routing problem. Therefore, we need to determine how to represent the candidate solution into a population set.

This research seeks to develop an algorithm to find the optimal route in four different variants of the vehicle routing problem (as mentioned in Objective 1) and with multiple goals. Therefore, we need to determine how to develop an algorithm that can be used to solve four different vehicle routing problem variants with multiple goals.

iv. Objective 4: To evaluate the functionality and performance of the algorithm, by carrying out several experiments.

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The Performances of the algorithm proposed in Objective 3 can be evaluated by:

- Comparing the proposed algorithm with algorithms presented by other researchers.
- Comparing the routes generated by the proposed algorithm with the existing case study route.

1.3 Research Methodology

This research was carried out using the following four phases.

Phase 1 - Identifying the problem.

To give a deeper understanding of the ship routing problem, we reviewed literature by collecting information on other vehicle routing problems and identifying the relevant issues of ship routing in our case study. A study was conducted to investigate the performance measurement tools of ship routing and identify their efficiency in the existing route. Data about ships, passengers, and ports used was collected for the existing route.

Phase 2 - Mathematical representation of the problem.

To represent the problem in a mathematical form, we determined the objective function and constraints of the problem. We studied the variety of vehicle routing problems that were similar to the ship routing in our case study. We summarized our findings in Table 1.3.

The overall problem consists of minimising fuel consumption, maximizing the number of ports of call, and the load factor. Meanwhile, the constraints relates to the ship's draft, load factor, travel time, travel distance, and inclusion of at least one fuel port for each route.

Variety VRP	Description	
Heterogeneous fleet vehicle routing problem (HVRP)	Ships operate with different sizes, types and capacity.	
Site dependent capacitated	Sea depth of each port may be different; the ship	
vehicle routing problem	draft should not be equal to or greater than the sea	
(SDCVRP)	depth.	
Multi depot vehicle	Each ship serves exactly one route and the route must	
routing problem	include at least one fuel port where the number of	
(MDVRP)	fuel ports is more than one.	
Asymmetric vehicle	Sailing distance from port i to port j and port j to port	
routing problem (AVRP)	<i>i</i> may be different.	

Table 1.3 Variety of VRP with similarities to our ship routing problem

• Phase 3 - Development of the algorithm

To develop the algorithm, the problem was represented in a mathematical model. The algorithm was based on a population search algorithm. The nearest neighbour method was used during the initialisation process to increase the performance of the population search algorithm. Three algorithms were tested using our case study data; namely the heuristic algorithm, the general genetic algorithm, and the proposed algorithm.

• Phase 4 - Evaluation of the algorithm

Finally, in order to evaluate the algorithm, we carried out several experiments to determine whether it was effective at solving the ship routing problem in our case study. We also carried out several other experiments to measure the performance of the algorithms by comparing the results produced with those of the existing method.

1.4 Thesis Layout

This thesis contains six chapters. In this chapter, we begun by defining the problem statement, highlighting the importance of the vehicle routing problem, explaining the aims and objectives of this thesis, and briefly describing the research methodology.

Chapter 2 is a literature review of the ship routing problem used in our case study. Three aspects of ship transportation are described i.e., ports, vehicles used and the passengers/cargo being transported. The survey which was conducted on passenger ships in our case study is also presented.

In Chapter 3, the literature review of the vehicle routing problem variants associated with the ship routing problem in our case study are investigated. Algorithms used in earlier researches for solving vehicle routing problems are discussed.

Chapter 4 describes the development of the heuristics algorithm, the general genetic algorithm, and the proposed algorithm. Meanwhile, Chapter 5 presents the results of our experiments. Data from different algorithms were compared and a discussion on the experimental result is also presented in this chapter.

Finally, Chapter 6 presents the conclusions of the present research and suggests possible directions for future research.

CHAPTER 2 SHIP ROUTING PROBLEM IN INDONESIA

Transportation can be defined as the movement of people or goods for a particular purpose from one location to another using a transfer mode together with the appropriate infrastructure. Efficient transportation affects individuals, communities and economies and it could increase the rate of growth of a community (Christiansen et al., 2005).

Transportation system pattern can be defined by three basic variables i.e., the transportation system (T), the activity system (A) and the pattern of flows in the transportation system (F). The activity system is the pattern of social and economic activities while the pattern of flows in the transportation system is the origins, destinations, routes, and volumes of goods and people moving through the system (Christiansen et al., 2005).

Figure 2.1 Pattern of the relationships in transportation system

The kind of relationship identified among these variables i.e., the flow pattern in the transportation system is determined by both the transportation system and the activity system. There are three components that influenced the interaction of transportation system (Christiansen et al., 2005):

- 1) User (individuals), whether a shipper of goods or a passenger, makes decisions about when, where, how, and whether to travel.
- 2) Operator (groups), the operator of particular transportation facilities or services makes decisions about vehicle routes and schedules, prices to be charged and services offered, the kinds and quantities of vehicles to be included in the fleet, the physical facilities to be provided.
- 3) Regulator (government/institutions), makes decisions on taxes, subsidies, and other financial matters that influence users and operators; on the provision of new or improved facilities, and on legal and administrative devices to influence, encourage, or constrain the decisions of operators or users.

One of the problems commonly encountered in transportation system is to determine that the area has transportation services which are economical, efficient, and feasible so as to meet the transportation needs of users. The efficiency of a transportation system relies on choosing optimal routes (Pertiwi, 2005).

In general, routes are designed with the interests of both users and operators, so we get the optimal route expected to meet the goals. The problems often faced by transportation service providers are financial and infrastructure limitations. Service providers must choose these attributes wisely as determining the optimal routes must take into account the allocation of finances and infrastructure.

There are various modes of transportation including rail, motor vehicle, air and sea. In archipelagic countries with long shorelines and many distant islands, such as Indonesia, ship transportation plays a significant role in domestic trades (Christiansen et al., 2005). Indonesia is an archipelago that includes roughly 17,508 islands with a total area of 741,052 square miles and an area of ocean of 35,908 square miles. The Indonesian

archipelago stretches 3,181 miles from east to west (Longitude: 97ºE - 141°E) and 1,094 miles from north to south (Latitude: 6°N - 11ºS).

Indonesia needs a system of inter-island transportation that can assist in overcoming isolation arising from geographic differences. Increasing economic growth will lead to further shifts in air travel, but ship transportation still holds a very important role in Indonesia, given the vastness of the Indonesian archipelago (Japan International Corporation Agency, 2004).

PT. PELNI is a state-owned ship company that handles ship transportation problems in Indonesia. The establishment of PT. PELNI backed by a national mission aimed to smooth national distribution flows in Indonesia; particularly through sea transportation. PT. PELNI provides inter-region and inter-insular transportation facilities (PELNI, 2010). PT. PELNI has a vision to be a solid shipping line with an optimal national network. In order to realise that vision, PT. PELNI has the following missions (PELNI, 2010):

- 1) Managing and developing sea transportation in order to ensure the community's accessibility to support the realisation of 'wawasan nusantara' (PELNI, 2010).
- 2) Increasing the contribution of income to the state, and employees, and playing a role in the environmental development and services to the community.
- 3) Applying good corporate governance principles in all aspects of the company.

Figure 2.2 Indonesia archipelago

High profit can be obtained by not servicing the area with fewer passengers. However PT. PELNI is required to reach the widest possible area in Indonesia so that it can serve the purpose of transportation in relatively undeveloped areas, stopping at islands, including the small outer islands in Indonesia's marine line (PELNI, 2010). Therefore, it is necessary to find a solution to enable PT. PELNI to serve the purpose of transportation in relatively undeveloped areas, whilst still considering the profit.

2.1 Port

Geographically, distribution networks in Indonesia are divided into two main regions namely East Indonesia Region (Kawasan Timur Indonesia, KTI) and Western Indonesia Region (Kawasan Barat Indonesia, KBI). The KTI consists of 16 provinces e.g. Nusa Tenggara Barat, Nusa Tenggara Timur, Kalimantan Barat, Kalimantan Tengah, Kalimantan Selatan, Kalimantan Timur, Sulawesi Utara, Sulawesi Tengah, Sulawesi Selatan, Sulawesi Tenggara, Gorontalo, Sulawesi Barat, Maluku, Maluku Utara, Papua Barat and Papua; while the KBI consists of 17 provinces e.g. Nanggroe Aceh Darussalam, Sumatera Utara, Riau, Jambi, Sumatera Selatan, Bengkulu, Lampung, Kepulauan Bangka Belitung, Kepulauan Riau, DKI Jakarta, Jawa Barat, Jawa Tengah, DI Yogyakarta, Jawa Timur, Banten and Bali.

In 2010, PT. PELNI was serving 85 ports (PELNI, 2010):

1) 19 ports in eight provinces in KBI region: Belawan, Gunung Sitoli, Sibolga, Padang, Blinyu, Tanjung Pandan, Batam, Kijang, Letung, Midai, Natuna, Serasan, Tarempa, Tanjung Balai, Tanjung Priok, Semarang, Surabaya, Benoa and Denpasar.

Figure 2.3 National shipping networks served by PT. PELNI in 2010

2) 66 ports in 15 provinces in KTI region: Bima, Lembar, Ende, Kalabahi, Kupang, Labuanbajo, Larantuka, Loweleba, Marapokot, Maumere, Waingapu, Pontianak, Kumai, Sampit, Batu Licin, Balikpapan, Nunukan, Samarinda, Tarakan, Bitung, Karatung, Lirung, Miangas, Tahuna, Ulusiau, Banggai, Kolonedale, Luwuk, Pantolan, Poso, Toli Toli, Makassar, Parepare, Bau Bau, Kendari, Raha, Wanci, Gorontalo, Tongkabu, Ambon, Banda, Bula, Dobo, Geser, Ilwaki, Kisar, Leti, Namlea, Namrole, Saumlaki, Tepa, Tual, Sanana, Ternate, Fak Fak, Kaimana, Manokwari, Sorong, Agats, Biak, Jayapura, Merauke, Nabire, Serui, Timika and Wasior.

	SHIP	2010	
No.		KTI	KBI
$\mathbf{1}$	KM. Awu	13	5
\overline{c}	KM. Binaiya	8	$\overline{4}$
$\overline{3}$	KM. Bukit Raya	$\overline{2}$	16
$\overline{4}$	KM. Bukit Siguntang	$\overline{19}$	$\boldsymbol{0}$
5	KM. Ciremai	14	5
6	KM. Dobonsolo	11	$\overline{5}$
7	KM. Dorolonda	17	$\overline{1}$
8	KM. Gunung Dempo	9	$rac{3}{3}$
$\overline{9}$	KM. Kelimutu	21	
10	KM. Kelud	$\overline{0}$	$\overline{6}$
11	KM. Kerinci	$\overline{11}$	$\overline{1}$
12	KM. Labobar	10	$\frac{3}{5}$
13	KM. Lambelu	11	
14	KM. Lawit	$\overline{2}$	$\overline{9}$
15	KM. Leuser	$\overline{5}$	$\overline{7}$
$\overline{16}$	KM. Nggapulu	19	$\overline{0}$
$\overline{17}$	KM. Pangrango	18	$\overline{0}$
18	KM. Sangiang	24	$\boldsymbol{0}$
19	KM. Sinabung	19	\overline{c}
20	KM. Sirimau	$\overline{8}$	7
21	KM. Tatamailau	12	$\overline{0}$
22	KM. Tidar	14	$\frac{2}{1}$
$\overline{23}$	KM. Tilong Kabila	$\overline{21}$	
24	KM. Umsini	11	$\overline{1}$
25	KM. Wilis	11	3
		310	89
TOTAL			399

Table 2.1 Number of segments in KTI and KBI served by PT. PELNI (2010)

The sea depth of each port may differ from the other as shown in Appendix A.3. There are 12 fuel ports in Indonesia namely Ambon, Balikpapan, Belawan, Benoa, Bitung, Kupang, Makassar, Pontianak, Semarang, Surabaya, Tanjung Priok and Ternate (PELNI, 2010).

2.2 Ship

Ships operate between ports and are used for loading and unloading of cargo and passengers. They also need to load fuel, fresh water, and supplies, as well as to discharge waste. Ports impose physical limitations on the dimensions of the ships (ship draft, length and width), and charge fees for their services.

Ships come in a variety of types for different uses and it can be categorised based on (Japan International Corporation Agency, 2004):

1) Cargo ship

Cargo ships can be classified as followed:

- **Container ships** are cargo ships that transport their entire load in truck-size containers, in a technique called containerisation. They form a common means of commercial inter-modal freight transport.
- **Bulk carriers** are cargo ships used to transport bulk cargo items such as ore or food staples (rice, grain, etc.). A bulk carrier could be either dry or wet.
- **Tankers** are cargo ships for the transportation of fluids, such as petroleum products, chemicals, and vegetable oils.
- 2) Passenger ship

Most passenger ships operate on regular, frequent and return services. Passenger ships are part of the public transport systems of many waterside cities and islands.
3) Cargo-passenger ships

Cargo-passenger ships (called Roll-On/Roll-Off (RORO) ships) are cargo ships designed to carry wheeled cargo such as automobiles, truck, trailers or railway carriages. RORO vessels have built-in ramps which allow the cargo to be efficiently 'rolled on' and 'rolled off' the vessel when in port. In archipelagic countries, RORO is used as to carry passengers and their vehicles.

N ₀	SHIP	Capacity (Seats)	Engine Power (HP)	Speed (Knot)	Fuel Consumption (Liter(s)/Hours)	Performance (Miles/Hour)
1	KM. A W U	1,312	2,176	11	557.06	12.661
\overline{c}	KM. BINAIYA	1,325	2,176	12	557.06	13.812
3	KM. BUKIT RAYA	1,518	2,176	13	557.06	14.963
4	KM. BUKIT SIGUNTANG	2,513	8,700	16	2,227.20	18.416
5	KM. CIREMAI	2,612	8,700	17	2,227.20	19.567
6	KM. DOBONSOLO	2,602	8,700	17	2,227.20	19.567
7	KM. DORO LONDA	3,204	11,587	17	2,966.27	19.567
8	KM. GUNUNG DEMPO	1,583	8,160	18	2,088.96	20.718
9	KM. KELIMUTU	1,198	2,176	10	557.06	11.510
10	KM. KELUD	2,404	11,587	18	2,966.27	20.718
11	KM. KERINCI	2,126	8,500	16	2,176.00	18.416
12	KM. LABOBAR	3,018	11,421	19	2,923.78	21.869
13	KM. LAMBELU	2,513	8,700	16.5	2,227.20	18.992
14	KM. LAWIT	1,198	2,176	11	557.06	12.661
15	KM. LEUSER	1,325	2,176	11	557.06	12.661
16	KM. NGGAPULU	3,410	11,587	18	2,966.27	20.718
17	KM. PANGRANGO	594	1,632	9	417.79	10.359
18	KM. SANGIANG	593	1,632	10	417.79	11.510
19	KM. SINABUNG	2,402	11,587	19	2,966.27	21.869
20	KM. SIRIMAU	1,312	2,176	11	557.06	12.661
21	KM. TATAMAILAU	1,312	2,176	11	557.06	12.661
22	KM. TIDAR	2,554	8,700	17	2,227.20	19.567
23	KM. TILONGKABILA	1,518	2,176	11	557.06	12.661
24	KM. UMSINI	1,518	8,500	16	2,176.00	18.416
25	KM. WILIS	595	1,632	10	417.79	11.510

Table 2.2 Ships owned by PT. PELNI (2010)

In 2010 PT PELNI operates 25 passenger ships to service its routes as summarised in Appendix C.1 and each route was served by exactly one ship. Table 2.2 showed the

capacity, engine power, speed, fuel consumption per hour, and performance of ships used.

According to PT. PELNI's 2010 annual report, fuel cost was the greatest cost in operating passenger ships, as shown in Figure 2.4. Allocation for fuel cost (HSD = High Solar Diesel) in 2010 was about 55% of total cost.

Figure 2.4 Operational cost of PT. PELNI in 2010

Table 2.3 showed the income, total cost and fuel cost of each ship operated in 2010. The fuel cost was about 55% of total cost. Based on Table 2.3, each ship spend more on fuel than the value of their income except for KM. Binaiya, KM. Bukit Raya, KM. Bukit Siguntang, KM. Leuser, KM. Pangrango and KM. Sangiang. Based on Table 2.3, the total cost was greater than the total income of all ships.

Table 2.3 Income and cost of the ships owned by PT. PELNI in 2010

2.3 Passenger

The population of the KTI region is approximately 44,737,300 people with a land area of about 1,294,919.70 km2. Meanwhile, the population of the KBI region is approximately 189,428,600 people, with a land area of about $616,011.62 \text{ km}^2$ (Statistik, 2010). The average population density in KTI is 35 people/ km^2 and in KBI it is about 308 people/km².

Table 2.4 shows the number of embarkations and disembarkations of passengers in each province in 2010. The total number of passengers was 8,881,436; of which 7,090,147 (80 %) were from the KTI region and 1,791,289 (20 %) were from the KBI region. This shows that passengers in the KTI region dominated the services of PT. PELNI.

Table 2.4 Passenger distribution based on province

We conducted a survey on PT. PELNI's passenger ships between June and September 2011. Samples were recorded in June 2011, July 2012, and September 2012. These periods were chosen because June 2011 represented average days, July 2011 represented school holidays, and September 2011 represented the peak time (Ied). The total number of respondents was 500, of which 17 could not be used (invalid).

The distribution of samples was comprised of 30 % from KM. Lambelu, 30 % from KM. Kelud, and 40% from KM. Bukit Raya. KM. Lambelu sailed within the KTI region, KM. Kelud sailed within the KBI region, and KM. Bukit Raya sailed within both of these regions. The results of the survey, which show the characteristics of PT. PELNI's passengers, are presented as follows:

Figure 2.5 Characteristics of PT. PELNI passengers; based on gender

Figure 2.5 shows the characteristics of PT. PELNI passengers based on gender, where 77 % were male and 23 % were female. This shows that males dominated the services of PT. PELNI.

Figure 2.6 shows the characteristics of PT. PELNI passengers based on age, where the 16-25 age group was accounted for 19 %, the 26-35 age group 31 %, the 36-45 age group 33 %, the 46-55 age group 3 %, and those above 55 years old accounted for 3 %. This shows that the 36-45 age group dominated the services of PT. PELNI.

Figure 2.6 Characteristics of PT. PELNI passengers; based on age

Figure 2.7 shows the characteristics of PT. PELNI passengers based on marital status, where single passengers accounted for 41 % and married passengers 59 %. This shows that married passengers dominated the services of PT. PELNI. Interviews revealed that PT. PELNI passengers generally travelled with their families and friends.

Figure 2.7 Characteristics of PT. PELNI passengers; based on marital status

Figure 2.8 shows the characteristics of PT. PELNI passengers based on occupation. Fulltime students accounted for 24 %, housewives/not working accounted for 13 %, employees 27 %, official servants/military 4 %, entrepreneurs 28 %, and retirees 3 %. This shows that entrepreneurs dominated the services of PT. PELNI. Based on interviews, entrepreneurs bought goods from other islands (such as; Java and Batam) using the services of PT. PELNI. They did this because shipping costs were cheaper; and the process was safer because they accompanied their goods. Other occupational groups that dominated the services of PT. PELNI included employees. Based on interviews, employees generally came from other islands.

Figure 2.8 Characteristic of PT. PELNI passengers; based on the occupation

Figure 2.9 shows the characteristics of PT. PELNI passengers based on education. Primary education accounted for 4 %, secondary school was about 21 %, high school 60 %, diploma 5 %, and graduates 10 %. This shows that passengers with a high school education dominated the services of PT. PELNI.

