MULTI-OBJECTIVE SHIP ROUTING PROBLEM IN MARITIME LOGISTICS COLLABORATION

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MULTI-OBJECTIVE SHIP ROUTING PROBLEM

IN MARITIME LOGISTICS COLLABORATION

Suranaree University of Technology has approved this thesis submitted in fulfillment of the requirements for the Degree of Doctor of Philosophy.

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งานวิจัยนี้ได้ศึกษาความร่วมมือระหว่างบริษัทสายการเดินเรือขนส่งสินค้าสองบริษัทที่มีการออกแบบโครงสร้างเส้นทางการเดินเรือร่วมกัน โดยมีวัตถุประสงค์ที่เกี่ยวข้อง 2 วัตถุประสงค์ แบบจำลองจำนวน 4 แบบได้ถูกพัฒนาในรูปแบบที่เพิ่มระดับความซับซ้อนของปัญหา แบบจำลองสองแบบแรกนำเสนอแนวคิดความร่วมมือกันของสายการเดินเรือ และแบบจำลองอีกสองแบบนั้นจะอภิปรายแนวทางการพัฒนาวิธีการแก้ปัญหา แบบจำลองนี้จะถูกสร้างโดยใช้ปัญหาการจัดการเส้นทางยานพาหนะเป็นแนวทาง แต่มีการปรับรูปแบบให้สอดคล้องกับการจัดการเส้นทางเดินเรือแทนโดยพิจารณาเรือที่มีขนาดแตกต่างกัน ช่วงเวลา และต้นทุนคงที่ ขั้นตอนวิธีเชิงพันธุกรรมที่ได้รับการปรับปรุงได้ถูกนำเสนอและหลักการต่าง ๆ ที่เกี่ยวข้องถูกเชื่อมโยงโดยขั้นตอนวิธีเชิงวิวัฒนาการแบบหลายวัตถุประสงค์เพื่อให้เกิดวิธีการแก้ปัญหาแบบใหม่สำหรับปัญหาความร่วมมือด้านโลจิสติกส์ทางทะเลแบบหลายวัตถุประสงค์ กรณีศึกษาต่าง ๆ จากข้อมูลในหมู่เกาะของประเทศอินโดนีเซียได้ถูกพัฒนาเป็นข้อมูลเชิงตัวเลขเพื่อใช้ในการทดสอบผลลัพธ์ของวิธีการที่นำเสนอ ซึ่งผลลัพธ์จากวิธีการที่นำเสนอนี้สามารถนำไปสู่ผลเฉลยที่ไม่มีการครอบงำของทั้งสองบริษัทสายการเดินเรือขนส่งสินค้า โดยวิธีการแก้ปัญหาและตัวอย่างการนำไปประยุกต์ใช้ไม่เคยมีการศึกษาหรือบันทึกในวรรณกรรมใด ๆ มาก่อนหน้า ดังนั้น งานวิจัยนี้จึงเป็นการศึกษาที่มีคุณค่ายิ่ง

สาขาวิชา วิศวกรรมอุตสาหการ ลายมือชื่อนักศึกษา_______________________

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ERIC WIBISONO : MULTI-OBJECTIVE SHIP ROUTING PROBLEM IN MARITIME LOGISTICS COLLABORATION. THESIS ADVISOR : ASST. PROF. PHONGCHAI JITTAMAI, Ph.D., 196 PP.

MULTI-OBJECTIVE OPTIMIZATION/SHIP ROUTING PROBLEM/MARITIME LOGISTICS COLLABORATION/EVOLUTIONARY ALGORITHM

This research studies the collaboration between two liner shipping companies in joint-routing network design involving two objectives. Four models are developed with increasing degree of complexity. The first two models introduce the idea of liner collaboration, and the other two models discuss methods development. The model is based on the vehicle routing problem but adjusted to the ship routing problem by considering heterogeneous vessels, time windows, and fixed cost. An improved version of genetic algorithm is proposed and its principles are combined with an elitist multi-objective evolutionary algorithm to form a novel method for a multi-objective problem in maritime logistics collaboration. Case studies are developed for numerical instances based on the Indonesian archipelago. The method is able to point out non-dominated solutions for both companies. Neither the algorithm nor an example of its application has ever been documented in the literature, therefore this research has a significant contribution in this field.