Figure 2.9 Characteristics of PT. PELNI passengers; based on education

Figure 2.10 shows the characteristics of PT. PELNI passengers based on salary. Salaries less than Rp. 1,000,000 accounted for 39 %, salaries between Rp. 1,000,000 and Rp. 1,999,999 was 25 %, salaries between Rp. 2,000,000 and Rp. 2,999,999 was 39 %, salaries between Rp. 3.000.000 and Rp. 3,999,999 was 6 %, and salaries Rp. 4,000,000 and above was 1 %. This shows that the services of PT. PELNI were dominated by passengers with salaries between Rp. 2,000,000 and Rp. 2,999,999.

Figure 2.10 Characteristics of PT. PELNI passengers; based on salary

The survey shows that most of the passengers using PT. PELNI services were male, aged 36-45, married, entrepreneurs, high school educated, and earned an average salary of between Rp. 2,000,000 and Rp. 3,000,000 per month.

Results of the survey show that:

1) 43 % of passenger's main purpose of journey was to visit friends or relatives (as shown in Figure 2.11).

Figure 2.11 Main purpose of journey (2010)

2) 70 % travelled between islands infrequently (once or twice a year) as shown in Figure 2.12.

Figure 2.12 Frequently travelled between islands (2010)

3) 86 % said that they used PT. PELNI because it was cheap (reasonably priced) as shown in Figure 2.13.

Figure 2.13 Reasons to use PT. PELNI services (2010)

4) 64% of respondents relied on the services of PT. PELNI when they travelled between islands as shown in Figure 2.14.

Figure 2.14 Rely on the services of PT. PELNI (2010)

Based on the results, the main reason for passenger's use of ship transportation was to reduce transportation costs.

2.4 Earlier Research about the Routing Problem in PT. PELNI

PT. PELNI is a state-owned shipping company that was established to address the issue of ship transportation in Indonesia. According to their financial reports, operational costs were always an issue, where HSD costs were greater than that of their income; which always led to large subsidies being given. This was caused by PT. PELNI's requirement to reach the widest possible areas in Indonesia; so that they could provide transportation to relatively underdeveloped areas with fewer passengers. One way to dramatically reduce this problem is through improved routes (Ginting, 2003; Pertiwi, 2005).

Ginting (2003) used the concepts of relationship between the components of public transport performance to solve PT.PELNI's routing issues. Ginting (2003) used three components:

1) Service input e.g., operating expenses

The amount of resources expended to produce output (transport services).

- 2) Service output e.g., available seat capacity The number of service provider outputs.
- 3) Consumption e.g., operating revenue

The usage of the service output produced.

The relationship between public transport performances components are described as follows (Ginting, 2003):

1) Cost efficiency

The concept of cost efficiency is compared between service output and service input. Cost efficiency occurs when service output is greater than the input.

2) Service effectiveness

The concept of service effectiveness is compared between service output and consumption. Service effectiveness occurs when service output is equal to consumption.

3) Cost effectiveness

The concept of cost effectiveness is compared between service input and consumption. Cost effectiveness occurs when service input is equal to consumption.

Three indicators of this relationship, which is defined into the load factor, are calculated by:

$$
Load Factor = \frac{Pax on Board}{Search capacity}
$$
 (2.1)

Ginting (2003) proposed route optimisation for PT. PELNI by considering two aspects: 1) Frequency of ship visits on a route, and

2) Operating costs and tariff rates.

Optimisation was applied to existing routes without the creation of new routes. The addition of frequency of visits was made to the route that demanded a high load factor with a value of over 100%, and a reduction in the frequency of visits to the low demand routes below 65%. As a result, the voyage frequency of KM. Bukit Siguntang, KM. Dobonsolo, KM. Lambelu and KM. Kambuna would be reduced once a year. However, this could not be used to solve the real problem in PT. PELNI. According to an interview conducted with Mr Adi Karsyaf, SH., on 25th April 2011 "ships operated in PT. PELNI have at least 23 voyage times where a voyage time is equal to 14 days".

Another research conducted by Pertiwi (2005) proposed to re-organise routes of PT. PELNI in 2004. The ship routing issue was solved by using a set of covering heuristics. The solution approach consisted of the following two steps:

1) Generating routes

Feasible routes were generated to establish a set of routes that did not violate the constraints of sea-depth, travel time, and routes having at least one fuel port.

This phase was carried out by choosing the first port for the first ship and the next port was selected based on the shortest distance from the previous port. This was done until the travel time of a route was equal to (or less than) 14 days. This process was repeated for all other ships, the complete process of which is shown in Figure 2.15.

Figure 2.1 5 Generating routes in Pertiwi (2005)

2) Choosing the best routes

This phase aimed to choose a set of routes that satisfied constraints with minimum cost. A penalty would be imposed for routes that violated one or more constraints.

This phase was carried out by choosing the best combination of routes that served all of the ports and used all of the ships. The process of choosing the best routes is shown in Figure 2.16.

Figure 2.16 Choosing the best routes in Pertiwi (2005)

According to an interview conducted with Mr. Adi Karsyaf SH on 25th April 2011, he said that there are some disadvantages to the algorithm proposed by Pertiwi (2005), namely:

1) The travel distance is ignored.

PT. PELNI operates different types of ships; therefore, the fuel tank capacity of each ship is different. Since the fuel tank capacity of each ship is different the maximum travel distance of each ship would also be different.

2) The load factor is ignored.

The ideal load factor in PT. PELNI is 65 %.

3) The number of ports of call is ignored.

Since the number of ports of call is ignored, the route made is not supportive of the vision of PT. PELNI (could not be applied into a real situation in PT. PELNI).

In the research by Pertiwi (2005), the goal was to minimise the total voyage cost where the load factor and number of ports of call would be ignored. The solution produced offered to lower the total voyage cost by 9.72 %; compared to the existing 2004 route.

2.5 Summary

In this chapter, we discussed our case study i.e., PT. PELNI. The two most important parts of the PT. PELNI study are accessibility and profitability. Accessibility usually reduces profit, while an increase in profit tends to reduce accessibility. To increase profit, a route needs to have minimum fuel consumption, which affects the number of ports of call. PT. PELNI's ships use a High Solar Diesel (HSD) fuel and PT. PELNI spent 55 % of their total costs on for fuel in 2010.

Previous researches, related to the routing problem in PT. PELNI are shown in Table 2.5. The goal of the existing routes proposed by PT. PELNI is to maximise the number of ports of call, and the goal of the routes proposed by Pertiwi (2005) is to minimise fuel consumption. Ginting's (2003) proposed routes considered two aspects; namely frequency of ship visits on a route, and operating costs and tariff rates. However, this method could not be used to solve the real problem in PT. PELNI, because several ships would be reduced to one voyage a year.

		Profitability	Accessibility	
	Method Used	Fuel consumption	Load Factor	Number of Ports of Call
Existing route PT. PELNI (2010)	PELNI method	NO.	N _O	YES
Pertiwi (2005)	Set covering	YES	N _O	NO.
Ginting (2003)	Components of the performance of public transport adjusted	YES	YES	NO.

Table 2.5 Method used to solve the vehicle routing problem in PT. PELNI

Based on the literature review, no other research exists with the goals to maximise number of ports of call, maximise load factor, and minimise fuel consumption, which could be used to solve the real problem in PT.PELNI. We have conducted a study, and we will discuss the vehicle routing problem in the next chapter in order to investigate the vehicle routing problem variants associated with the ship routing problem, along with the methods used to solve each variant of the vehicle routing problem.

CHAPTER 3 VEHICLE ROUTING PROBLEM

A vehicle routing problem is a general combinatorial optimization problem that has become a key component of transportation management. Dantzig & Ramser (1959) first introduced vehicle routing problems. General vehicle routing problems are defined on connected graph *G*. Let $G = (V, A)$ be a graph where *V* is a set of nodes (vertices) and *A* is the set of arcs (edges). Let $C = (c_{ij})$ be a cost matrix associated with *A*. The matrix *C* is symmetric when $c_{ij} = c_{ji}$ and asymmetric otherwise.

A general vehicle routing problem consists of determining several vehicle routes with the minimum cost for serving a set of customers, whose geographical coordinates and demands are known in advance. A vehicle visits each customer only once. Typically, vehicles are homogeneous and have the same capacity restrictions. The vehicle must start and finish its tour at the depot, and the problem is to construct a route at the minimum travel cost. The VRP lies between the travelling salesman problem (TSP) and the bin-packing problem (BPP) (Falkenauer, 1996; Lupsa et al., 2010; Reinelt, 1994).

The travelling salesman problem aims to determine the shortest tour in which all the specified disjointed subsets of the vertices of a graph are visited. The travelling salesman needs to visit each city exactly once, starting and ending in his home town (Bonyadi et al., 2008; Greco & Gerace, 2008; Wei, 2008). The goal is to find the shortest tour through all the cities. To describe a travelling salesman problem as a vehicle routing problem, a vehicle routing problem with one depot, one vehicle with an unlimited capacity (or set all demands to zero), a cost function proportional to only the distance, and an arbitrary number of customers (cities) are used (Liu, 2008; Matai et al., 2010).

A bin-packing problem is described as follows: given a finite set of numbers (the item sizes) and a constant to specify the capacity of the bin, determine the minimum number of bins needed where all the items have to be inside exactly one bin and the total capacity of the items in each bin has to be within the capacity limits of the bin. In a bin packing problem, objects of different volumes must be packed into a finite number of bins to suit the vehicle capacity in a way that minimizes the number of bins used. A binpacking problem can be described as a vehicle routing problem by considering the variant of the vehicle routing problem with one depot and a cost matrix of all the zeroes (Falkenauer, 1996).

Some vehicle routing problem variants and the unique constraints are:

1. Multiple Depot Vehicle Routing Problem (MDVRP)

The multiple depot vehicle routing problem is a vehicle routing problem with multiple depots (Cordeau et al., 1997; Dondo & Cerdá, 2007; Nagy & Salhi, 2005; Renaud et al., 1996; Salhi & Sari, 1997).

2. Capacitated Vehicle Routing Problem (CVRP)

The capacitated vehicle routing problem is a vehicle routing problem with an additional constraint requiring all vehicles within the fleet to have a uniform carrying capacity for a single commodity. The commodity demands along any route assigned to a vehicle must not exceed the capacity of the vehicle. There are two types of capacitated vehicle routing problems:

i. Homogeneous fleet vehicle routing problem

In a homogeneous fleet vehicle routing problem (or uniform fleet vehicle routing problem), each vehicle in the fleet has the same capacity. The only difference is that a route is considered feasible if the total demand of all the customers on a route does not exceed the capacity Of the vehicle. The total demand of all the customers cannot be greater than the total capacity of all

the vehicles, and those vehicles must be big enough, i.e. the demand of a customer is never greater than the capacity of the vehicles (Lin et al., 2009; Nagata & Bräysy, 2009).

ii. Heterogeneous fleet vehicle routing problem

In a heterogeneous fleet vehicle routing problem (or HVRP), the fleet is composed of different vehicle types, each with its own capacity. Restrictions, similar to the ones defined for the homogeneous vehicle routing problem apply, for the maximum demand per route, and the maximum total demand is in relation to the capacity of the vehicles (Brandão, 2011; Choi & Tcha, 2007; Li et al., 2007; Ochi et al., 1998).

3. Site Dependent Capacitated Vehicle Routing Problem (SDCVRP)

A site dependent capacitated vehicle routing problem is a variant of the heterogeneous capacitated vehicle routing problem where not every type of vehicle can serve every type of customer because of site-dependent restrictions (Chao et al., 1998; Cordeau & Laporte, 2001; Nag et al., 1988).

4. Asymmetric Vehicle Routing Problem (AVRP)

An asymmetric vehicle routing problem is a vehicle routing problem with a travel distance from port *i* to port *j*, i.e., l_{ij} is not necessary equal to l_{ji} (Choi et al., 2003).

3.1 Multi Depot Vehicle Routing Problem

The multi-depot vehicle routing problem (MDVRP) is a general vehicle routing problem with multiple depots. A company may have several depots from which it serves customers. If the customers are clustered around the depots, it is possible to model these distribution problems as a set of vehicle routing problems. However, if it isn't clear which customers should be served from which depot, a multi-depot vehicle routing problem can be used to find the best solution (Nagy & Salhi, 2005; Salhi & Sari, 1997).

In a multi depot vehicle routing problem, each depot stores and supplies various products, and has a number of identical vehicles with the same capacity to serve customers who demand different quantities of various products. Each vehicle starts the tour from its resident depot, delivers products to a number of customers, and returns to the same depot (Cordeau et al., 1997; Renaud et al, 1996). The goal of a multi-depot vehicle routing problem, in which the total demand of commodities is served from several depots, is to make each route satisfy the constraints while beginning and returning to the same.

Ho et al. (2008) proposed using a hybrid genetic algorithm to solve multi-depot vehicle routing problem. They used three steps in the initialization, i.e. grouping, routing and scheduling. The grouping was done based on the distance between the customers and the depots, the routing was based on Clarke and Wright's saving method, while the scheduling was by the nearest neighbour heuristic. The objective was to minimise the total delivery time spent in the distribution by assigning the customers to the nearest depot. A computational study showed that the best results were achieved for the initial population by using the 'Clarke and Wright saving' method (Clarke & Wright, 1964). The nearest neighbours were randomly compared to the initial population.

3.2 Heterogeneous Fleet Vehicle Routing Problem

The capacitated vehicle routing problem (CVRP) is the most common and basic variant of the vehicle routing problem. The capacitated vehicle routing problem is a generic name given to a whole class of problems in which each vehicle has the same loading capacity, starts from only one depot, and then routes through to a number of customers (Lin et al., 2009).

A set of routes for a fleet of vehicles based together must be determined for a number of geographically dispersed customers, and the vehicles must be loaded to the maximum capacity. All customers have a known demand for a single commodity, each customer can only be visited by one vehicle, and each vehicle has to return to the depot. The service time unit can be transformed into a distance unit. The loading and travelling distance of each vehicle cannot exceed the loading capacity and the maximum travelling distance respectively of each vehicle. All the vehicles in the capacitated vehicle routing problem are homogeneous and have the same capacity, while the size of the fleet is unlimited (Nagata & Bräysy, 2009).

Many variants of the capacitated vehicle routing problem relax one or both of these conditions. One variant of the capacitated vehicle routing problem is the heterogeneous fleet vehicle routing problem (HVRP). In a heterogeneous fleet vehicle routing problem, the fleet is composed of a fixed number of vehicles with differences in their equipment, capacity, or cost, and in which the number of available vehicles is fixed as a priori (Baldacci et al., 2008; Gendreau et al., 1999; Pessoa et al., 2009; Taillard, 1999). The decision is how to best utilize the existing fleet to serve customer demands (Choi $\&$ Tcha, 2007; Li et al., 2007; Prins, 2009).

Vehicle routing problems are complicated in real-life contexts when the vehicle fleets are heterogeneous. Using a heterogeneous fleet of vehicles has multiple advantages. In some cases, it is possible to service customers requiring small vehicles because of accessibility restrictions. Notable examples are size and weight constraints which may even vary over time, as exemplified by the physical dimension constraints of a ship, including the draft restrictions of the ship that vary with the tide, the available berth space in ports and the sea depth of ports (Ochi et al., 1998; Penna et al., 2011; Yaman, 2006; Tarantilis et al., 2004).

In a heterogeneous fleet, vehicles of different carrying capacities provide the flexibility to allocate capacity according to the customers' varying demands in a cost effective way by deploying appropriate vehicle types to areas with analogous concentrations of customers (Prins, 2002; Subramanian et al., 2012; Tarantilis et al., 2003).

Jeon et al., (2007) used a hybrid Genetic Algorithm to solve the heterogeneous fleet vehicle routing problem (HVRP) and the multi-depot vehicle routing problem (MDVRP), where the initial population method simultaneously used both an initial solution by using a heuristic and a random generation method. The random generation method provided solutions created from random numbers and a global search. The initial population underwent the following techniques: a minimization process for an infeasible solution, a gene exchange process, a route exchange process, and a flexible mutation rate. The objective was to minimize distance and the results proved that the hybrid genetic algorithm performed better than the general Genetic Algorithm.

3.3 Site Dependent Capacitated Vehicle Routing Problem

A site-dependent capacitated vehicle routing problem is a variant of the heterogeneous capacitated vehicle routing problem where not every vehicle type is suitable for serving every customer because of site-dependent restrictions (Archetti et al., (2010); Cordeau & Laporte, 2001).

In a site-dependent capacitated vehicle routing problem, the fleet has many types of vehicles and there are vehicle site compatibilities between the customer sites and vehicle types. The problem consists of assigning compatible vehicle types to each customer and designing vehicle routes for the vehicles of each type, as in a vehicle routing problem (Chao et al., 1998; Nag et al., 1988). Chao et al. (1999) proposed an algorithm for

solving the dependent capacitated vehicle routing problem. The algorithm consists of two steps: obtain a feasible solution, and improve the feasible solution via a sequence of uphill and downhill moves.

3.4 Asymmetric Vehicle Routing Problem

An asymmetric vehicle routing problem (AVRP) is a variant of the heterogeneous capacitated vehicle routing problem (HCVRP), where travel distance from port *i* to port *j*, i.e., *lij,* does not necessary equal *lji* (Choi et al., 2003). An asymmetric vehicle routing problem is related to the asymmetric travelling salesman problem (ATSP). An asymmetric travelling salesman problem is a generalized travelling salesman problem in which the distance between a pair of cities is not the same from the opposite direction.

3.5 Solution to the VRP

The vehicle routing problem (VRP) occurs between the travelling salesman problem (TSP) and the bin-packing problem (BPP). The TSP and BPP are types of NP-hard combinatorial optimization problems. Thus, the existence of a known algorithm that can solve all cases to optimality in a reasonable execution time is not guaranteed.

Methods have been proposed for addressing the VRP. These methods are distinguished by using heuristics and metaheuristics. Some of the widely used solutions for various VRP combinations are illustrated in Figure 3.1.

Figure 3.1 Method used for VRP

3.5.1 Heuristic for VRP

The heuristic method is a procedure for solving mathematical problems by using an intuitive approach, wherein the structure of the problem can be interpreted and analysed intelligently to obtain a reasonable solution (Silver et al., 1980). Laporte and Semet (2002) classified the VRP heuristic methods based on the route construction methods into two groups: two-phase methods, and route improvement methods.

Novoa et al. (2006) developed a heuristic algorithm based on the maximum insertion concept to solve the VRP. Pertiwi (2005) used a set-covering heuristic to solve the ship routing problem. This solution approach consists of two steps, namely, the generation of shipping routes, and the selection of the best shipping routes.

Pertiwi (2005) adopted a nearest neighbour method to generate shipping routes. The nearest neighbour method compares the distribution of distances from a given point to its nearest neighbour. The nearest neighbour starts with a randomly chosen port and adds the nearest unvisited port to the last port in the tour until all the ports are visited.

3.5.1.1 Route Construction

Route construction methods are among the first heuristic methods for the VRP and are still implemented for several routing applications. These algorithms typically start from an empty solution and construct routes iteratively by inserting one or more customers until all the customers are served. Route construction methods have three primary components:

- 1. Initialization criterion
- 2. Selection criterion that specifies which customers are chosen for insertion at the current iteration
- 3. Insertion criterion to determine the location of chosen customers in the current routes

A heuristic approach in the route construction method is the saving algorithm. This algorithm was proposed by Clarke & Wright (1964). The saving algorithm is based on the concept of saving an estimate of the cost reduction obtained by sequentially serving two customers in the same route rather than in two separate routes. If *i* is the last customer of a route and j is the first customer of another route, the associated saving is defined as $s_{ij} = c_{i0} + c_{0j} - c_{ij}$.