School of Industrial Engineering Student's Signature__________________

Academic Year 2014 Advisor's Signature__________________

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I dedicate this work to my lovely family: my wife Cia Ling and my kids Beatrice and William. They also endured hardships as they are the ones who managed home during my time away. But the thought of their sacrifices has been a constant reminder for me to perform well and I believe I have done just that because of them.

Eric Wibisono

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SYMBOLS AND ABBREVIATIONS

VRP	=	Vehicle Routing Problem
SRP	=	Ship Routing Problem
VRPTW	=	VRP with Time Windows
VRPPDTW	=	VRP with Pickups-Deliveries and Time Windows
VRPSD	=	VRP with Stochastic Demand
SDVRP	=	Site-Dependent / Split-Delivery VRP
FSMVRP	=	Fleet Size & Mix VRP
VFMP	=	Vehicle Fleet Mix Problem
HVRP	=	Heterogeneous VRP
HVRPTW	=	Heterogeneous VRPTW
MOO	=	Multi-Objective Optimization
MOEA	=	Multi-Objective Evolutionary Algorithms
GA	=	Genetic Algorithm
VEGA	=	Vector Evaluated Genetic Algorithm
MOGA	=	Multi-Objective Genetic Algorithm
MACS	=	Multiple Ant Colony System
NSGA	=	Non-Dominated Sorting Genetic Algorithm
NSGA-II	=	Elitist Non-Dominated Sorting Genetic Algorithm
SPEA	=	Strength Pareto Evolutionary Algorithm
SPEA2	=	Strength Pareto Evolutionary Algorithm version 2

CHAPTER I

INTRODUCTION

1.1 Background

Globalization takes form in the expansion of social and economic networks and activities among countries. A significant part of it that cannot be overlooked is in the area of international trade. Products (manufactured goods) and services in one country become more easily accessible in other different parts of the world. These exchanges are progressively made easier as we enter the 21st century with the help of advanced communication technologies and various multilateral agreements. Nations realized the benefits of engaging in international economic cooperation thus regulations fostering this idea is continuously sought for, discussed, jointly agreed, and put in the ground of implementation. Free trade areas are examples of such regulations and in a regional scale we have witnessed the inauguration of the ASEAN Economic Community in 2015.

One of the driving forces behind the flourishing international trade, inarguably, lies in the increasingly better practice of logistics and distribution systems. These systems facilitate the transfer of products and services from the point of origin to the point of consumption and better systems result in more efficient transfers in terms of speed, cost, and reliability. Their role in the betterment of overall company performance is therefore as critical as other company functions. Academics and practitioners are continuously developing, testing, and exploring new frontiers in this area and a growing number of studies and publications are testament of such phenomena.

Transfers of physical products can be made over land, sea, or air. Land-based logistics such as trains, trucks, or buses, are the most popular option, partly due to their high visibility, but mainly on their flexibility in handling various types of products. Their major limitation, however, is in the area of inefficiency with regard to the amount of cargo they can carry per trip and the distance they can cover. Long-distance transfers therefore require other modes of transportation, either by air or sea. Air-based logistics are represented by airplanes and these are characterized by the following attributes (Liu, 2012): (1) fast, making them ideal for the transportation of perishable products; (2) secure, given the well-established and tightly regulated safety standards that make them the preferred shipping option for valuable goods; and (3) reliable, in relation to the superior punctuality compared to other shipping modes. The major drawback of this logistics mode is on its limitations in dealing with sizes, weights, and high costs.

The last of the three modes of logistics is maritime logistics (also commonly referred to as sea/maritime transportation). Its visibility is low compared to the other two modes, much to the fact that people rarely use it for commuting. However, for transporting goods, the world trade depends largely on sea-borne transportation. Christiansen *et al* (2007) estimate the share of weight of international trade borne by sea is in the range of 65% to 85%, whereas Singapore Logistics Association (2010) estimates that 90% of global freight are transported via shipping, using different types of vessels across the world's oceans and through man-made waterways. The ships' capacity is many times larger than that of trucks/trains/airplanes and ships can travel far carrying cargo across seas and oceans. In countries with long shorelines or thousands of islands such as Indonesia, the Philippines, Japan, Greece, and Norway, the role of maritime logistics for domestic transportation is even more critical. It is far from exaggeration to express that maritime logistics is the bloodline of world trade/economy and a key actor in globalization.