The steps in the saving algorithm process are as follows:

- Step 1: *n* dedicated routes (round trips that service only one store) are determined; one route corresponds to one *n* store.
- Step 2: Savings in distance, s_{ii} , are computed by combining every possible pair of stores into one: $s_{ij} = c_{i0} + c_{0j} - c_{ij}$
- Step 3: Savings are ordered in a decreasing fashion. Given that negative *S* values are undesirable, negative values are omitted from the list.
- Step 4: A route is built by adding pairs that do not violate any of the set constraints in order to allow the pairs to appear in the list until the route is full or until the list has been exhausted. The resulting suppliers form a cluster.
- Step 5: Step 4 is repeated until all the stores are routed or until the list has been exhausted.

3.5.1.2 Two Phase (Clustering and Routing) Method

Two-phase methods are based on the decomposition of the VRP solution process into two separate sub problems:

1. Clustering

The partition of customers is defined as subsets that correspond to a route.

2. Routing

The sequence of customers is determined on each route.

In a cluster first - route second method, customers are first grouped into clusters, and the routes are determined by appropriately sequencing the customers within each cluster. In a route first - cluster second method, a giant tour of all the customers is constructed in the first phase and then subdivided into feasible routes.

A. Cluster First - Route Second Method

Different techniques have been proposed for the clustering phase, where the cluster first - route second method is employed in the routing phase. The sweep algorithm is often considered a cluster first - route second approach. This algorithm was developed by Gillett & Miller (1974), Wren (1971), and Wren $\&$ Holliday (1972).

The algorithm begins with an arbitrary customer and then sequentially assigns the remaining customers to the current vehicle. The assignment is accomplished by considering customers in the order of increasing polar angles with respect to the depot and the initial customer. If the assignment of the current customer to the current vehicle is not feasible, a new route is initialized for the current customer. Once all the customers are assigned to the vehicles, each route is defined separately by solving a vehicle routing problem.

Another algorithm under the cluster first - route second approach is the truncated branch-and-bound method developed by Christofides et al. (1979). In this algorithm, a set of routes is determined through an adaptation of an exact branchand-bound algorithm that employs a branching-on-routes strategy. The decision tree contains as many levels as the number of available vehicles. At each level of the decision tree, a given node corresponds to a partial solution that is composed of complete routes. The descendant nodes correspond to all possible routes including a subset of the un-routed customers. The running time of the algorithm is controlled by limiting the number of routes generated at each level to one.

B. Route First - Cluster Second Method

The route first - cluster second method is an alternative method for solving the vehicle routing problem. It starts from the route construction phase. In the route construction, the path representation encodes a unique, big journey that serves all the customers. The second step is clustering. The clustering procedure starts from an initial solution obtained based on the route construction phase, and it is clustered into feasible routes. The clustering procedure attempts to find a better neighbouring solution in terms of the number of vehicles, while maintaining solution feasibility (Beasley, 1983). Beasley (1983), Haimovich & Kan (1985),

and Bertsimas & Simchi-Levi (1996) provided several examples of algorithms classified under the route first -cluster second method.

3.5.1.3 Route Improvement

The problem in route improvement is the improvement of initial solutions generated by other heuristics. This problem can be solved by a Local Search algorithm. A Local Search algorithm starts from a given solution; hence, a Local Search method applies simple modifications, such as arc exchanges or customer movements, to obtain the neighbouring solutions efficiently. If an improved solution is identified, the new solution is used as the current solution and the process iterates; otherwise a local minimum is identified (Lin, 1965).

3.5.2 Metaheuristic for VRP

The word metaheuristic is derived from two Greek words: "heuristic" which means "to find" and "meta" which means "in an upper level." A metaheuristic is a high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristic optimization algorithms. Nowadays, metaheuristics are widely used to solve important practical combinatorial optimization problems. Several metaheuristics have been applied to the vehicle routing problem, e.g. Simulated Annealing (Kuo, 2010), Tabu Search (Lin et al., 2009), Genetic Algorithms (Liu et. al., 2009), and Ant Colony Optimization (Mazzeo & Loiseau 2004).

A. Simulated Annealing

Simulated Annealing is derived from the annealing process, in which a solid is heated until it melts. Subsequently, the temperature is slowly decreased (according to the annealing schedule) until the solid reaches the lowest energy or ground state. If the initial temperature decreases rapidly, the solid in the ground state will contain defects or imperfections. The simple implementation of the simulated annealing algorithm, which usually provides a local search with better results, facilitates its adoption into local search methods (e.g. the best improvement local search). However, although the algorithm has been proven to converge to the optimum, it converges in infinite time. Thus, in addition to the slow cooling requirements of the solid, this algorithm is not as fast as its counterparts (Kirkpatrick et al., 1983).

Kuo (2010) used the Simulated Annealing to solve the vehicle routing problem. The Simulated Annealing model requires the temperature to be cooled at each iteration. To decide on the initial temperature and the final temperature, Kuo (2010) applied the Simulated Annealing as follows:

- Choose temporary Simulated Annealing parameters.
- Use the temporary Simulated Annealing parameters to solve the proposed problem with several different initial solutions.
- Let *Z_{max}* be the maximum value when using different initial solutions to maximize the proposed problem.
- Let *Z_{min}* be the minimum value when using different initial solutions to minimize the proposed problem.
- Let $e^{(-(Zmax Zmin)/U)} = 0.5$ and $e^{(-(Zmax Zmin)x0.0001/UA)} = 0.05$, then find *U* and *U_A* where; *U* is the initial temperature and *U^A* is the final temperature.

B. Tabu Search

Glover proposed the Tabu Search in 1986 (Brandao, 2011; Zachariadis et al., 2009). The word "taboo" is derived from Tongan, which is a Polynesian language,

used by natives of the island of Tonga to refer to holy objects that cannot be touched. The basic principle of the Tabu Search is to pursue the best improvement of the Local Search whenever the latter encounters a local minimum by allowing non-improving moves. The rule employed in defining neighbourhoods is important to most local search heuristics (Gendreau et al., 1994; Gendreau et al., 2006; Glover, 1990; Osman, 1993).

Lin et al., (2009) used the Simulated Annealing method and combined it with the Tabu Search to solve the vehicle routing problem. Let,

X be generated using neighbourhood algorithm;

Xbest be the current best solution;

Y be the next solution;

 F_x be the objective function value of *X*;

Fcur be the current objective function; and

T be the current temperature.

First, the current temperature T is set to $T₀$ for the proposed algorithm. Next, an initial solution, *X,* is generated by a neighbourhood algorithm. The current best solution, *Xbest,* is set to be equal to *X*, and the current objective function value, *Fcur,* is set to be equal to the objective function value F_x of X . The obtained best objective function value, *Xbest,* is set to be equal to *Fcur*. For each iteration, the next solution *Y* is generated from *X* either by swap or by insertion where the new solution *Y* cannot belong to the Tabu move unless a new solution *Y* is the best solution found so far. *T* is decreased after running I_{iter} iterations from the previous decrease, according to the formula $T \leftarrow \alpha T$, where $0 < \alpha < 1$. The tenure of tabu move is reassigned by choosing an integral value when *T* is decreased once. The Tabu Search is terminated when a number of added moves are performed without any improvement over the best objective function value.

C. Genetic Algorithm

The Genetic Algorithm is derived from Darwin's Theory of Natural Selection and Mandel's work on genetics and inheritance. The Genetic Algorithm uses a stochastic search technique based on the mechanism of natural selection and natural genetics (Goldberg, 1989). The Genetic Algorithm differs from conventional search techniques because it begins with an initial set of random solutions called a population. Each individual in the population is called a chromosome, which represents a solution to the problem at hand.

Liu et. al. (2009) used the Genetic Algorithm to solve the vehicle routing problem. To populate the initial population, some of the chromosomes are generated as random sequences, and some by heuristics. The savings algorithm and the sweep algorithm are adapted. The tournament selection is chosen as the selection process. It is runs a tournament among a few individuals chosen at random from the population and selects the one with the best fitness. Individual chromosomes are ranked by their total cost. A chromosome with a smaller total cost has a better fitness. In Liu et. al. (2009), a string relocation, string crosses and a string exchange were used for the mutation, while an order crossover (OX) was used for the crossover.

D. Ant Colony Optimization

While walking from the food source toward the nest; and vice versa, ants deposit a substance called pheromone on the ground. This behaviour allows ants to determine the shortest path between the nest and the food source. When ants decide on the direction to follow, they choose the path that is characterized by a high probability level of pheromone concentration. This behaviour is the basis for the cooperative interactions that lead to the emergence of the shortest path

(Bianchi, 2006; Branke & Guntsch, 2004; Bullnheimer et al., 1999; Colorni et al., 1991; Dorigo & Stutzle, 2004; Fuellerer et al., 2009; Li et al., 2009).

Mazzeo & Loiseau (2004) used the Ant Colony Optimization for solving the capacitated vehicle routing problem and the details are provided as follows:

Step 1: Route building

In each iteration of the Ant Colony Optimization each ant builds a solution for the route, moving to the next client (stated in the general Ant Colony Optimization scheme) according to the transition rules based on a combination of the amount of pheromone at each arc.

Step 2: Transition rules

A neighbour client is randomly chosen according to the probability $P_k(i, j)$, where *k* is the number of vehicles starting with customer *i* and stopping with customer *j*.

Step 3: Pheromone actualization

There are two types of actualization; global actualization and local actualization. Global actualization is done after each iteration is completed, while local actualization is done each time an ant moves from customer i to the next customer j to decrease the amount of pheromone of a used edge (i,j) in order to diversify the solutions obtained by the ants.

Step 4: Reduced neighbour list

This is needed when the problem is too big for all the potential moves of the ant to be explored. A reduced list of best candidates is then used.

Step 5: Improved heuristics

Improved heuristics are used to modify the ant solutions after each iteration.

Step 6: Stopping rules

The Ant Colony Optimization procedure stops when there is no improvement to the solution after several iterations or when the number of iterations is reached.

3.6 Genetic Algorithm

In a Genetic Algorithm, the problem to be optimized must be stated in the objective function and it is called fitness. The individual with the best fitness value is given a high probability to reproduce in the next generation. For each generation in the evolutionary process, the best fitness value is referred to as the optimal solution.

The methodology of a general Genetic Algorithm is illustrated in Figure 3.2. The process follows five steps:

- Step 1: Generate a population, including chromosomes
- Step 2: Evaluate each chromosome
- Step 3: Selection process to choose chromosome with the best fitness
- Step 4: Manipulation for generating a new population of the current population
- Step 5: Return to step 2 and step 3 for *n* number of iterations. The process ends after the stopping criteria are met.

Figure 3.2 Genetic Algorithm; generate chromosomes, evaluate the fitness value, selection and recombination

The Genetic Algorithm is an unusual search strategy. In the Genetic Algorithm, a set of candidate solutions exists for problems. Typically, the set is initially filled with random possible solutions, all not necessarily distinct. Each candidate is an ordered fixed-length array of values (called alleles) for attributes (genes). Each gene is regarded as an atom in what follows; a set of alleles for a gene is the set of values that the gene can theoretically take. Thus, in building a Genetic Algorithm for a specific problem, the first task is to determine how to represent the possible solutions.
Chromosomes evolve through successive iterations called generations. The chromosomes with the highest fitness have the highest probability of being selected. After several generations, the algorithm selects the best chromosome, which is hoped to be the optimal solution to the problem. Two such mechanisms that link a Genetic Algorithm to the solved problem are a method of encoding solutions to the problem on chromosomes, and an evaluation function that returns a measurement of the worth of any chromosomes in the context of the problem.

During each generation, the chromosomes are evaluated using some measures of fitness. In each generation, all the chromosomes go through the processes of:

1. Evaluation

Using some predefined problem-specific measure of fitness, every member of the current set is evaluated to determine how good a solution it is to the problem. The measurement is called the candidate's fitness, and the idea is that the fitter the candidates are, the closer they are to being the sought after solution. However, the Genetic Algorithm does not require fitness to be a perfect measure of quality; often, poor solutions are assigned high fitness scores, despite being the less effective solution.

2. Selection

Pairs of candidate solutions are selected to form the current generation used for breeding. This may be done entirely randomly or stochastically based on fitness.

3. Breeding

New individuals are produced using genetic operators on the individuals chosen in the selection step. There are two main kinds of operators:

a. Merging two chromosomes from the current generation using a crossover operator where a new individual is produced by recombining the features of a pair of parents' solutions.

55

- b. Modifying a chromosome using a mutation operator, where a new individual is produced by slightly altering an existing one.
- 4. Recombination

The set is altered, typically by choosing to remove some or all of the individuals in the existing generation (usually beginning with the least fit) and replacing these with individuals produced in the breeding step. A population update is needed to keep the population size constant. The new population produced thus becomes the current generation.

The Genetic Algorithm has been reported to successfully solve the vehicle routing problem. Lau et al. (2010) compared the performance of four algorithms, namely the Branch and Bound algorithm (BB), the Simulated Annealing algorithm (SA), the Tabu Search algorithm (TS), and the Genetic Algorithm (GA). Tests were conducted for 25 depots and 250 customers. All the results are summarized in Table 3.1.

NO.			TOTAL COST	
	BB	SА	TS	GA
1	58379.31	54368.57	56229.26	51508.97
2	59264.72	52153.39	54384.11	51692.06
3	58103.46	53686.48	54921.08	50438.02
4	59759.41	53981.97	56537.65	49859.48
5	61037.95	52649.06	55446.69	50294.93
6	60648.28	51979.13	55263.52	48327.65
7	59519.53	54876.55	56785.27	51096.49
8	60229.11	53360.82	54276.68	49774.34
9	59398.03	52007.58	55894.92	50836.72
10	61645.27	51264.19	54690.81	48970.26

Table 3.1 Comparison of four algorithms (Lau et al., 2010)

From the results, the Branch and Bound algorithm shows the worst performance for all the ten sets while the Genetic Algorithm shows the best performance in all the sets.

A. Representing a Chromosome

Representing a chromosome is a key issue in the genetic algorithm, where chromosomes can be represented in real numbers or in a binary code. When real numbers are used for representing chromosomes, no encoding and decoding processes are needed to directly offer a solution. This saves computer memory and operating time (Goldberg, 1989). These factors are important considerations for large scale problems.

Figure 3.3 illustrates the chromosome encoding method by Lau et al. (2010). Each chromosome includes two parts for two factors. The first part is the number of customers each vehicle of each depot serves, and the second part is the order of customers each vehicle will serve.

Figure 3.3 Chromosome encoding method

From Figure 3.3, it is assumed that there are 20 customers and 2 vehicles in each of the 2 depots being considered. Vehicle 1 of depot 1 serves 6 customers (18, 5, 12, 10, 4, and 9) in order. Vehicle 2 of depot 1 serves 3 customers (7, 15, and 1) in order. Vehicle 1 of depot 2 serves 5 customers (16, 17, 20, 3, and 11) in order. Finally, vehicle 2 of depot 2 serves 6 customers (2, 6, 8, 14, 13, and 19) in order.

Ho et al. (2008) used path representation to encode solutions for the multi-depot vehicle routing problem. The idea of using path representation is so that customers are listed in the order in which they are visited and each chromosome contains *n* links if there are *n* depots in the multi-depot vehicle routing problem. For example, suppose there are 6 customers numbered 1 - 6 which the depot has denoted as 0. If the path representation is (**0 2 4 1 0 3 6 5 0**), then two routes are required to serve all these six customers. In the first route, a vehicle starts from the depot, travels to customers 2, 4, and finally customer 1. After that, the vehicle returns to the depot. In the second route, the vehicle starts with customer 3, moves to customer 6, and finally serves customer 5. The vehicle travels back to the depot after serving the customers.

B. Initial Population

Many researchers have proposed a hybrid method to increase the performance of the genetic algorithm. The hybrid Genetic Algorithm usually starts by modifying the initialization process. The initial population in a general Genetic Algorithm is generated randomly, while a heuristic method is used in the hybrid Genetic Algorithm.

The initialization process consists of three phases: grouping, routing and scheduling. Ho et al. (2008) developed two different initialization procedures called HGA1 and HGA2. The grouping, routing and scheduling are done randomly in HGA1. In HGA2, the grouping is based on the distance between the customers and the depots. The routing uses the 'Clarke and Wright Saving' method and the scheduling uses the Nearest Neighbour heuristic. A computational study was carried out to compare HGA1 and HGA2. It was shown that the performance of HGA2 is superior to that of HGA1 in terms of the total delivery time.

C. Evaluation

Evaluation is the process of calculating the objective function for each chromosome. The intention is to calculate a fitness value for each individual after the genetic manipulation process. An individual is evaluated, based on a certain function as the measurement performance. In the evolution of nature, the highest fitness values survive, whereas the low fitness values die (maximization); the fitness function is *F*. Fitness is a measure of the most practical solution for a particular problem.

There are two ways to overcome values that are found to be infeasible, usually because of constrained optimization, namely:

1. Modifying the Genetic Operator Strategy (Jeon et al., 2007)

One approach to the feasibility problem is to create a special operation to maintain the feasibility of the chromosomes.

2. Repairing Strategy (Lau et al., 2010)

Another option is to fix infeasible chromosomes with a repair procedure. The downside of the repairing strategy is that it is only workable for specific issues. For some problems, the repairing strategy process may be more complex than the problems it is applied to.

D. Selection

The selection process involves the selection of parent chromosomes and chromosome derivatives (offspring) based on fitness values, and the ordering of a new and better generation to find the optimal solution. Two basic rules are considered in the selection process, i.e.:

- 1. The number of chromosomes in each new generation is the same.
- 2. The duplication of some chromosomes in the new generation should be prevented to avoid the search being trapped in a local optimum. In addition, the values of the functions of the chromosomes that are close together are not preferred because these narrow the space of the exploration.

The most employed selection method is the roulette wheel. The roulette wheel selection enlarges the selection solution space to allow the parents and the next generation to compete (Jeon et al, 2007; Ho et al., 2008). The roulette wheel makes the selection probability for each chromosome a direct ratio to its fitness.

E. Crossover

A crossover is a genetic operation that is adopted to exchange information between two chromosomes for genetic exploration. Not all the chromosomes are chosen for a crossover. The number of chromosomes that undergo the gene exchange process in a generation is random and is chosen based on the probability of the gene exchange allowed, called the crossover rate (P_c) . For a high crossover rate, the process of finding the optimum solution can venture further into the exploration space, thus avoiding the likelihood of being trapped in a local optimum. However, it results in a long computer processing time, and the process can become excessive.

Figure 3.4 Single point crossover: One offspring consists of the gene from one parent into the left of the point, and from the other parent to the right of the point

A commonly used crossover process is the single cut-point crossover (Gen & Cheng, 1997), as as shown in Figure 3.4. This process allows one offspring to consist of the gene values from one parent, which is to the left of the point, and from the other parent which is right of the point. Swapping the parents and repeating the procedure produces a second offspring.

The steps for the single-point crossover process are as follows:

- Step 1: Select the crossover by using the crossover probability from the selected two parent chromosomes.
- Step 2: Select the crossing point(s) using the crossover probability and generate two children.
- Step 3: The first part that was not selected from parent 2 is passed to child 1 and is exchanged, and the second part that was not selected from parent 1 is passed to child 2 and is exchanged.

F. Mutation

Mutation is another genetic operation which provides diversity for the solutions so as to prevent them from falling into local optima. The mutation process produces genes that are more capable of keeping the chromosomes in the selection process and it is expected to produce a more optimal solution. The gene mutations that result in the least fit chromosomes are eliminated in the selection process.

Whether a gene is selected or not is determined by the mutation rate (P_m) . If the probability of mutation is low, then a possibly useful gene is noticed but should not be selected. Conversely, if the probability of mutation is high, then the offspring might lose the characteristics of its parents. This process results in the Genetic Algorithm losing the ability to learn in the process of finding the optimal solution (Gen $&$ Cheng, 1997). The process of gene selection replaces missing genes from the population caused by the selection process, and enables the re-emergence of genes that do not appear in the initial population. The selection process randomly selects genes to be altered. The number of selected genes depends on the probability of a predetermined mutation rate.