The picture of international shipping in the last decade is decorated with major events including the world economic crisis in 2008, debt crises in several European countries in the subsequent years, the rise and volatility of oil prices, and political and social unrest as well as natural disasters in some countries with irregular patterns that disrupted the global supply chains whenever occurred. These caused fluctuations in both the supply and demand sides that worth a closer look. Firstly, on the demand side, the aforementioned factors to a certain extent have shrunk the world economic capacity. Table 1.1 details the story for the last five years: after a big shock in 2008, the world gross domestic product (GDP) suffered a negative growth (2009), recovered in the next year (2010), but the growth continued to diminish afterwards (2011-2013). The world exports (measured in volume of merchandise trade) and seaborne trade are also trending in a similar fashion. Secondly, on the supply side, an opposite direction is encountered: the world fleet capacity is steadily increasing from 1.28 billion deadweight tons (dwt) in 2009 to 1.63 dwt in 2012, and the growth had also been expanding until 2012 (Table 1.2). This trend had actually been seen since 2001 where year after year between 2001 and 2011, this growth figure always recorded new historical highs and only in 2012, for the first time since 2001, it slowed down. It should be highlighted that the capacity still grew from 2011 to 2012, only at a slower rate than in 2011. Overall, the world fleet capacity has more than doubled since 2001.

Table 1.1 World economy growths

	2009	2010	2011	2012	2013	2014 [a]
GDP	-2.2%	4.1%	2.8%	2.3%	2.3%	2.7%
Exports	-13.3%	13.9%	5.5%	2.3%	2.2%	n.a.
Seaborne trade	-4.5%	7.0%	4.5%	4.3%	3.8%	n.a.

Source: UNCTAD (2013, 2014)
[a] Forecast

Table 1.2 World fleet capacity

	2009	2010	2011	2012	2013
Billion dwt	1.28	1.40	1.54	1.63	1.69
Growth	7.0%	9.4%	9.9%	6.0%	4.1%

Source: UNCTAD (2010, 2011, 2012, 2013, 2014)

The above data indicate a mismatch between supply and demand in the shipping business. While the decreasing demand is attributed to the world economic downturn, the increasing supply is reported due to the reluctance of major shipbuilder countries such as China, Japan, and the Republic of Korea, to cancel or postpone deliveries for orders placed prior to the economic crisis (UNCTAD, 2012), and only in 2012 onwards the impact was manifested. Regardless of the causes, oversupply of ships is a fierce challenge today faced by the companies in this industry. Shipping companies must rethink on the way they operate and seek better methods at all managerial levels to improve their performance and profitability. Collaboration, partnership, and forging alliances, are some possible paths that could enable companies to serve today’s depressing markets with more efficient operations.

An important segment in maritime logistics is the container ships. While the total fleet accounts for only 13% of total world fleet capacity, much lower than the other segments, for example, bulk carriers (43%) and oil tankers (29%) (UNCTAD, 2014), container ships are estimated to carry 52% of global seaborne trade in terms of value, or more than US$ 4 trillion worth of goods annually (World Shipping Council, 2014). Indeed, as The Economist put it: "*... container has been more of a driver of globalization than all trade agreements in the past 50 years taken together.*" (The Economist, 2013). The shipping service associated with this segment is called *liner shipping* (from the word *container line*). A container ship is responsible for cargoes (containers) from multiple owners. Because a liner company serves many shippers, it needs to publish a timetable and its routing in advance so shippers can schedule their shipment. The design of network for routing has to take into account many considerations such as the company's fleet size, fleet deployment, demand/market growth in the ports of call, port development, government regulations, etc. It is therefore an important strategic decision, because once the network is established, it is usually adopted for months or years depending on the scale of the company's operations.

The practice of liner shipping collaboration stretched back to 1875 with the formation of the U.K.-Calcutta Conference. Known under various names such as liner conferences, shipping conferences, and ocean shipping conferences, these are the primary form for liner companies to setup agreements in such scopes as route allocation, capacity management, price fixing, and loyalty discounts (Sjostrom, 2009). In the last decade, however, conferences have lost its charm and companies have collaborated in other forms that generally can be grouped into two types. Firstly, it can take a form as global/strategic alliances. This type of collaboration involves more than one company and is usually under long-term contracts. Secondly, it is in the form of collaborative agreements between two companies and is usually short-term in nature and targeted at the operational level. The activities in either type can be on route specific ventures, vessels sharing, or slot sharing. It is also possible that companies may follow more than one of them (Heaver *et al*, 2001).