Point mutation was applied to vehicle allocations in Jeon et al. (2007). The steps for point mutation are as follows:

- Step 1: Select a gene randomly for mutation.
- Step 2: Change the vehicle number randomly.

G. Genetic Algorithm Parameters

The parameters of the Genetic Algorithm consist of the population size, the number of iterations, and the value of the mutation and crossover rates. Nothing definite is specified regarding the parameters of a Genetic Algorithm that is used to solve all problems. Table 3.2 shows a summary of the combinations of Genetic Algorithm parameters that can be used.

Paper	Population size	Iteration Number	Crossover rate (Pc)	Mutation rate (Pm)
Yan et al. (2006)	100	250	0.7; 0.8	0.2
Jeon et al. (2007)	200	10000	0.8	0.01
Ho et al. (2008)	25	500; 1000	0.4	0.2

Table 3.2 Summary of literature review for GA parameter

H. Improving the Performance of a Genetic Algorithm

An improvement procedure is usually needed for the multi-depot vehicle routing problem. The improvement procedure is used to improve the links of each initial solution and of each offspring generated by the genetic operators.

The improvement procedure may involve the interchange of customers within the same route (intra-route improvement), or within the same depot (intra-depot improvement). The improvement procedure may also involve swapping a customer from one route to another route (inter-route improvement), or from one depot to another depot (inter-depot improvement) (Ho et al., 2008).

Ho et al., (2008) adopted the iterated swap procedure (ISP) (Ho & Ji, 2003; 2004) to increase the performance of a Genetic Algorithm. The procedure for the iterated swap is as follows:

Step 1: Randomly select two genes from the link of a parent.

Step 2: Exchange the positions of the two genes to form an offspring.

- Step 3: Swap the neighbours of the two genes to form four more offspring.
- Step 4: Evaluate all the offspring to find the best one.
- Step 5: If the best offspring is better than a parent, replace the parent with the best offspring and go back to Step 1. Otherwise, discontinue the process.

3.7 Summary

This chapter reviewed some variants of the vehicle routing problem i.e. the multi-depot vehicle routing problem (MDVRP), the heterogeneous fleet vehicle routing problem (HVRP), the site-dependent capacitated vehicle routing problem (SDCVRP), and the asymmetric vehicle routing problem (AVRP). A summary of the literature that was reviewed in relation to the problems and the methods used to solve the problems is given in Table 3.3.

The discussion shows that there is no method that combines all four vehicle routing problem variants that are similar to the problem to be solved. The case studies have subject goals for accessibility and profitability. Thus, combining a fourth vehicle routing problem variant with goals should be considered, one that is not limited to a minimum travel distance, minimum cost or maximum profit.

Table 3.3 Summary of literature review on vehicle routing problem

CHAPTER 4 DEVELOPMENT OF ALGORITHM FOR SHIP ROUTING

This chapter presents the direction of the study and an overview of the methods used. It begins with building a vehicle routing problem model suitable for ship routing. The model design begins by determining and formulating the objective functions and constraints imposed by the model. These constraints are classified based on soft and hard constraints. Then the optimization model is developed using heuristic and metaheuristic concepts.

Figure 4.1 Research framework

The first step to solve vehicle routing problem in the case study is using genetic algorithm. A robust hybrid Genetic Algorithm is developed to increase the performance of genetic algorithm. Optimization results were obtained rather than verification and validation. The general steps of this research framework are summarized in Figure 4.1.

4.1 Ship Routing Problem Model

This study is focused on solving a problem with multiple depots, site dependent constraints, and heterogeneous vehicles, with asymmetric distances needing to be travelled. It is a combination of four variants of a vehicle routing problem, i.e. multi depot vehicle routing problem (MDVRP), heterogeneous fleet vehicle routing problem (HVRP), site dependent capacitated vehicle routing problem (SDCVRP), and asymmetric vehicle routing problem (AVRP).

4.1.1 Objective

The objectives of the problem are minimum fuel consumption, maximum number ports of call, and maximum load factor:

i. Minimum fuel consumption

The fuel consumption of each vehicle depends on the type of engine used. It is given by Equation 4.1 (PERTAMINA, 2010):

$$
f_{ij}^k = \eta^* P^k * \Phi^k * t_{ij}^k * \mu \tag{4.1}
$$

$$
t_{ij}^k = \frac{l_{ij}^k}{v^k} \tag{4.2}
$$

where,

 f_{ii}^k \equiv Fuel consumption for ship *k* sailing from port *i* to port *j η* = Constant (0.16)

 P^k = Engine power of ship *k* (HP)

- Φ^k = Number of engines used in ship *k*
- t_{ii}^k \equiv Voyage time for ship *k* sailing from port *i* to port *j*
- μ = Efficiency (0.8)
- l_{ii}^k *ij l =* Distance travelled by ship *k* sailing from port *i* to port *j*; *lij* is necessity equal to *lji*
- v^k $=$ Speed of ship k

The following is an example. Suppose depot v_0 serves three customers $(1, 2,$ and 3) with two different vehicles $(k_1 \text{ and } k_2)$ in its fleet. The total distance of the route: (0,1) (1,2) (2,3) (3,0) is 270 miles. The speed of *k¹* is 19 knots and that of *k²* is 17 knots, and the number of engines used is 1, respectively, whilst the power of k_l is 8,700 HP and *k²* is 2,176 HP. According to Equation 4.1 and Equation 4.2, the fuel consumption of k_l is 15,825.18 litres and k_2 is 4,424 litres. Although the ships serve the same route, travel costs are not the same because fuel consumptions are not equal.

ii. Maximum load factor

The load factor for ship *k* sailing from port *i* to port *j* donated by b_{ij}^k .

iii. Maximum number of ports of call

The number of ports of call of route *r* served by ship *k* donated by Y_r^k .

4.1.2 Constraints

Vehicle fleets tends to be mixed; vehicle types are slightly different. This implies that the ships have different load capacities, speeds and costs. There are two types of constraints: soft and hard constraints.

a. Soft Constraints

Two soft constraints for the ship routing problem are:

i. Ship draft and sea depth

If the ship-draft is equal to or more than the sea depth, it is anchored a few miles from the port. This incurs additional costs to carry passengers and cargo from ship to port and from port to ship. Thus, ship draft should not be equal or greater than the sea depth.

ii. Load factor

Ships with a large capacity should serve ports with more passengers to reduce costs due to the load factor. The load factor between two ports is calculated by Equation (4.3).

$$
b_{ij}^k = \frac{\gamma_{ij}^k}{q^k} \tag{4.3}
$$

where,

$$
b_{ij}^k = \text{Load factor for ship } k \text{ sailing from port } i \text{ to port } j
$$
\n
$$
\gamma_{ij}^k = \text{Load factor for ship } k \text{ sailing from port } i \text{ to port } j
$$
\n
$$
q^k = \text{Search capacity of ship } k
$$

Soft constraints are dealt with by imposing a penalty if a route exceeds the limit. The penalties imposed are:

- i. Ship draft and sea depth: 2000 litres when ship draft is equal to or more than the sea depth;
- ii. Load factor: imposed penalty of 5000 litres for loads more than 100 %; imposed penalty of 2000 litres for load factors less than 50 %; and an imposed penalty of 1000 litres for load factor between 50 % and 65 %.

b. Hard Constraints

Hard constraints are dealt with by removing unfeasible routes. Hard constraints in the ship routing problem include:

i. Travel time

The maximum duration of each tour is called commission days, T^k , which is 14 days in this case. Hence, a ship must return to the depot within T^k . If T_r^k is the ship's travel time, then $T_r^k \leq T^k$.

 T_r^k is calculated by Equation 4.4 and Equation 4.5.

$$
T_{ij}^k = \left(\frac{l_{ij}^k}{v^k} + t_j^k\right) + \left(\frac{l_{ji}^k}{v^k} + t_i^k\right)
$$
\n
$$
(4.4)
$$

where,

 T_{ii}^k $=$ Travel time by ship *k* sailing from port *i* to port *j* and stays in port *i* added travel time for sailing from port *j* to port *i* and stays in port *j*

$$
l_{ij}^k
$$
 = Distance travelled by ship *k* sailing from port *i* to port *j*; *l_{ij}* is necessity equal to *l_{ji}*

- l^k_{ii} *ji l =* Distance travelled by ship *k* sailing from port *j* to port *i*; *lji* is necessity equal to *lij*
- *k i t =* Port time of ship *k* that stays in port *i*
- *k j t =* Port time of ship *k* that stays in port *j*

$$
v^k = \text{Speed of ship } k
$$

$$
T_r^k = \sum T_{ij}^k \tag{4.5}
$$

where,

 T_r^k *T^r =* Total time travelled for route *r* served by ship *k*

 T_{ii}^k $=$ Travel time by ship *k* sailing from port *i* to port *j* and stays in port *i* added travel time for sailing from port *j* to port *i* and stays in port *j*

ii. Travel distance

Each ship has a different fuel tank size, hence the maximum distance, L^k , travelled is different. The total distance of route *r*, L_r^k , must be less or equal to the maximum distance, *i.e.* $L_r^k \leq L^k$.

 L^k is calculated by Equation 4.6 while L^k is calculated by Equation 4.7 and Equation 4.8.

$$
L^k = \frac{\theta^k * v^k}{\eta * P^k * \Phi^k * \mu} - (v^k * 24)
$$
\n(4.6)

$$
L_{ij}^k = l_{ij}^k + l_{ji}^k \tag{4.7}
$$

$$
L_r^k = \sum L_{ij}^k \tag{4.8}
$$

where,

 L^k *L =* Maximum allowed routing distance for ship *k*

 θ^k *=* Maximum capacity of the ship's tank

$$
v^k = \text{Speed of ship } k
$$

η = Constant (0.16)

- P^k = Engine power of ship *k* (HP)
- Φ^k = Number of engines used in ship *k*

 μ = Efficiency (0.8)

- L_{ii}^k *Lij =* Travel distance by ship *k* sailing from port *i* to port *j* and stays in port *i* added travel distance for sailing from port *j* to port *i* and stays in port *j*
- l_{ii}^k *ij l =* Distance travelled by ship *k* sailing from port *i* to port *j*; *lij* is necessity equal to *lji*
- l_{ii}^k Distance travelled by ship k sailing from port j to port i ; l_{ji} is necessity equal to *lij*
- L^k *L^r =* Total distance travelled for route *r* served by ship *k*
- iii. Fuel port

A route includes by necessity at least one fuel port.

4.1.3 Mathematical Model

Let, $G = (P, A)$ be a graph, where $P = \{1, 2, ..., M+N\}$ is the index set of ports (nodes) and $A = \{(i, j) \mid i, j; i \leq j\}$ is the set of arcs (links). Every arc (i, j) is associated with a distance matrix $L = l_{ij}^k$, which represents the asymmetric travel distance from port *i* to port *j*, i.e., *lij* is not necessarily equal to *lji.* In order to present the mathematical formulation of the models, we used the following:

Notation

C is the index set of customer ports, $C = \{1, 2, ..., M\}$ *D* is the index set of fuel ports, $D = \{1, 2, ..., N\}$ *K* is the index set of ships, $K = \{1, 2, ..., S\}$

Parameter

Decision variables

- \bullet $\overline{\mathcal{L}}$ $\left\{ \right.$ $=\begin{cases} 1 & \text{if ship } k \text{ s} \\ 0 & \text{otherwise} \end{cases}$ 1 if ship k sailing from port i to port j on route , $x_{r,ij}^k = \begin{cases} 1 & \text{if ship } k \text{ sailing from port } i \text{ to port } j \text{ on route } r \\ 0 & \text{otherwise.} \end{cases}$
- \bullet *α* denotes the penalties incurred when the ship draft of ship k is equal to or more than the sea depth of port i. Imposed penalty of 2000 litres when the ship draft is equal to or more than the sea depth.

$$
\alpha = \begin{cases} 2000 & \delta_k \ge h_i \\ 0 & \text{otherwise} \end{cases}
$$

 β denotes the load factor penalties for ship k sailing from port *i* to port *j*. Imposed penalty of 5000 litres for loads more than 100 %, imposed penalty of 2000 litres for a load factor less than 50 %, and 1000 litres for a load factor between 50 % and 65 $\%$.

 \mathbf{I} \downarrow \mathfrak{r} \vert ₹ $\left\lbrack \right.$ $\leq b_{ii}^{\,\kappa} <$ \lt $>$ $=$ 0 otherwise 1000 $50 \le b_{ii}^k < 65$ 2000 $b_{ii}^k < 50$ 5000 $b_{ii}^k > 100$ *k ij k ij k ij b b b* β

 γ denotes the penalties for the number of ports of call when ship *k* serves route *r*. Imposed penalty of 2000 litres for the number of ports of call between 15 and 20.

 $\overline{\mathcal{L}}$ $\left\{ \right.$ \int \leq Y_{r}^{k} \leq \lt \overline{a} 0 otherwise 1000 $15 \le Y_r^k \le 20$ 2000 Y_r^k <15 *k r k r Y Y* γ

Problems arise in constructing routes with minimum fuel consumption with a feasible set of routes for each vehicle. A feasible route for ship *k* serves ports without exceeding the constraints:

- 1. Total travel time T_r^k for any vehicle is no longer than T^k
- 2. Total travel distance L_r^k for any vehicle is no longer than L^k
- 3. The feasible route includes by necessity at least one fuel port

The mathematical formulation is given in Equation 4.9:

$$
min \sum_{k \in K} \sum_{i,j \in P} f_{ij}^k \cdot x_{r,ij}^k + \sum_{k \in K} \sum_{i,j \in P} \alpha \cdot x_{r,ij}^k + \sum_{k \in K} \sum_{i,j \in P} \beta \cdot x_{r,ij}^k + \gamma \sum_{k \in K} Y_{r}^k \qquad (4.9)
$$

where,

 f_i^k \bar{f} **finally** Fuel consumption for ship *k* sailing from port *i* to port *j*

- α = Penalties when ship draft of ship *k* is equal to or more than the sea depth of port *i*
- β = Penalties of the load factor of ship *k* when sailing from port *i* to port *j*
- *γ* = Penalties of the number of ports of call when ship *k* serve route *r*
- *k r Y* = Number of ports of call of ship *k* when serving route *r*

The objectives is to minimize total fuel consumption on routes travelled, the penalty cost for violations of the ship draft and sea depth, the penalty cost for violations of the load factor, and the penalty cost for violations of the number of ports of call. Subject to:

1. All ports (customer and fuel ports) *i* are serviced by ship *k* at least once.

- 2. Travel time of ship *k* is no longer than the maximum allowed routing time T^k .
- 3. Total distance travelled for route *r* served by ship *k* is no longer than the maximum allowed routing distance of ship *k*.
- 4. Ship draft of ship *k* must be less than the sea depth of port *i*.
- 5. Route *r* served by ship *k* should possess a fuel-port.

The feasible route combination should meet the requirements:

- Each route is served by one ship
- Each port is served at least once
- Each route has at least one fuel port
- Each ship has a total travel time within 14 days
- Each ship does not exceed the allowed travel distance

4.2 Heuristic Method

This study uses a heuristic method 'cluster first and route second' (Gillett & Miller, 1974), adopted for solving four VRP variants. The method involves three phases; clustering, assigning of vehicles, and finding the best routes by combining feasible solutions.

4.2.1 Heuristic for Ship Routing Problem

The three phases of the algorithm are:

(i) Phase I: Clustering

Routes are clustered to solve the problem based on the constraints of travel time and travel distance allowed for each route. Travel time is less than or equal to the maximum travel time allowed, and the travel distance is less than or equal to the maximum travel distance allowed. The output is a feasible route set for the solution candidate. Process for clustering shows in flowchart, Figure 4.2.

(ii) Phase II: Assigning Vehicle

Vehicles are assigned in a cluster to ensure each route has at least one fuel port. A route is removed if this condition is violated. In this phase, fuel consumption is calculated with penalty α imposed if the ship's draft is equal to or greater than the sea depth, penalty *β* for the load factor conditions, and penalty *γ* for the number of ports of call. Assigning vehicle processes shown in flowchart, Figure 4.3.

(iii) Phase III: Finding Best Routes

A robust algorithm was developed based on the maximum-insertion concept (Pertiwi, 2005). The heuristic model with the maximum-insertion concept is modified with the idea of successively inserting a route into the best combination of routes with minimum fuel consumption. Finding best routes processes shown in flowchart, Figure 4.4.

Figure 4.2 Clustering

Figure 4.4 Finding best routes

4.2.2 Illustration of Heuristic

Understanding diagram of how the proposed algorithm works is seen below. The specification data on the ports is in Table 4.1. The distance between ports is found in Table 4.2. Table 4.3 shows, the number of passengers on board. Ships' specifications are described in Table 4.4.

Port	Sea Depth	Port Time of Ship (hour)	Fuel Port	
	(meter)		$\mathbf{2}$	(Yes / No)
	10		3	N _o
2	5.6	3	3	N ₀
3	7.5	5	5	No
				No
	13	3		Yes
	10		3	Yes

Table 4.1 Specification of the ports

Table 4.2 Distances

(i, j)	1	2	3	4	5	6
	$\overline{0}$	2675	1443	1859	1055	524
$\boldsymbol{2}$	2672	0	1206	568	1089	1804
3	1443	1216	θ	796	128	1021
$\overline{\mathbf{4}}$	1859	568	793	θ	611	1542
5	1055	1089	128	611	θ	801
6	532	1804	1037	1542	794	

Table 4.3 Passengers on board

(i, j)	1	2	3	4	5	6
	$\overline{0}$	1331	1237	1102	1203	1905
$\boldsymbol{2}$	2135	θ	1300	1500	2975	1180
3	1237	1420	θ	1525	2198	1325
4	2102	1500	1525	θ	2090	1770
5	1204	1275	1198	1200	θ	1260
6	1405	1180	1325	2570	1160	0

		Ship		
No.	Specification	1	2	
$\mathbf{1}$	Seat Capacity	3,018	1,325	
$\mathbf{2}$	Engine Power (HP)	11,421	2,176	
3	Speed (Knot)	19	11	
4	Ship Draft (meter)	5.9	4.2	
5	Fuel Consumption (liter/hour)	140.24	45.65	
6	Commission Days	336	336	
7	Tank Capacity (liters)	870,230	342,300	
8	Number of Machine Used	2	2	

Table 4.4 Specification of the ships

Phase I: Clustering routes based on the constraints of travel time and distance allowed.

Step 1: Check for the ship

 $K = \{1, 2\}$ is the index set of ships where the number of ships is 2.

Ship $k = 1, k \in K$

Step 2: Check for the port

 $P = \{1, 2, 3, 4, 5, 6\}$ is the index set of ships where the number of ports is 6.

Port $i = 1$; put port₁ into the temporary set of routes.

Step 3: Find the next nearest port

Find port *j,* $j \in P$; where *j* is the next nearest port to *i*. The next nearest port is calculated

by Equation 4.10.

$$
l_{\min(i,j)} = \frac{l_{ij} + l_{ji}}{2} \tag{4.10}
$$

(i, j)	1	2	3	4	5	6
1	$\boldsymbol{0}$	2675	1443	1859	1055	524
$\overline{2}$	2672	θ	1206	568	1089	1804
3	1443	1216	θ	796	128	1021
$\overline{\mathbf{4}}$	1859	568	793	θ	611	1542
5	1055	1089	128	611	$\overline{0}$	801
6	532	1804	1037	1542	794	θ

Table 4.5 The next nearest port to port-1

Port $j =$ port₆; $j \in P$.

Put port $_6$ into the temporary set of routes.

The temporary route is 1 - 6.

Step 4: Check for $T_r^k \leq T^k$

Check for $T_r^k \leq T^k$.

 T^k is the maximum allowed routing time (*commission days*) for ship *k*.

Count T_{ij}^k and T_r^k by Equations 4.4 and 4.5.

For $i =$ port₁, $j =$ port₆.

$$
T_{ij}^{k} = \left(\frac{l_{ij}^{k}}{v^{k}} + t_{j}^{k}\right) + \left(\frac{l_{ji}^{k}}{v^{k}} + t_{i}^{k}\right) \rightarrow T_{(1,6)}^{1} = \left(\frac{l_{(1,6)}^{1}}{v^{1}} + t_{6}^{k}\right) + \left(\frac{l_{(6,1)}^{1}}{v^{1}} + t_{1}^{k}\right) = \left(\frac{524}{19} + 8\right) + \left(\frac{532}{19} + 5\right) = 68.58
$$

$$
T_{r}^{k} = T_{ij}^{k} + (T_{ij-1}^{k}) \rightarrow 68.58 + 0 = 68.58
$$

Since $T_r^k \leq T^k$ then continue to count of L^k

Step 5: Check for $L_r^k \leq L^k$

Check for $L_r^k \leq L^k$.

Count L^k by Equation 4.6; For $k = \text{ship}_1, L^1 = 5088.7$

For $i =$ port₁, $j =$ port₆

Count L_r^k by Equations 4.7 and 4.8.

$$
L_{ij}^k = l_{ij}^k + l_{ji}^k \rightarrow L_{(1,6)}^1 = l_{(1,6)}^1 + l_{(6,1)}^1 = 524 + 532 = 1056
$$

$$
L_r^k = L_{ij}^k + (L_{ij-1}^k) \rightarrow L_1^1 = 1056 + 0 = 1056
$$

$$
L^k \rightarrow L^1 = 5088.7
$$

Since $L_r^k \le L^k$ then continue to Step 6.

Step 6: Find the next nearest port to port *x* or port *y*

Since $p \le nP$ then search port p , $p \in P$; where p is the next nearest port to *x* or *y*.

Set port $i \rightarrow x = 1$ and port $j \rightarrow y = 6$

For $x =$ port-1, the next nearest port to port₁ is port₅ (port *p*);

$$
(p, x) \rightarrow \frac{l_{ij}^k + l_{ji}^k}{2} = \frac{l_{(1,5)}^k + l_{(5,1)}^k}{2} = \frac{1055 + 1055}{2} = 1055
$$

For $y =$ port₆, the next nearest port to port₆ is port₅ (port *p*);

$$
(y, p) \rightarrow \frac{l_{ij}^k + l_{ji}^k}{2} = \frac{l_{(6,5)}^1 + l_{(5,6)}^1}{2} = \frac{794 + 801}{2} = 797.5
$$

If the nearest port to port p is x , set (p, x) as the next path. Otherwise, set (y, p) as the next path. In the case of this study, the next nearest port to port *p* was *y*, therefore (*y, p*) was set as the next path. The new route becomes: $1 - 6 - 5$. Figure 4.5 shows the process of steps 6 and 7.

Figure 4.5 Steps for finding the next nearest port

Step 7: Check $T_r^k \leq T^k$ for temporary route Temporary route: $1 - 6 - 5$

Check for $T_r^k \leq T^k$.

 T^k is the maximum allowed routing time (*commission days*) for ship *k*.

Count T_{ij}^k and T_r^k by Equations 4.4 and 4.5.

For $i =$ port₆, $j =$ port₅.

$$
T_{ij}^k = \left(\frac{l_{ij}^k}{v^k} + t_j^k\right) + \left(\frac{l_{ji}^k}{v^k} + t_i^k\right) \rightarrow T_{(6,5)}^1 = \left(\frac{l_{(6,5)}^1}{v^1} + t_5^k\right) + \left(\frac{l_{(5,6)}^1}{v^1} + t_6^k\right) = \left(\frac{794}{19} + 3\right) + \left(\frac{801}{19} + 8\right) = 94.95
$$

 $T^k_{ij-l} = 68.58$

$$
T_r^k = T_{ij}^k + (T_{ij-1}^k) \rightarrow T_r^k = 68.58 + 94.95 = 163.53
$$

Since $T_r^k \leq T^k$ then continue to count of L^k

Step 8: Check $L_r^k \le L^k$ for temporary route

Check for $L_r^k \leq L^k$.

Count L^k by Equation 4.6; For $k = \text{ship}_1, L^1 = 5088.7$

For $i =$ port₆, $j =$ port₅.

Count L_r^k by Equations 4.7 and 4.8.

$$
L_{ij}^k = l_{ij}^k + l_{ji}^k \rightarrow L_{(6,5)}^1 = l_{(6,5)}^1 + l_{(5,6)}^1 = 794 + 801 = 1595
$$

$$
L_r^k = L_{ij}^k + (L_{ij-1}^k) \rightarrow L_1^1 = 1056 + 1595 = 2651
$$

$$
L^k \rightarrow L^1 = 5088.7
$$

Since $L_r^k \leq L^k$ then repeat step 4 until all ports are served or restraints $T^k \leq T$ and $L_i^k \leq L^k$ are violated.

Starting from Port	Ports	T^k	L_r^k
1	$1 - 6 - 5 - 3 - 4$	280.63	4,496
2	$2 - 4 - 5 - 3 - 6$	286.89	4,672
3	$6 - 3 - 5 - 4 - 2$	286.89	4,672
4	$6 - 3 - 5 - 4 - 2$	286.89	4,672
5	$2 - 4 - 5 - 3 - 6$	286.89	4,672
6	$4 - 3 - 5 - 6 - 1$	280.63	4,496

Table 4.6 Routes for ship $k = 1$

The first route is $1 - 6 - 5 - 3 - 4$; where $T^k = 280.63$ and $L_r^k = 4,496$. Repeat step 2 for port $i =$ port₂ and continue to the next step until all ports are checked. Table 4.6 shows complete routes for ship $k = 1$.

Repeat step 1 for the next ship $k = 2$, repeat all steps until $i = 6$. Table 4.7 shows complete routes for ship $k = 2$.

Starting from Port	Ports	T^k	L_r^k
1	$1 - 6 - 5 - 3$	296.23	2,907
2	$2 - 4 - 5 - 3$	265.64	2,614
3	$3 - 5 - 4 - 2$	265.64	2,614
4	$3 - 5 - 4 - 2$	265.64	2,614
5	$2 - 4 - 5 - 3$	265.64	2,614
6	$3 - 5 - 6 - 1$	296.23	2,907

Table 4.7 Routes for ship $k = 2$

Phase II: Check for vehicles assigned. Routes without fuel ports are eliminated. Fuel consumption of routes is calculated based on distance and penalties *α*, *β* and *γ*.

The results for phase II are shown in Table 4.8.

Table 4.8 Output of phase II

Phase III: Finding the best combination of routes.

The best combination of routes with minimum fuel consumption and maximal ports of call is found using the 'maximum-insertion concept' (Pertiwi, 2005).

Step 1: Ascending routes

Sort all routes based on fuel consumption, as shown in Table 4.9.

Table 4.9 Sort all routes based on fuel consumption

Step 2: Check the best route for the first ship

 $R = \{1, 2, ..., 12\}$ is an index set of the routes, where the number of routes is 12.

Check for first route $r = 8$.

Save $r = 8$ into temporary best solution.

Step 3: Check the best route for the second ship

Check for the next route, $r = 9$.

Identification of ship and port served. If route $r = 8$ and $r = 9$ are served by the same ship then continue to search for the next route.

Check for the 7^{th} route, $r = 1$; $r < nR$.

Identification of ship and port served. If route $r = 1$ is served by a different ship then save route $r = 1$ into temporary best solution. Check ports served; if all ports are served then it is chosen as the best combination, otherwise, the temporary solution is cleared and continues to check for the next route.

Since route $r = 8$ and $r = 1$ are served by different ships and all ports are served then it is chosen as the best combination route.

• Ship $k = 1$ serves route $r = 1$ (ports: $1 - 6 - 5 - 3 - 4$) Fuel consumption $= 824,004$ litres Average of load factor $= 121\%$ Number of ports of call = 9 (ports: $1 - 6 - 5 - 3 - 4 - 3 - 5 - 6 - 1$) • Ship $k = 2$ serves route $r = 8$ (ports: $2 - 4 - 5 - 3 - 5 - 4 - 2$) Fuel consumption $= 163,976$ litres Average of load factor $= 51\%$

Number of ports of call $= 7$
4.3 Genetic Algorithm

A general Genetic Algorithm (Gen & Cheng, 1999) can be represented by following these major steps:

- Step 1: Represent the problem as a chromosome; choose the population size, the crossover rate and the mutation rate.
- Step 2: Define a fitness function to measure the performance, or fitness, of an individual chromosome in the problem domain.
- Step 3: Randomly generate chromosomes in a population of size, *pop_size*.
- Step 4: Calculate fitness values.
- Step 5: Select chromosomes from the current population.
- Step 6: Create offspring by using crossover and mutation.
- Step 7: Place the created offspring chromosomes into a new population.
- Step 8: Repeat step 5 until the number of chromosomes equals to the population size.
- Step 9: Replace the parent with the new population (offspring).
- Step 10: Return to step 4, and repeat the process until termination criteria are satisfied.

4.3.1 Genetic Algorithm for a Ship Routing Problem

Representing chromosomes is the first step in Genetic Algorithm. This is followed by generate chromosomes in the first generating, evaluating fitness values, selection, crossover, and mutation. The processes are depicted in Figure 4.6.

Figure 4.6 Genetic Algorithm for vehicle routing problem

i. Represent Chromosome

In this case study, a ship serves a regular route. The ship starts the tour from a depot and visits all ports assigned before returning to the depot within in 14 days.

The length of a chromosome depends on the number of ships in a fleet. Each ship is represented as a sub-chromosome, and each sub-chromosome consists of 14 genes. A sub-chromosome consists of Q-arm, P-arm, and two centromeres. The structure of a subchromosome is shown in Figure 4.7.

Figure 4.7 Q-arm and P-arm in chromosome proposed

A chromosome in a Genetic Algorithm is represented as a number of sub-chromosomes; each sub-chromosome consists of a Q-arm, P-arm and two centromeres. The 1st and the 10th genes are called centromere, and they contain a value that refers to the fuel port; the 2nd to the 9th genes are called the Q-arm and the 11th to the 14th genes are called the Parm. The Q-arm and P-arm contain values that refer to customer ports. Figure 4.8 shows a representation of a chromosome. The values of each gene (called alleles) were randomly obtained, from *0* to *n*, where n is the total number of ports.

Figure 4.8 Representation of the chromosome for two ships

ii. Generate Feasible Route

Each chromosome must qualify as a feasible chromosome to be included in the population. A feasible chromosome is determined by the following criteria:

- 1. Total travel time T_r^k for any vehicle is no longer than T^k
- 2. Total travel distance L_r^k for any vehicle is no longer than L^k
- 3. Must include at least one fuel port
- 4. All ports are served
- 5. All ships are used

iii. Fitness Function

After we represent the chromosomes, the second step is to determine fitness functions. Fitness functions are based on the basic survival of the fittest premise in Genetic Algorithm. The objective is to minimize fuel consumption, maximize the load factor, and maximize the number of ports of call. Penalty costs are imposed when a ship's draft doesn't meet requirements, the load factor is too high, or when the number of ports of call. It is out of an optimal range. It is minimization problem, thus the smallest value is the best. Fitness functions are represented as:

$$
f = \left(\frac{1}{\sum f_r^k + \sum f_a^k + \sum f_\beta^k + \sum f_r^k + 1}\right) * 10000000
$$
\n(4.11)

where,

k r $f{f}$ = Fuel consumption for ship *k* to serve route *r* f_α^k *f* = Fuel consumption penalties with respect to the ship draft and the sea depth *k b f* = Fuel consumption penalties with respect to the load factor $f_{\rm \nu}^{\,k}$ = Fuel consumption penalties with respect to the number of ports of call

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iv. Selection

In this case, 'roulette wheel selection' was used. This involves selecting a new population with respect to the probability distribution based on the fitness values of chromosomes. Roulette wheel selection is constructed as follows (Gen & Cheng, 1999):

1. Calculate the fitness value $eval(v_k)$ for each chromosome v_k .

- 2. Calculate total fitness for the population.
- 3. Calculate selection probability p_k for each chromosome v_k .
- 4. Calculate cumulative probability q_k for each chromosome v_k .

The selection process begins by spinning the roulette wheel *pop_size* times; each time a single chromosome is selected for a new population in the following 2 steps:

Step 1: Generate a random number *r* in a range [0, 1].

Step 2: If $r \leq q_i$, then select the first chromosome v_i . Otherwise select the *k*-th chromosome v_k (1 \leq *k* \leq *pop_size*) such that q_{k-1} \lt $r \leq q_k$.

v. Crossover

Crossover operators should be implemented carefully to avoid invalid chromosomes. There are two important factors in crossover (Gen & Cheng, 1999):

- 1. Determination of chromosome for the crossover
- 2. Crossover processes

To determine a chromosome in-crossover, start by generating random numbers in the same quantity as the population. Random numbers are generated and compared with the value of the crossover rate. If a random number is less than or equal to the crossover rate, then the chromosome is selected for the crossover process.

Figure 4.9 Multi Cut Point Crossover

The process of crossover is to exchanges portions of a chromosome with another chromosome eligible for in-crossover.

Multi cut point chromosome is applied in this research and the steps are as follow:

- Step 1: Select two chromosomes eligible for in-crossover.
- Step 2: Check whether the arms that are exchanged qualify as a feasible chromosome.

If the offspring violates a constraint it must be repaired.

vi. Mutation

There are two important things in mutation (Gen & Cheng, 1999):

- 1. Determination of chromosome for the mutation
- 2. Mutation processes

To determine a chromosome in-mutation, generate random numbers in the same quantity as the population and multiple numbers of the P-arm. The random numbers are generated and compared with the value of the mutation rate. If a random number is less than or equal to the mutation rate, then the chromosome is selected for the mutation

process. The process of mutation involves exchanging of a chromosome within the chromosome eligible for in-mutation. Pairs exchange is applied in this study. This is achieved by randomly choosing the arms of a chromosome and exchanging the location by using a pair's structure. The number of eligible genes must be even.

The pairs exchange process is as follows:

- Step 1: Randomly select the P-arms that will be mutated.
- Step 2: Change the genes in a P-arm with the next P-arm as show in Figure 4.10. The second ship is not changed since it is not eligible for mutation and the fourth route is not changed since it is unpaired.

Figure 4.10 Pairs Exchange Mutation

Step 3: Check whether the P-arm exchanged qualifies as a feasible chromosome. If the offspring has violated a constraint it must be repaired.

vii. Repairing

A chromosome needs to be repaired before continuing to the next process. Repairing a chromosome ensures that only fitness values of feasible chromosomes are counted. The process of repairing a chromosome is as follows:

- Step 1: If $T_r^k \leq T^k$ and $L_r^k \leq L^k$ is violated, check the similar numbers in the same arm and same sub-chromosome and remove them. Repeat step 1 until no similar numbers in the same arms of the same sub-chromosome are left.
- Step 2: If $T_r^k \leq T^k$ and $L_r^k \leq L^k$ are violated, check the similar numbers in a different arm but within the same sub-chromosome, and remove them. Repeat step 2 until no similar numbers in the same arm type of different sub-chromosomes exist.
- Step 3: If $T_r^k \leq T^k$ and $L_r^k \leq L^k$ are violated, check the similar numbers in the same arm and different sub-chromosome and remove them. Repeat step 3 until no similar numbers in different arm types with the same sub-chromosome exist.
- Step 4: If $T_r^k \leq T^k$ and $L_r^k \leq L^k$ are violated, check the similar numbers in different arms and different sub-chromosome and remove them. Repeat step 4 until no similar numbers in different arm types of different subchromosomes exist.
- Step 5: If $T_r^k \leq T^k$ and $L_r^k \leq L^k$ are still in violation, then the recombination process is cancelled.

4.3.2 Illustration of General Genetic Algorithm

An illustration of how a general Genetic Algorithm is used for solving vehicle routing problem is seen below. Data of specifications of the ports are seen in Table 4.1, the distance between ports is in Table 4.2, the number of passengers on board is in Table 4.3 and the specifications of the ships are in Table 4.4.

98 The genetic operators used were selected by roulette wheel, crossover by multi cut point and mutation by pairs exchange. The genetic parameters used were: population size of 10, crossover rate of 0.4, mutation rate of 0.05, and maximum generation of 100 (stopping criteria).

Phase 1: Representing the Chromosome

Figure 4.11 Shows structure of chromosome Used.

Figure 4.11 Chromosome: 2 ships, 4 customer ports and 2 fuel ports

A chromosome consists of two sub-chromosomes. Each sub-chromosome refers to a ship, and each ship serves a route. Each sub-chromosome consists of a Q-arm, a P-arm and two centromeres. Q-arm and P-arm refer to Customer Ports, $C \in \{1, 2, 3, 4\}$ while the centromeres refers to Fuel Ports, $D \in \{5, 6\}.$

Phase 2: Generate Chromosomes

Generate the first chromosome in the first generation randomly. The results are seen in Figure 4.12.

					Ship k_1														Ship k_2							
		4		ь		8	9	10	11	12	13	14	15	16	-17	18	19	20	21	22	23	24	25	26	-27	-28
僧 -0			Q -arm					c		P-arm			윋 ω c å				Q -arm					윋 ω ٥ ්		P-arm		
							0						b													0

Figure 4.12 Generated chromosomes

- $k_1 = 5 4 3 5 2$
- $k_2 = 6 1 5$

Since all ports are served then continue to check T_r^k

Check for $T_r^k \leq T^k$.

 T^k is the maximum allowed routing time (*commission days*) for ship $k=1$; 336. Count T^k_{ij} and T^k_r of each route by Equations 4.4 and 4.5.

$$
k_1 = 5 - 4 - 3 - 5 \text{ and } 5 - 2
$$

\n
$$
T_{(5,4)}^1 = \left(\frac{l_{(5,4)}^1}{v^1} + t_4^1\right) + \left(\frac{l_{(4,5)}^1}{v^1} + t_5^1\right) = \left(\frac{611}{19} + 7\right) + \left(\frac{611}{19} + 3\right) = 74.32
$$

\n
$$
T_{(4,3)}^1 = \left(\frac{l_{(4,3)}^1}{v^1} + t_3^1\right) + \left(\frac{l_{(3,4)}^1}{v^1} + t_4^1\right) = \left(\frac{793}{19} + 3\right) + \left(\frac{796}{19} + 7\right) = 95.63
$$

\n
$$
T_{(3,5)}^1 = \left(\frac{l_{(3,5)}^1}{v^1} + t_5^1\right) + \left(\frac{l_{(5,3)}^1}{v^1} + t_3^1\right) = \left(\frac{128}{19} + 3\right) + \left(\frac{128}{19} + 5\right) = 21.47
$$

\n
$$
T_{(5,2)}^1 = \left(\frac{l_{(5,2)}^1}{v^1} + t_2^1\right) + \left(\frac{l_{(2,5)}^1}{v^1} + t_5^1\right) = \left(\frac{1089}{19} + 3\right) + \left(\frac{1089}{19} + 3\right) = 120.63
$$

\n
$$
T^1 = 312.05; \ T_r^k \le T^k
$$

 T^k is the maximum allowed routing time (*commission days*) for ship $k = 2$; 336.

$$
k_2 = 6 - 1 - 5
$$

\n
$$
T_{(6,1)}^2 = \left(\frac{l_{(6,1)}^2}{v^2} + t_1^2\right) + \left(\frac{l_{(1,6)}^2}{v^2} + t_6^2\right) = \left(\frac{532}{11} + 5\right) + \left(\frac{524}{11} + 8\right) = 109
$$

\n
$$
T_{(1,5)}^2 = \left(\frac{l_{(1,5)}^2}{v^2} + t_5^2\right) + \left(\frac{l_{(5,1)}^2}{v^2} + t_1^2\right) = \left(\frac{1055}{11} + 3\right) + \left(\frac{1055}{11} + 5\right) = 199.82
$$

\n
$$
T^2 = 308.82; \ T_r^k \le T^k
$$

Since $T_r^k \leq T^k$ then continue to check $L_r^k \leq L^k$ of each route.

 L^k of each route is counted by Equation 4.6.

For
$$
k = \text{ship}_1
$$
, $L^k_{(1-10)\text{max}} = 5199 \text{ and } L^k_{(10-14)\text{max}} = 2599.5$
\n $k_I = 5 - 4 - 3 - 5 \text{ and } 5 - 2$
\n $L^k_{ij} = l^k_{ij} + l^k_{ji} \rightarrow L^1_{(5,4)} = l^1_{(5,4)} + l^1_{(4,5)} = 611 + 611 = 1222$
\n $L^k_{ij} = l^k_{ij} + l^k_{ji} \rightarrow L^1_{(4,3)} = l^1_{(4,3)} + l^1_{(3,4)} = 793 + 796 = 1589$
\n $L^k_{ij} = l^k_{ij} + l^k_{ji} \rightarrow L^1_{(3,5)} = l^1_{(3,5)} + l^1_{(5,3)} = 128 + 128 = 256$
\n $L^k_{(1-10)} = 3067$, $L^k_{(1-10)} \le L^k_{(1-10)\text{max}}$
\n $L^k_{ij} = l^k_{ij} + l^k_{ji} \rightarrow L^1_{(5,2)} = l^1_{(5,2)} + l^1_{(2,5)} = 1089 + 1089 = 2178$
\n $L^k_{(1-10)} = 2178$, $L^k_{(10-14)} \le L^k_{(10-14)\text{max}}$

For $k = \text{ship}_2$, $L_{(1-10) \text{max}}^k = 6495$ and $L_{(10-14) \text{max}}^k = 3297.5$ $k_2 = 6 - 1 - 5$ $L_{ij}^k = l_{ij}^k + l_{ji}^k \rightarrow L_{(6,1)}^2 = l_{(6,1)}^2 + l_{(1,6)}^2 = 532 + 524 = 1056$ $L_{ij}^k = l_{ij}^k + l_{ji}^k \rightarrow L_{(1,5)}^2 = l_{(1,5)}^2 + l_{(5,1)}^2 = 1055 + 1055 = 2110$ $L_{(1-10)}^k = 3166$, $L_{(1-10)}^k \le L_{(1-10) \max}^k$

Since $L_r^k \leq L^k$, the first chromosome is eligible and continues to generate the next chromosome. Since the number of the population is 10, it is necessary to generate 10 chromosomes in the first generation. Table 4.10 shows the completed chromosomes for the first generation generated randomly.

Phase 3: Evaluate the Fitness Value

In phase 3, the fitness value of the chromosome is calculated using Equation 4.11. The fitness value is:

$$
f = \left(\frac{1}{\sum f_r^k + \sum f_a^k + \sum f_\beta^k + \sum f_r^k + 1}\right) * 1000000 = 0.3948
$$

Table 4.11 shows the completed fitness value of each chromosome.

Table 4.10 Chromosomes for the first generation

Table 4.11 Fitness value of each chromosome

Phase 4: Roulette Wheel Selection

This phase shows the process of roulette wheel selection. It is constructed as follows:

Step 1: Calculate the fitness value $eval(v_k)$ for each chromosome v_k .

 $eval(v_k) = f(x)$ $k = 1, 2, ..., pop_size$

The fitness values for each chromosome are in Table 4.11.

Step 2: Calculate the total fitness of the population:

$$
F = \sum_{k=1}^{\text{pop_size}} \text{eval}(v_k)
$$

$$
F = \sum_{k=1}^{10} \text{eval}(v_k) = 9.3948
$$

Step 3: Calculate the selection probability (p_s) of each chromosome *s*.

Total fitness *F* of the population is 9.3948, so the selection probabilities p_k of each chromosome are:

For the first chromosome, $s = 1$.

$$
p_k = \frac{eval(v_k)}{F}, \ \ p_1 = \frac{0.9226}{9.3948} = 0.0982
$$

The second chromosome*, s = 2*

$$
p_k = \frac{eval(v_k)}{F}, \ \ p_2 = \frac{0.9709}{9.3948} = 0.1033
$$

The complete value of p_k is in the Table 4.12.

Table 4.12 Fitness value, selection probability, cumulative probability and random number for selection

Step 4: Calculate the cumulative probability q_k of each chromosome *s*.

The cumulative probabilities q_k for each chromosome are calculated as: $q_1 = p_1 = 0.0982$ $q_2 = q_1 + p_2 = 0.0982 + 0.1033 = 0.2015$ $q_3 = q_2 + p_3 = 0.2015 + 0.1054 = 0.3069$

The complete value of (q_k) that can be seen in the Table 4.12.

The selection process begins by spinning the roulette wheel *n* times, *n* the being population size; each time a single chromosome is selected for the new population. If the population size is 10, it is necessary to sequence 10 random numbers in a range [0, 1]. Let us assume that there is a random sequence of 10 numbers as shown in Table 4.12.

The first random number is $r_1 = 0.6957$; $r_1 > q_7$ and $r_1 < q_8$, meaning that chromosome s_8 is selected for the new population. The second random number is $r_2 = 0.7244$; $r_2 > q_7$ and $r_2 < q_8$, meaning that chromosome s_8 is also selected for the new population. The third random number is $r_3 = 0.4407$; $r_3 > q_4$ and $r_3 < q_5$, meaning that chromosome *s⁵* is again selected for the new population, and so on. After reviewing all the numbers, the new population consists of the chromosomes as shown in Table 4.13.

Table 4.13 New population after selection

Table 4.14 Check eligibility for crossover

Phase 5: Multi Cut Point Crossover

To choose chromosomes for crossover, random numbers must be generated over a range [0 1]. A sequence of random numbers is shown in Table 4.14 suitable for a population of 10.

If the probability of crossover is $p_c = 0.4$, an average 40 % of the chromosomes are expected to undergo crossover. For $r \leq p_c$, it is necessary to select relative chromosomes for crossover.

From Table 4.14, chromosomes *s'¹* vs. *s'⁸* are selected for crossover. Multi-point cut chromosome is applied in this research in the steps that follows:

- Step 1: Take two chromosomes eligible for in-crossover as shown in Table 5.14.
- Step 2: Offspring are obtained by exchanging arms between the two chromosome parents, as shown in Figure 4.13.

				Ship k_1								Ship k_2				
	3		4 5 6 7 8											9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28		
Φ ò F ੋ Centr		Q-arm			ō	P-arm		ω 통 Centr		Q-arm			ω ō Centrom	P-arm		fitness
																0.9709

Figure 4.13 Crossover for *s'¹* **vs.** *s'⁸*

Step 3: Check if arms exchanged qualify as feasible chromosomes. Check whether Parm exchanged qualifies as a feasible chromosome. If the offspring has violated a constraint it needs to be repaired.

Complete results of the new chromosome structure after crossover are shown in Table 4.15.

Table 4.15 New population after crossover

Table 4.16 Fitness value and random number for mutation

Phase 6: Pairs Exchange Mutation

To choose gene for the mutation, process random numbers must be generated over a range [0 1]. If the probability of mutation is 0.05, an average of 0.5 % of the genes will undergo mutation. Two sub-chromosomes exists in a population size of 10, and 2 genes will undergo mutation in each generation. The random number for mutation is shown in Table 4.16.

For $r \leq p_m$, relative chromosome is selected for mutation. As shown in Table 4.16, chromosome s_4 is selected for mutation. Pairs exchange mutation is applied in the following steps:

- Step 1: Randomly select the P-arms eligible for in-mutation.
- Step 2: Offspring are obtained by exchanging the genes in a P-arm with the next Parm as show in Figure 4.14.

Before mutation

After mutation

				Ship k								Ship k_2				
		2 3 4 5 6 7 8												9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28		
Φ omer Centri		Q -arm			ω ۰	P-arm		Φ Φ ╘ ۰ 횯 Φ			Q -arm		Φ Φ 틍 entr	P-arm		fitness

Figure 4.14 Pairs exchange mutation

Step 3: Check whether the P-arm exchanged qualifies as a feasible chromosome. If the offspring violates a constraint it must be repaired.

Phase 7: Repairing

Since $T_r^k \leq T^k$ and $L_r^k \leq L^k$ are violated, there is need for repairing the new chromosome.

The process of repairing chromosomes is depicted can be seen in Figure 4.15.

Repairing - Step 1

Repairing - Step 2

After repairing

				Ship k_1								Ship k_2				
		2 3 4 5 6 7 8												9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28		
Ψ ω ۰ 쿋 ඊ		Q -arm			틍 Ë		P-arm	ω E ō 부			Q -arm		E ō	P-arm		fitness
									٩							3960

Figure 4.15 Repairing chromosomes

The process is as follows:

- Step 1: If $T_r^k \leq T^k$ and $L_r^k \leq L^k$ are violated, check similar numbers in the same arm in the same sub-chromosome and remove them. Since $T_r^k \leq T^k$ and $L_r^k \leq L^k$ are still violated, go to step 2.
- Step 2: If $T_r^k \leq T^k$ and $L_r^k \leq L^k$ are violated, check similar numbers in different arms within the same sub-chromosomes and remove them.

Complete results of the structure of the new chromosome after mutation are shown in the Table 4.17. The new population after mutation is the one used in the next generation.

Next iteration of Genetic Algorithm is completed. The test run is terminated after 100 generations (maximum generation). The best chromosome out of the 100 generations is as follows:

• Ship $k = 1$ serves route $r = 1$ (ports: $6 - 1 - 5$) Fuel consumption $=$ 548,592 litres Average of load factor $= 74\%$

Number of ports of call $= 5$

• Ship $k = 2$ serves route $r = 8$ (ports: $5 - 3 - 5 - 4 - 2$)

Fuel consumption $= 163,723$ litres

Average of load factor $= 123\%$

Number of ports of call $= 9$

Table 4.17 New population

4.4 Hybrid Genetic Algorithm for Ship Routing Problem

A hybrid Genetic Algorithm is proposed to improve the performance of the general Genetic Algorithm.

Figure 4.16 Hybrid Genetic Algorithm proposed

The hybrid Genetic Algorithm proposed is described in Figure 4.16. Its process is described by the following steps:

- Step 1: Represent a problem as a chromosome; choose a population size, the crossover rate, and the mutation rate.
- Step 2: Define a fitness function to measure the performance, or fitness, of an individual chromosome in a problem domain.
- Step 3: Generate chromosomes in a population of size, *pop_size*.
	- Centromeres generated randomly
	- Q-arm and P-arm generated by nearest neighbour method
- Step 4: Calculate the fitness value of each chromosome. The chromosome with the highest value saved into temporary memory.
- Step 5: Select a chromosome from the current population.
- Step 6: Create offspring by using crossover and mutation.
- Step 7: Place the created offspring chromosomes in the new population.
- Step 8: Repeat step 5 until the number of chromosomes is equal to the population size.
- Step 9: Replace the parents with the new population (offspring).
- Step 10: Calculate of the fitness value of each chromosome. The chromosome with the highest value is saved into temporary memory. Compare the two chromosomes that are saved in temporary memory. The chromosome with the highest fitness value replaces the other and is chosen for the next population.
- Step 11: Go to Step 4, and repeat the process until the termination criteria are satisfied.

A chromosome in the hybrid Genetic Algorithm employed is represented similarly to in a general Genetic Algorithm. The fitness function is also similar, but it differs in how chromosomes are generated in the initial population. The initial population's

centromeres in the hybrid Genetic Algorithm are randomly generated while the Q-arm and P-arm are generated by the nearest neighbour method.

Process of determining the initial population in the hybrid Genetic Algorithm is as follows:

- Step 1: Generate the centromeres random
- Step 2: Find ports for the Q-arm and the P-arm through the nearest neighbour method, satisfying a number of predetermined constraints: $T_r^k \leq T^k$ and $L_r^k \leq L^k$.

Figure 4.17 shows a sample of a chromosome in the hybrid Genetic Algorithm.

				Ship k_1										Ship k_2			
		2 3 4 5 6 7 8			-9		10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28										
Φ omer Centr		Q-arm				Φ omer Centr		P-arm		ω Φ ŧ		Q-arm			ω ⋿ ۰ E	P-arm	

Step 1 - Generate the centromere

Step 2 - Generate the arm

				Ship k										Ship k_2			
	2 3	4 5 6 7 8			-9					10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28							
Φ omer Centr		Q-arm				ω Φ 틍 entr		P-arm	ω Φ E ۰ 눧 Φ			Q-arm			⋿ ۰	P-arm	
															ь		

Figure 4.17 Chromosomes for initial population using the hybrid Genetic Algorithm

This research proposes an improvement procedure to ensure chromosomes with the best fitness values are carried forward into the next generations. The improvement procedure is as follows:

- Step 1: Calculate the fitness value of the parent's chromosomes with the highest fitness values are saved into temporary memory.
- Step 2: Selection and recombination process is carried out for the offspring.
- Step 3: Calculate fitness values of the offspring, and chromosomes with the highest fitness values are saved into temporary memory.
- Step 4: Compare the chromosomes saved in temporary memory. Chromosome with the highest fitness values replace the others and are chosen for the next population.

4.5 Summary

Three methods were used to solve a ship routing problem in the case study i.e. a heuristic algorithm, a general Genetic Algorithm and a hybrid Genetic Algorithm.

The heuristic procedure involved three algorithm phases, namely clustering, assigned vehicle and finding the best routes by a combination of feasible solution.

- Phase I aims to cluster routes and solve the problem based on the constraint of travel time and distance allowed for each ship.
- Phase II checks involves checking vehicles assigned in a cluster to ensure each route has at least one fuel port. In this phase, fuel consumption is calculated.
- Phase III involves developing a robust algorithm based on the maximum insertion concept. The idea is to successively insert a route into the best combination of routes with minimum fuel consumption.

In the hybrid Genetic Algorithm, the length of a chromosome depends on the number of ships. Each ship is represented as a sub-chromosome and each sub-chromosome consists of 14 genes. A sub-chromosome consists of a Q-arm, a P-arm and two centromeres. The

1st and the 10th genes are called centromeres, which contain values that refer to the fuel port. The 2nd to the 9th genes are called the Q-arm, while the 11th to the 14th genes are called the P-arm. The Q-arm and P-arm contain values that refer to the customer port.

Roulette wheel selection, multi cut point crossover, and pairs exchange mutation is applied in the general Genetic Algorithm and the hybrid Genetic Algorithm. Using the general Genetic Algorithm, the initial population is generated randomly. The initial population in the hybrid Genetic Algorithm process is generated by a random mix using the nearest neighbour method. An improvement procedure is proposed in the hybrid Genetic Algorithm to ensure chromosomes with the best fitness are carried forward into the next generation.

CHAPTER 5 RESULT AND ANALYSIS

In this chapter, the computational results of the heuristic algorithm, the general Genetic Algorithm and the hybrid Genetic Algorithm methods proposed in Chapter 4 are presented. All the computational experiments were carried out using an Intel(R) Core(TM) i5 CPU M430 @2.27GHz.

5.1 Experiment 1 - Performance of Three Algorithms Compared with Prior Work

The first experiment described herein examined the performance of the three algorithms i.e. the heuristic algorithm, general genetic algorithm and proposed hybrid genetic algorithm. It was compared with the existing route. Since there was no information about the method used to generate the existing route, for simplicity the PELNI method (PELNI, 2010) was denoted for use.

5.1.1 The Benchmarks Problem

Since there was no vehicle routing problem that was exactly similar to the problem needing to be solved in the case study, the benchmarks were generated based on the existing routes in the PT. PELNI for 2010. The benchmarks were generated to represent different performances, i.e.:

- \bullet 40c-9d-8k = routes served by ships where capacity is 1000 1500 seats
- $28c-9d-9k$ = routes where the number of ports of call is 10 15
- \bullet 45c-11d-11k = routes where the number of ports of call is 16 20
- \bullet 32c-4d-8k = routes where the number of ports of call is 20 and above
- \bullet 34c-11d-11k = routes where the number of ports of call is 16 and less

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- $63c-14d-11k$ = routes where the number of ports of call is 17 and above
- \bullet 18c-6d-8k = routes where the number of ports of call is 13 ports
- $28c-6d-11k$ = routes with the highest number of fuel ports (8 ports)
- \bullet 12c-4d-8k = routes where the number of fuel ports is more than the number of customer ports
- \bullet 53c-12d-11k = routes where the number of fuel ports is 6 or less
- $24c-5d-10k$ = routes where the number of fuel ports is 7

All the benchmarks can be seen in Table 5.1.

		Number of		Best known solution (PELNI Method)		
Benchmarks	Customer Ports	Fuel Ports	Vehicles	Fuel Consumption	Number of Ports of Call	Load Factor
$40c-9d-8k$	40	9	8	1,275,883	154	3.60
$28c-9d-9k$	28	9	9	2,375,323	119	5.41
45c-11d-11k	45	11	11	3,868,567	203	5.35
$32c-4d-8k$	32	$\overline{4}$	8	1,036,758	95	5.57
34c-11d-11k	34	11	11	2,743,105	142	5.30
63c-14d-11k	63	14	11	4,755,085	282	3.75
$18c-6d-8k$	18	6	8	1,491,149	81	4.22
$28c - 6d - 11k$	28	6	11	2,134,324	104	4.14
$12c-4d-8k$	12	$\overline{4}$	8	1,263,833	55	4.42
53c-12d-11k	53	12	11	2,945,322	194	3.54
24c-5d-10k	24	5	10	1,267,387	87	3.95

Table 5.1 Best known solution for 11 benchmarks (PELNI, 2010)

Figure 5.1 Routes of the benchmark; 40c-9d-8k

Figure 5.2 Routes of the benchmark; 28c-9d-9k
Figure 5.3 Routes of the benchmark; 45c-11d-11k

Figure 5.4 Routes of the benchmark; 32c-4d-8k

Figure 5.5 Routes of the benchmark; 34c-11d-11k

Figure 5.6 Routes of the benchmark; 63c-14d-11k

Figure 5.7 Routes of the benchmark; 18c-6d-8k

Figure 5.8 Routes of the benchmark; 28c-6d-11k

Figure 5.9 Routes of the benchmark; 12c-4d-8k

Figure 5.10 Routes of the benchmark; 53c-12d-11k

Figure 5.11 Routes of the benchmark; 24c-5d-10k

5.1.2 Result

The computational results for the 11 benchmarks for the heuristic algorithm can be seen in Table 5.2, while the computational results for general Genetic Algorithm can be seen in Table 5.3 and those for the hybrid Genetic Algorithm are given in Table 5.4.

Benchmarks Number of Heuristic Algorithm Customer Ports Fuel Fuel Vehicles Fuel
Ports Vehicles Consump Consumption Number of Ports of Call Load Factor 40c-9d-8k 40 9 8 1,067,352 49 17.13 28c-9d-9k 28 9 9 9 1,900,067 40 26.01 45c-11d-11k | 45 | 11 | 11 | 3,029,397 | 58 | 23.16 32c-4d-8k 32 4 8 888,475 41 24.02 $34c-11d-11k$ | 34 | 11 | 11 | $2,177,213$ | 49 | 26.47 63c-14d-11k | 63 | 14 | 11 | 3,699,584 | 76 | 9.81 18c-6d-8k 18 6 8 1,231,551 28 21.03 28c-6d-11k 28 6 11 1,716,760 41 25.11 12c-4d-8k 12 4 8 1,060,131 21 42.45 53c-12d-11k | 53 | 12 | 11 | 2,328,848 | 67 | 18.79 24c-5d-10k 24 5 10 1,061,950 36 24.74

Table 5.2 Solution of 11 benchmarks solved by heuristic algorithm

		Number of		General GA		
Benchmarks	Customer Ports	Fuel Ports	Vehicles	Fuel Consumption	Number of Ports of Call	Load Factor
$40c-9d-8k$	40	9	8	1,122,712	79	44.90
28c-9d-9k	28	9	9	2,064,836	64	47.93
$45c-11d-11k$	45	11	11	3,340,013	101	43.82
$32c - 4d - 8k$	32	$\overline{4}$	8	919,118	59	56.61
34c-11d-11k	34	11	11	2,377,556	83	50.85
$63c-14d-11k$	63	14	11	4,095,004	99	41.63
$18c-6d-8k$	18	6	8	1,308,901	51	44.22
$28c - 6d - 11k$	28	6	11	1,858,045	71	46.62
$12c-4d-8k$	12	$\overline{4}$	8	1,114,330	42	45.47
53c-12d-11k	53	12	11	2,549,070	89	46.12
$24c - 5d - 10k$	24	5	10	1,116,445	56	46.59

Table 5.3 Solution of 11 benchmarks solved by general Genetic Algorithm

Table 5.4 Solution of 11 benchmarks solved by hybrid Genetic Algorithm

		Number of		Hybrid GA			
Benchmarks	Customer Ports	Fuel Ports	Vehicles	Fuel Consumption	Number of Ports of Call	Load Factor	
$40c-9d-8k$	40	9	8	954,654	70	46.44	
28c-9d-9k	28	9	9	1,711,743	67	50.16	
$45c-11d-11k$	45	11	11	2,680,247	98	46.58	
$32c-4d-8k$	32	4	8	798,467	63	58.61	
$34c-11d-11k$	34	11	11	1,930,129	72	49.74	
63c-14d-11k	63	14	11	3,269,042	91	45.83	
$18c-6d-8k$	18	6	8	1,121,831	72	46.62	
$28c - 6d - 11k$	28	6	11	1,526,019	65	49.37	
$12c-4d-8k$	12	4	8	994,332	64	48.34	
$53c-12d-11k$	53	12	11	2,063,132	87	49.21	
$24c - 5d - 10k$	24	5	10	950,480	62	49.79	

A. Heuristic Algorithm vs. PELNI Method

The comparison of heuristic Algorithm vs. PELNI Method can be seen in Table 5.5. Based on the Table 5.5, PELNI shows the worst performance in terms of fuel consumption and load factor while heuristic algorithm shows the best performance in terms of fuel consumption and load factor for all sets. Routes constructed using PELNI method shows the best performance in terms of number of ports of call while heuristic algorithm shows the worst performance for all sets.

		Heuristic Algorithm		PELNI			
Benchmarks	Fuel Consumption	Number of Ports of Call	Load Factor	Fuel Consumption	Number of Ports of Call	Load Factor	
$40c-9d-8k$	1,067,352	49	17.13	1,275,883	154	3.60	
$28c-9d-9k$	1,900,067	40	26.01	2,375,323	119	5.41	
45c-11d-11k	3,029,397	58	23.16	3,868,567	203	5.35	
$32c-4d-8k$	888,475	41	24.02	1,036,758	95	5.57	
34c-11d-11k	2,177,213	49	26.47	2,743,105	142	5.30	
$63c-14d-11k$	3,699,584	76	9.81	4,755,085	282	3.75	
$18c-6d-8k$	1,231,551	28	21.03	1,491,149	81	4.22	
28c-6d-11k	1,716,760	41	25.11	2,134,324	104	4.14	
$12c-4d-8k$	1,060,131	21	42.45	1,263,833	55	4.42	
53c-12d-11k	2,328,848	67	18.79	2,945,322	194	3.54	
$24c - 5d - 10k$	1,061,950	36	24.74	1,267,387	87	3.95	

Table 5.5 Solution of 11 benchmarks solved by Heuristic Algorithm vs. PELNI

The average of increased fuel consumption efficiency of the heuristic algorithm compared to the PELNI method (PELNI, 2010) was about 17.65%, the average of decreased number of ports of call of the heuristic algorithm compared to the PELNI method (PELNI, 2010) was 64.84% and the average load factor of the PELNI method (PELNI, 2010) is about 4.48%, while the average of the load factor of the heuristic algorithm was about 23.52%.

B. General Genetic Algorithm (general GA) vs. PELNI Method

The experiment was conducted using a general Genetic Algorithm where the initial population was generated randomly without an improvement procedure. The genetic operators used were selection by roulette wheel, crossover by multi-cut point and mutation by pair exchange, while the genetic parameters used were: population size of 50, maximum generation is 100, and crossover rate of 0.7 and mutation rate of 0.5. The comparison of general Genetic Algorithm vs. PELNI Method can be seen in Table 5.6.

		General GA		PELNI		
Benchmarks	Fuel Consumption	Number of Ports of Call	Load Factor	Fuel Consumption	Number of Ports of Call	Load Factor
$40c-9d-8k$	1,122,712	79	44.90	1,275,883	154	3.60
$28c-9d-9k$	2,064,836	64	47.93	2,375,323	119	5.41
45c-11d-11k	3,340,013	101	43.82	3,868,567	203	5.35
$32c-4d-8k$	919,118	59	56.61	1,036,758	95	5.57
$34c-11d-11k$	2,377,556	83	50.85	2,743,105	142	5.30
63c-14d-11k	4,095,004	99	41.63	4,755,085	282	3.75
$18c-6d-8k$	1,308,901	51	44.22	1,491,149	81	4.22
$28c - 6d - 11k$	1,858,045	71	46.62	2,134,324	104	4.14
$12c-4d-8k$	1,114,330	42	45.47	1,263,833	55	4.42
53c-12d-11k	2,549,070	89	46.12	2,945,322	194	3.54
$24c - 5d - 10k$	1,116,445	56	46.59	1,267,387	87	3.95

Table 5.6 Solution of 11 benchmarks solved by General GA vs. PELNI

Based on the Table 5.6, PELNI shows the worst performance in terms of fuel consumption and load factor while heuristic algorithm shows the best performance in

terms of fuel consumption and load factor for all sets. Routes constructed using PELNI method shows the best performance in terms of number of ports of call while heuristic algorithm shows the worst performance for all sets.

The average of increased fuel consumption efficiency of the general Genetic Algorithm compared to the PELNI method (PELNI, 2010) was about 11.62%, the average of decreased number of ports of call of the general Genetic Algorithm compared to the PELNI method (PELNI, 2010) was 42.88% and the average load factor of the PELNI method (PELNI, 2010) is about 4.48%, while the average of the load factor of the general Genetic Algorithm was about 46.80%.

C. Hybrid Genetic Algorithm (Hybrid GA) vs. PELNI Method

The experiment was conducted using a hybrid Genetic Algorithm. The initial population in the hybrid genetic algorithm was generated randomly for the centromere, while the Qarm and P-arm were generated by the nearest neighbour method. An improvement procedure was proposed to ensure a chromosome with the best fitness was carried forward into the next generation. The genetic operators used were selection by roulette wheel, crossover by multi-cut point and mutation by pair exchange, while the genetic parameters used were: population size of 50, maximum generation of 100, and crossover rate of 0.7 and mutation rate of 0.5. The comparison of hybrid Genetic Algorithm vs. PELNI Method can be seen in Table 5.7.

		Hybrid GA		PELNI		
Benchmarks	Fuel Consumption	Number of Ports of Call	Load Factor	Fuel Consumption	Number of Ports of Call	Load Factor
$40c-9d-8k$	954,654	70	46.44	1,275,883	154	3.60
$28c-9d-9k$	1,711,743	67	50.16	2,375,323	119	5.41
45c-11d-11k	2,680,247	98	46.58	3,868,567	203	5.35
$32c-4d-8k$	798,467	63	58.61	1,036,758	95	5.57
$34c-11d-11k$	1,930,129	72	49.74	2,743,105	142	5.30
63c-14d-11k	3,269,042	91	45.83	4,755,085	282	3.75
$18c-6d-8k$	1,121,831	72	46.62	1,491,149	81	4.22
$28c - 6d - 11k$	1,526,019	65	49.37	2,134,324	104	4.14
$12c-4d-8k$	994,332	64	48.34	1,263,833	55	4.42
53c-12d-11k	2,063,132	87	49.21	2,945,322	194	3.54
$24c-5d-10k$	950,480	62	49.79	1,267,387	87	3.95

Table 5.7 Solution of 11 benchmarks solved by Hybrid GA vs. PELNI

The average of increased fuel consumption efficiency of the hybrid Genetic Algorithm compared to the PELNI method (PELNI, 2010) was about 26.06%, the average of decreased number of ports of call of the hybrid Genetic Algorithm compared to the PELNI method (PELNI, 2010) was 40.87% and the average load factor of the PELNI method (PELNI, 2010) is about 4.48%, while the average of the load factor of the hybrid Genetic Algorithm was about 49.15%.

5.1.3 Analysis

The summaries of the fuel consumption of each algorithm can be seen in Table 5.8.

	Fuel Consumption					
Benchmarks	PELNI	Heuristic	GA	Hybrid GA		
$40c-9d-8k$	1,275,883	1,067,352	1,122,712	954,654		
$28c-9d-9k$	2,375,323	1,900,067	2,064,836	1,711,743		
$45c-11d-11k$	3,868,567	3,029,397	3,340,013	2,680,247		
$32c-4d-8k$	1,036,758	888,475	919,118	798,467		
34c-11d-11k	2,743,105	2,177,213	2,377,556	1,930,129		
$63c - 14d - 11k$	4,755,085	3,699,584	4,095,004	3,269,042		
$18c-6d-8k$	1,491,149	1,231,551	1,308,901	1,121,831		
$28c - 6d - 11k$	2,134,324	1,716,760	1,858,045	1,526,019		
$12c-4d-8k$	1,114,330	1,060,131	1,114,330	994,332		
53c-12d-11k	2,945,322	2,328,848	2,549,070	2,063,132		
$24c - 5d - 10k$	1,267,387	1,061,950	1,116,445	950,480		
TOTAL	25,007,233	20, 161, 328	21,866,030	18,000,076		

Table 5.8 Fuel consumption of 11 benchmarks in the four algorithms

The minimum fuel consumption used to serve all ports in 11 benchmarks was for routes generated by the hybrid genetic algorithm. The increased fuel consumption efficiency of the hybrid Genetic Algorithm compared to the PELNI method (PELNI, 2010) was about 28.02%, the increased fuel consumption efficiency of the hybrid Genetic Algorithm compared to the heuristic algorithm was about 10.72%, and the increased fuel consumption efficiency of the hybrid Genetic Algorithm compared to the general Genetic Algorithm was about 17.68%. Comparison of all the results obtained can be seen in Figure 5.12.

Figure 5.12 Performance of four algorithms in terms of fuel consumption

Based on fuel consumption, the performance of the hybrid Genetic Algorithm was the best, and PELNI method shows the worst performance for all sets.

The results for the number of ports of call are tabulated in Table 5.9.

	Number of Ports of Call					
Benchmarks	PELNI	Heuristic	GA	Hybrid GA		
40c-9d-8k	154	49	79	70		
$28c-9d-9k$	119	40	64	67		
45c-11d-11k	203	58	101	98		
32c-4d-8k	95	41	59	63		
34c-11d-11k	142	49	83	72		
63c-14d-11k	282	76	99	91		
$18c-6d-8k$	81	28	51	72		
$28c - 6d - 11k$	104	41	71	65		
$12c-4d-8k$	55	21	42	64		
53c-12d-11k	194	67	89	87		
24c-5d-10k	87	36	56	62		
TOTAL	1,516	506	794	811		

Table 5.9 Number of ports of call from 11 benchmarks in the four algorithms

The decreased number of ports of call of the hybrid Genetic Algorithm compared to the PELNI method (PELNI, 2010) was 46.50%, the increased number of ports of call of the hybrid Genetic Algorithm compared to the heuristic algorithm was 60.27%, and the increased number of ports of call of the hybrid Genetic Algorithm compared to the general Genetic Algorithm was 2.14%. Comparison of all the results obtained can be seen in Figure 5.13.

Figure 5.13 Performance of four algorithms in terms the number of ports of call

Based on the number of ports of call, the PELNI method (PELNI, 2010) gave the best performance in all sets.

The results for the average of load factor are tabulated in Table 5.10. From Table 5.10 it can be seen that the average load factor of the PELNI method (PELNI, 2010) is about 4.48%, the average of the load factor of the heuristic algorithm was about 23.52%, the average of the load factor of the general Genetic Algorithm was about 46.80%, and the average of the load factor of the hybrid Genetic Algorithm was about 49.15%. Based on the load factor, the hybrid Genetic Algorithm gave the best performance, while the performance of the PELNI method (PELNI, 2010) was the worst. Comparison of all the results obtained can be seen in Figure 5.14.

	Load Factor					
Benchmarks	PELNI	Heuristic	GA	Hybrid GA		
$40c-9d-8k$	3.60	17.13	44.90	46.44		
$28c-9d-9k$	5.41	26.01	47.93	50.16		
$45c - 11d - 11k$	5.35	23.16	43.82	46.58		
$32c - 4d - 8k$	5.57	24.02	56.61	58.61		
34c-11d-11k	5.30	26.47	50.85	49.74		
$63c - 14d - 11k$	3.75	9.81	41.63	45.83		
$18c-6d-8k$	4.22	21.03	44.22	46.62		
28c-6d-11k	4.14	25.11	46.62	49.37		
$12c-4d-8k$	4.42	42.45	45.47	48.34		
$53c-12d-11k$	3.54	18.79	46.12	49.21		
$24c - 5d - 10k$	3.95	24.74	46.59	49.79		
AVERAGE	4.48	23.52	46.80	49.15		

Table 5.10 Load factor from 11 benchmarks in the four algorithms

Figure 5.14 Performance of four algorithms in terms of the load factor

5.1.4 Comparing the Performances of PELNI Method, Heuristic Algorithm, General Genetic Algorithm and Hybrid Genetic Algorithm

The four algorithms were tested with the 11 benchmarks. To assess the quality of the results, a statistical comparison has been realized between the four algorithms for 11 benchmarks. We use the Wilcoxon non-parametric paired test and the algorithms are compared two by two. If the returned *p-value* is higher than 0.05, the two algorithms are considered as equivalent, whereas if the *p-value* is strictly under 0.05, the wilcoxon test indicates the best one. All reports these results can be seen in Appendix D. Based on the reports, the hybrid Genetic Algorithm seems to dominate the other three algorithms on the 11 benchmarks. Indeed, it finds the best value on 11 benchmarks and gets the best mean values for all the benchmarks. This result is confirmed by the Wilcoxon test which gives a strong dominance to hybrid Genetic Algorithm.

5.2 Experiment 2 - Implementation of Algorithm

The second experiment was the implementation of algorithms for the ship routing of the PT. PELNI. In 2010, the PT. PELNI operated a service of 25 passenger ships throughout the Indonesian archipelago. The PT. PELNI served 84 ports and 12 of them were fuel ports. Each ship served exactly one route and a route included by necessity at least one fuel port.

5.2.1 Existing Routes in PT. PELNI 2010

Table 5.11 shows the fuel consumption, number of ports of call and load factor of routes generated by the PELNI method (PELNI, 2010). Each route served by a ship where the complete routes can be seen in Table 5.12.

Routes	Ships	Fuel Consumption	Number of Ports of Call	Load Factor
R1	AWU	184,943	19	47.26
R2	BINAIYA	179,372	13	81.81
R ₃	BUKIT RAYA	186,614	19	35.97
R4	BUKIT SIGUNTANG	743,885	20	97.61
R ₅	CIREMAI	746,112	20	58.05
R ₆	DOBONSOLO	726,067	17	80.35
R7	DOROLONDA	969,971	19	47.91
R8	GUNUNG DEMPO	555,663	13	113.11
R ₉	KELIMUTU	273,514	25	34.42
R10	KELUD	952,173	τ	55.90
R11	KERINCI	396,032	13	111.78
R12	LABOBAR	923,913	14	53.61
R13	LAMBELU	806,246	17	87.50
R14	LAWIT	191,627	12	36.37
R15	LEUSER	164,332	13	80.91
R ₁₆	NGGAPULU	978,870	20	50.46
R17	PANGRANGO	135,365	19	75.33
R18	SANGIANG	140,378	25	114.68
R ₁₉	SINABUNG	993,701	22	47.88
R20	SIRIMAU	165,446	16	39.41
R21	TATAMAILAU	138,707	13	29.29
R22	TIDAR	708,250	17	66.01
R23	TILONGKABILA	144,278	23	44.25
R24	UMSINI	724,608	13	156.55
R25	WILIS	97,763	15	64.20

Table 5.11 Fuel consumption, number of ports of call and load factor of routes generated by PELNI method (PELNI, 2010)

Table 5.12 Routes generated by PELNI method (PELNI, 2010)

Figure 5.15 Routes generated by PELNI method (PELNI, 2010)

5.2.2 Routes Generated Using a General Genetic Algorithm

The experiment in this part was to generate routes using a general Genetic Algorithm that could be used in the real world. The first population was generated randomly without an improvement procedure. The genetic operators used were selection by roulette wheel, crossover by multi cut point and mutation by pair exchange, while the genetic parameters used were: population size of 50, maximum generation of 100, crossover rate of 0.7 and mutation rate of 0.5.

Fuel consumption, number of ports of call and load factor of routes generated by the general Genetic Algorithm shown in Table 5.13. Each route served by a ship where the complete routes can be seen in Table 5.14.

Table 5.13 Fuel consumption, number of ports of call and load factor of routes generated by general Genetic Algorithm

Table 5.14 Routes generated by general Genetic Algorithm

Figure 5.16 Routes generated by general Genetic Algorithm

5.2.3 Routes Generated Using a Hybrid Genetic Algorithm

The next experiment was to generate routes using a hybrid Genetic Algorithm. The first population in the hybrid Genetic Algorithm was generated randomly for the centromere, while the Q-arm and the P-arm were generated by the nearest neighbour.

Fuel consumption, number of ports of call and load factor of routes generated by the hybrid Genetic Algorithm shown in Table 5.15. Each route served by a ship where the complete routes can be seen in Table 5.16.

Table 5.15 Fuel consumption, number of ports of call and load factor of routes generated by hybrid Genetic Algorithm

Table 5.16 Routes generated by hybrid Genetic Algorithm

Figure 5.17 Routes generated by hybrid Genetic Algorithm

5.2.4 Analysis

In the existing routes, the total fuel consumption used for 25 ships was 12,227,830 litres, the total number of ports of call was 424 and the average of the load factor was about 68.43%. The total fuel consumption for the routes generated by the general Genetic Algorithm was 11,579,291 litres, the total number of ports of call was 480 and the average load factor was 64.68%, while the total fuel consumption for the routes generated by the hybrid Genetic Algorithm was 11,508,248 litres, the total number of ports of call was 493 and the average of the load factor was 63.08%.

Figure 5.18 Performance of three algorithms in terms the fuel consumption

The increased fuel consumption efficiency of the hybrid Genetic Algorithm compared to the PELNI method (PELNI, 2010) was 5.88%, and the increased fuel consumption efficiency of the hybrid Genetic Algorithm compared to the general Genetic Algorithm was 0.61%. Based on the fuel consumption, the hybrid Genetic Algorithm gave the best performance, while the performance of the PELNI method was the worst. Comparison of

the performance of three algorithms in terms the fuel consumption can be seen in Figure 5.18.

Figure 5.19 Performance of three algorithms in terms the number of ports of call

The increased number of ports of call of the hybrid Genetic Algorithm compared to the PELNI method (PELNI, 2010) was 16.27% and the increased number of ports of call of the hybrid Genetic Algorithm compared to the general Genetic Algorithm was 2.71%. Based on the number of ports of call, the performance of the hybrid Genetic Algorithm was the best, while that of the PELNI method (PELNI, 2010) was the worst. Comparison of the performance of three algorithms in terms the number of ports of call can be seen in Figure 5.19.

The average load factor of the routes generated by the PELNI method (PELNI, 2010) was 68.43%, while the average load factor of the routes generated by the general Genetic Algorithm was 64.68% and the average load factor of the routes generated by the hybrid

Genetic Algorithm was 63.08%. Based on the average load factor, the performance of the PELNI method (PELNI, 2010) was the best. Comparison of the performance of three algorithms in terms the load factor can be seen in Figure 5.20.

Figure 5.20 Performance of three algorithms in terms the load factor

As mentioned in the first chapter, the objective function in this research is to minimize conflicts between accessibility and profitability. Accessibility is associated with the number of ports of call while profitability is associated with the load factor. The goal of increasing profit will contradict the goal of greater accessibility. Since the goal is to minimize conflicts of interest between accessibility and profitability, a measurement tool called the 'quadrant scale' is proposed. The quadrant scale consists of load factors for the *x*-axis and the number of ports of call for *y*-axis.
There are 4 areas in the quadrant scale:

- I is the area for high accessibility but low profitability
- II is the area for high accessibility and high profitability
- III is the area for low accessibility but high profitability
- IV is the area for low accessibility and low profitability

The quadrant scale presented for the PELNI method (PELNI, 2010) is shown in Figure 5.21, while the quadrant scale presented for the general Genetic Algorithm is shown in Figure 5.22, and the quadrant scale presented for the hybrid Genetic Algorithm is shown in Figure 5.23.

Figure 5.21 Quadrant scale of PELNI method (PELNI, 2010)

The quadrant scale in Figure 5.21 shows that the routes generated using the PELNI method (PELNI, 2010) were scattered in four areas; 7 routes were in area I, 6 routes were in area II, 4 routes were in area III and 2 routes were in area IV. In general it can be said that most of the routes had a high number of ports of call but a low load factor. This was because the number of ports of call and the load factor were not balanced. There is a possibility that the number of passengers in a path was low but the port is served more than twice in a week. Figure 5.1 shows that there were 3 routes that had a load factor of more than 100%. This situation indicates that the number of passengers was more than the available seat capacity.

Figure 5.22 Quadrant scale of general Genetic Algorithm

164 Figure 5.22 shows the quadrant scale for the general Genetic Algorithm. It shows that 3 routes were in quadrant I, 16 routes were in quadrant II, 5 routes were between quadrants II and III, and 1 route was between quadrants I and II. In general it can be said that the routes generated using the general genetic algorithm had a high number of ports of call and high load factor but there were 2 routes which had a low load factor.

Figure 5.23 shows the quadrant scale for the hybrid Genetic Algorithm. It shows that 20 routes were in quadrant II, 4 routes were between quadrant II and III, and 1 route was between quadrant I and II. In general, the routes generated using the hybrid Genetic Algorithm shows that both the number of ports of call and the load factor are high.

Figure 5.23 Quadrant scale of hybrid Genetic Algorithm

Figure 5.23 shows the quadrant scale for the hybrid genetic algorithm. It shows that 20 routes were in quadrant II, 4 routes were between quadrant II and III, and 1 route was between quadrant I and II. In general, the routes generated using the hybrid genetic algorithm shows that both the number of ports of call and the load factor are high.

Based on the results presented, the best routes were generated by the hybrid Genetic Algorithm, followed by the general Genetic Algorithm, while the PELNI method (PELNI, 2010) showed the worst performance.

5.3 Experiment 3 - Routes Proposed

This part proposes routes which can be used to solve the routing problem of the ships in Indonesia with greater efficiency than the existing routes. It was solved by a minimum number of vehicles scenarios. The problem was to find optimal routes with minimum vehicles used to serve all ports. The routes were generated by a hybrid Genetic Algorithm, where genetic operators used were selection by roulette wheel, crossover by multi-cut point and mutation by pair exchange. While the genetic parameters used were: population size of 50, maximum generation of 100, crossover rate of 0.7 and mutation rate of 0.5.

The minimum number of vehicles used to serve all ports was 17, the total fuel consumption was 6,618,819 litres, the total number of ports of call was 319 and the average of the load factor is about 63.31%. Table 5.17 shows the fuel consumption, number of ports of call and load factor of routes proposed that generated by hybrid Genetic Algorithm. Each route served by a ship where the complete routes can be seen in Table 5.18.

Table 5.17 Fuel consumption, number of ports of call and load factor of routes proposed that generated by hybrid Genetic Algorithm

Table 5.18 Routes proposed that generated by hybrid Genetic Algorithm

Figure 5.24 Routes proposed for minimum ships scenarios that generated by hybrid Genetic Algorithm

The quadrant scale for the minimum ships scenario is presented in Figure 5.25.

Figure 5.25 Quadrant scale for minimum ships scenarios

Based on the results in Table 5.19, it can be concluded as follows:

- 1. The increased efficiency fuel consumption efficiency of the proposed route compared to the existing route (PELNI, 2010) was 45.87%.
- 2. The decreased percentage total of the number of ports of call for the proposed route compared to the existing route (PELNI, 2010) was 24.76%.
- 3. The decreased average load factor for the proposed route compared to the existing route (PELNI, 2010) was 5.12%

Table 5.19 Comparison between existing routes and proposed routes

5.4 Summary

In this chapter, the proposed algorithm was evaluated by three experiments using the heuristic algorithm, general genetic algorithm and hybrid genetic algorithm. From the experiments it was found:

1. **The hybrid genetic algorithm showed the best performance in fuel consumption and average load factor over 11 benchmarks.**

Based on fuel consumption, the performance of the hybrid genetic algorithm showed the best performance, and the heuristic algorithm was better than the general genetic algorithm while the worst performance came from the PELNI method (PELNI, 2010). The increased efficiency in the fuel consumption of the hybrid genetic algorithm was 28.02% when compared to the PELNI method (PELNI, 2010), and 10.72% when compared to the heuristic algorithm, and 17.68% when compared to the general genetic algorithm.

Based on the average load factor, the performance of the hybrid genetic algorithm showed the best performance and the general genetic algorithm was better than the heuristic algorithm while the worst performance came the PELNI method (PELNI, 2010). The average of the load factor of the hybrid genetic algorithm was about 49.15%, the average load factor of the general genetic algorithm was about

46.80%, the average load factor of the heuristic algorithm was about 23.52%, and the average load factor of the PELNI method (PELNI, 2010) was about 4.48%.

2. The hybrid genetic algorithm showed the best performance in fuel consumption and number of ports of call in solving the routing problems of the ship in Indonesia.

Based on fuel consumption, the performance of the hybrid genetic algorithm showed the best performance while the worst performance was from the PELNI method (PELNI, 2010). The increased efficiency in the fuel consumption of the hybrid genetic algorithm was 5.88% when compared to the PELNI method (PELNI, 2010), and 0.61% when compared to the general genetic algorithm. Based on the number of ports of call, the performance of the hybrid genetic algorithm showed the best performance while the worst performance came the PELNI method. The increased number of ports of call of the hybrid genetic algorithm was 16.27% when compared to the PELNI method (PELNI, 2010), and 2.71% when compared to the general genetic algorithm.

- **3. The routes produced by the hybrid genetic algorithm for the minimum number of vehicles scenario were 45.87% more efficient with regard to fuel consumption than the existing routes by the PT. PELNI (PELNI, 2010).**
- 4. **Hence, the hybrid genetic algorithm showed the best overall performance** When the quadrant scale was applied for the analysis of the performances of the algorithms, hybrid genetic algorithm clearly outperformed the others.

Therefore, it was concluded conclude that the new hybrid algorithm is far superior to the current available method for the research problem discussed.

CHAPTER 6 CONCLUSIONS AND FUTURE WORK

This chapter summarizes and concludes our research into solving the vehicle routing problem (VRP), as discussed. Several recommendations for future work and algorithm improvements are also included.

6.1 Research Summary

The general vehicle routing problem consists of determining several vehicle routes, with minimum cost, to serve a set of customers. Each customer is required to be visited only once by one vehicle. Typically, vehicles are homogeneous and have the same capacity restriction. This research used heuristics and metaheuristics to solve the ship routing problem. There are four vehicle routing problem variants, which are similar to the ship routing problem, namely the multi-depot vehicle routing problem (MDVRP), the heterogeneous fleet vehicle routing problem (HVRP), the site dependent capacitated vehicle routing problem (SDCVRP) and the asymmetric vehicle routing problem (AVRP).

The vehicle fleet is a mixture of different vehicle types. Ships are of different capacities, speeds and costs. There are two types of constraints, namely; soft constraints and hard constraints.

1. Soft constraints

There are two soft constraints for the ship routing problem i.e. ship draft and sea depth, and load factor. Soft constraints are dealt with by imposing a penalty.

2. Hard constraints

There are three hard constraints for the ship routing problem i.e, travel time, travel distance, and a route included due to the necessity of having at least one fuel port within the route. Hard constraints are dealt with by removing unfeasible routes.

Vehicle routing problem is a general combinatorial optimization and is an NP-hard problem. This means that it is not guaranteed that there is a known algorithm that solves all cases to optimality in a reasonable execution time. As this problem cannot be solved by optimal (exact) methods in practice, heuristic and metaheuristics are used. In this research, a heuristic algorithm (based on the next nearest neighbour concept) was modified and applied to the case study.

We implemented a new model for chromosome where the length of a chromosome depends on the number of ships. Each ship is represented as a sub-chromosome where each sub-chromosome consists of 14 genes. A sub-chromosome consists of Q-arm, Parm, and two centromeres. The 1st and 10th genes contain a value that refers to the fuel port. The 2nd - 9th are called Q-arm, while the 11th - 14th are called P-arm. Q-arm and P-arm contain a value that refers to the customer's port.

The crossover method is based on a modified multi-cut point crossover. The crossover is done by exchanging Q-arm and P-arm between two parents' chromosomes. Pairs exchange mutation is applied to P-arm. After recombination, all chromosomes are checked to ensure that the travel time constraint and travel distance is not violated. When a chromosome violates these constraints, it is repaired. During the repairing process, the ports that are served more than once are deleted.

The objectives that can be used to analyse the performance of public transportation routes that are owned and operated by government are fuel consumption, number of ports of call, and load factor. Since the objective of solving our problem is how to determine the combination of routes that give minimum fuel consumption, maximum number of ports of call and maximum load factor by satisfying a number of predetermined constraints, it is difficult to calculate one best solution.

Hence, we used a measurement tool known as a quadrant scale. The quadrant scale consists of load factor for the *x* axis and number of ports of call for the *y* axis. There are 4 areas in the quadrant scale:

- I is the area used for high accessibility and low profitability
- II is the area used for high accessibility and high profitability
- III is the area used for low accessibility and high profitability
- IV is the area used for low accessibility and low profitability

Based on the quadrant scale analysis:

- The quadrant scale for the routes generated using the PELNI method are scattered in four areas i.e., 7 routes in area I, 6 routes in area II, 4 routes in area III, and 2 routes in area IV. Most of the routes have a high number of ports of call, but they have a low load factor. This situation is due to the number of ports of call and the load factor not being balanced. There is a possibility that the number of passengers in a path is low but the port is served more than twice in one week.
- The quadrant scale for the general Genetic Algorithm shows that 3 routes are in quadrant I, 16 routes are in quadrant II, 5 routes are between quadrants II and III, and 1 route is between quadrants I and II. The routes generated using the general

Genetic Algorithm have a high number of ports of call and a high load factor but there are 2 routes that have a low load factor.

 The quadrant scale for the hybrid Genetic Algorithm shows that 20 routes are in quadrant II, 4 routes are between quadrants II and III, and 1 route is between quadrants I and II. Thus, the routes generated using the hybrid Genetic Algorithm show that both the number of ports of call and the load factor are high.

Based on the results presented in Chapter 5, the hybrid Genetic Algorithm shows the ability to obtain a better solution to the ship routing problem than the PELNI method and the general Genetic Algorithm. All of the results can be summarized as follows:

- The increased fuel consumption efficiency of the hybrid Genetic Algorithm compared to the PELNI method is 5.88 %; and the increased fuel consumption efficiency of the hybrid Genetic Algorithm, compared to the general Genetic Algorithm, is 0.61%.
- The increased number of ports of call of the hybrid Genetic Algorithm compared to the PELNI method is 16.27%; and the increased number of ports of call of the hybrid Genetic Algorithm compared to the general Genetic Algorithm, is 2.71%.
- The decreased load factor of the hybrid Genetic Algorithm compared to the PELNI method is approximately 3.75%; and the decreased load factor of the hybrid Genetic Algorithm compared to the general Genetic Algorithm, is approximately 1.60%.

We proposed an optimum route, where 17 vehicles are used to serve all ports. The comparison of the existing routes and the proposed routes is summarized as follows:

4. Total fuel consumption used to serve all ports in the routes proposed is 6,618,819 litres while the total fuel consumption in the existing routes is 12,227,830 liters.

Fuel consumption efficiency is increased by approximately 45.87% compared to the existing routes.

- 5. The total the number of ports of call in the routes proposed is 319 while the total number of ports of call in the existing routes is 424. The number of ports of call is decreased by 24.76% compared to the existing routes.
- 6. The load factor average of the routes proposed is 63.31%, while the load factor average of the existing routes is 68.43%. Therefore, load factor average decreased by 5.21% compared to the existing routes.

6.2 Contribution

The following are some of the contributions to this study:

Identification of the nature of the ship routing problem in Indonesian waters.

A ship routing problem consists of four different Vehicle Routing Problem (VRP) variants, namely the multi-depot vehicle routing problem (MDVRP), the heterogeneous fleet vehicle routing problem (HVRP), the site dependent capacitated vehicle routing problem (SDCVRP) and the asymmetric vehicle routing problem (AVRP).

New chromosome model

A chromosome in the hybrid Genetic Algorithm is represented as a number of subchromosomes. Each sub-chromosome consists of Q-arm, P-arm and two centromeres. The 1st and 10th genes (known as centromere) contain values that refer to the fuel port. The 2nd to the 9th genes are known as the Q-arm and the 11th to the 14th genes are known as the P-arm. Q-arm and P-arm both contain values that refer to the customer's port.

Method to solve the ship routing problem.

o The heuristic method is which 'cluster first and route second'.

Three phases are included in this method i.e. clustering, assigning of vehicle, and finding the best routes by combining feasible solutions.

(i) Phase I: Clustering

Routes are clustered in order to solve the constraint based on problems of travel time and travel distance allowed for each route. Travel time is less than or equal to the maximum travel time allowed and travel distance is less than or equal to the maximum travel distance allowed. The output is a feasible route set for the solution candidate.

(ii) Phase II: Assigning a vehicle

Vehicles are assigned in a cluster to ensure that each route has at least one fuel port (the route is removed if this condition is violated) During this phase, fuel consumption is calculated with a penalty α imposed if the ship's draft is equal to or greater than the sea depth; penalty β is imposed for the load factor conditions; and penalty γ is imposed for the number of ports of call condition.

(iii) Phase III: Finding the best routes

A robust algorithm was developed based on the maximum-insertion concept where a heuristic model with a maximum-insertion concept was modified, where the objective was to successively insert a route within the best combination of routes with the minimum fuel consumption.

o Hybrid Genetic Algorithm

A hybrid genetic algorithm (hybrid Genetic Algorithm) was proposed to improve the performance of the general Genetic Algorithm. The differences between the general Genetic Algorithm and the hybrid Genetic Algorithm are as follows:

(i) Initial population

The initial population of the general Genetic Algorithm is generated randomly while in the hybrid Genetic Algorithm is generated using a random mix with the nearest neighbour concept. The centromere generated is random, while the Q-arm and the P-arm are generated using the nearest neighbour.

(ii) Improvement procedure

This procedure compares the best parent and offspring fitness's, and the chromosome with the best fitness is perpetuated into the next generation.

6.3 Limitations

There are several limitations of this study:

Determination of penalty for soft constraints is only done by forecasting.

Two soft constraint penalty values cannot be precisely determined, namely:

- i. Load factor
- ii. Number of ports of call

Determinations of penalty values for these soft constraints affect the accuracy of achievement of the objective function. If the penalty values can be determined precisely, then a comparison between the three objectives would be more appropriate.

Scheduling issues of routes are not addressed in detail.

6.4 Further Work

There is a need for future works to address the limitations listed above:

Determination of the penalty's value

Penalty values can be made more precise, so that a comparison between the three objectives can be made more accurately.

Two ships anchored in the same port at the same time

Two ships can be anchored in the same port at the same time. Some passengers may change their journey to another route. If this facility is available, then travelling times can be reduced for passengers.

6.5 Conclusion

From the detailed discussion contained within this thesis, we have shown that the objective of our research has been achieved. In doing so, we have also contributed a new method to solve the ship routing problem discussed.

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APPENDIX

Appendix A - Ports and Routes

- A.1 Ports Code
- A.2 Ships
- A.3 Sea Depth
- A.4 Distance between Ports
- A.5 Number of Passenger on Board between Ports

Appendix B - Benchmarks

- B.1 40c-9d-8k
- B.2 28c-9d-9k
- B.3 45c-11d-11k
- B.4 32c-4d-8k
- B.5 34c-11d-11k
- B.6 63c-14d-11k
- B.7 18c-6d-8k
- B.8 28c-6d-11k
- B.9 12c-4d-8k
- B.10 53c-12d-11k
- B.11 24c-5d-10k

Appendix C - Routes

- C.1 Existing Routes (PT. PELNI in 2010)
- C.2 Routes Generated by PELNI Method
- C.3 Routes Generated by General Genetic Algorithm
- C.4 Routes Generated by Hybrid Genetic Algorithm
- C.5 Routes Generated by Hybrid Genetic Algorithm in Minimum Vehicle Scenario

Appendix D - Comparison of Four Algorithms

A.1 Ports Code

A.2 Ships

A.3 Sea Depth

A.4 Distance between Ports

Appendix B - Benchmarks

B.1 40c-9d-8k

B.2 28c-9d-9k

B.3 45c-11d-11k

B.4 32c-4d-8k

B.5 34c-11d-11k

B.6 63c-14d-11k

B.7 18c-6d-8k

B.8 28c-6d-11k

B.9 12c-4d-8k

B.10 53c-12d-11k

Ships	Capacity (seats)	Engine Power (HP)	Speed (Knot)	Ship Draft (meter)	Fuel Consumption (Liter(s)/Mile)	Comission Days	Tank Capacity	Number of Machine
k2	1325	2176	12	4.2	51.67	336	360200	\overline{c}
k ₃	1518	2176	13	4.2	49.85	336	360200	\overline{c}
k9	1198	2176	10	4.2	56.82	336	327940	\overline{c}
k10	2404	11587	18	5.9	127.51	336	853230	$\overline{2}$
k11	2126	8500	16	5.9	117.02	336	1048100	\overline{c}
k12	3018	11421	19	5.9	140.24	336	853230	\overline{c}
k16	3410	11587	18	5.9	143.4	336	853230	\overline{c}
k17	594	1632	9	4.2	42.12	336	130600	$\mathfrak{2}$
k21	1312	2176	11	4.2	51.85	336	360300	\overline{c}
k23	1518	2176	11	4.2	47.94	336	360200	\overline{c}
k24	1518	8500	16	5.9	116.38	336	1048100	\overline{c}
k25	595	1632	10	4.2	38.08	336	130600	\overline{c}

B.11 24c-5d-10k

C.2 Routes Generated by PELNI Method

C.3 Routes Generated by General Genetic Algorithm

C.4 Routes Generated by Hybrid Genetic Algorithm

C.5 Routes Generated by Hybrid Genetic Algorithm in Minimum Vehicle Scenario

Appendix D - Comparison of Four Algorithms