From 1996 to 2011, the world liner shipping had witnessed the establishment of three big alliances: the Grand Alliance (GA), the New World Alliance (NWA, formerly the Global Alliance), and the CKYH Alliance (formerly Hanjin/Tricon, then the United Alliance). These three alliances account for one-third of the world line capacity (Panayides and Wiedmer, 2011). In the late 2011, GA and NWA formed the G6 Alliance and began operation in March 2012 (Hapag-Lloyd, 2013). The top three liner companies (APM-Maersk, MSC, and CMA CGM) have been known to operate independently, or labeled as 'soloists', but recent news suggests they are set forth to form the so-called P3 Alliance. This gigantic business entity will assume more than 40% of world line capacity and criticisms have been expressed by cargo owners and shippers' groups for the fear of their market domination that would decline competition and possibly lead to oligopolistic markets (Reuters, 2014). Immediately after this movement, Evergreen, currently rank fifth in the world with regard to capacity and who would be left out as a leading soloist if P3 takes place, announced that it will join the CKYH Alliance that will make the resulting CKYHE Alliance controls 21% of world line capacity and 26% of routes (Taipei Times, 2014). These dynamics in world liner shipping competition indicate that liner companies are relentlessly in pursuit of efficiency to help them reduce costs and increase profits. The downside is that the new alliances will clearly dominate the market and very likely put the small companies out of business. This could worsen much faster the trend that UNCTAD reported, where during the last 11 years, the average number of companies per country has decreased from 22 in 2004 to just 16 in 2014 (UNCTAD, 2014).

1.2 Rationale and Problem Definition

There are a number of motives as to why liner companies collaborate, but generally it is to exploit the economies of scale by extending the service coverage and adding more service frequencies. Panayides and Wiedmer (2011) examined the announcements between 2000 and 2010 from member companies of the three big alliances and conclude that these motives include strategic reasons, operational reasons, to increase or decrease connectivity, to increase or decrease capacity, to introduce a new service, to suspend a service, to merge services, to demerge services, to offer slots for charter and to offer slots. The authors also provide taxonomy of liner alliance literature, from which it can be seen that the number of literature in this area is quite few (17 papers for the period 1999-2010) and the majority used qualitative approach. They further argue that the current literature in the container shipping industry is rich in qualitative assessments but is lacking quantitative evaluations and that further research is needed in the area of alliance performance measurement.

If studies on liner collaboration are viewed as a system of input-process-output, it can be said that the system is rich with information on the input, but is lacking in both the process and output. The studies of motivational background for collaboration are analogous with the input; the studies of how the collaboration should be translated at the operational level are equivalent with the process; and the studies of what the impacts of collaboration are and how they can be measured correspond to the output. The current literature has shown a growing interest in the input side, with most of it in the domain of qualitative approach. There are still few academic papers concerning this, but the number is relatively high compared to that of the process and output sides.

The process and output sides are obviously as much important as the input. Knowing the rationale behind collaboration without understanding how the follow ups should be pursued clearly has minimum value for the collaborating members. Moreover, results from operations should also be measurable and performances between with- and without-collaboration should be able to be compared and validated. All these are integral part of an input-process-output system as one part is heavily linked to and as important as the others. However, in the field of liner-shipping collaboration, the how-to (process) and impact (output) parts, specifically in the quantitative section, are yet to receive more attention from the academic world and as of today remain a vast research ground to be explored.

From a different perspective, discussions on what to measure, as part of revealing more shed of light in the output side, can be taken to a higher level by considering other stakeholders in the business. Any managerial effort is naturally oriented to benefit the company’s shareholders. At the operational level, this can translate to the maximization of profits or minimization of costs. However, complexity arises when other stakeholders are involved. In collaborative activities, the partner company acts as a stakeholder and there exist possibilities to optimize other objectives than profits/costs by considering joint preferences from both parties. For example, how can the companies divide the geographic coverage service areas between them equally or fairly while at the same time still working on maximizing the total revenues? Another example has actually been mentioned in the preceding paragraph with regard to the forthcoming P3 Alliance. In this case, if the shippers are considered as a stakeholder, their expressed concern for the negative outcomes from such an alliance (market domination that will cut their negotiating power) is conflicting with the intention of the alliance members to enhance their business standing.

Methods-wise, such a situation as described above falls in the domain of multi-objective optimization. In this branch of knowledge, decision makers are faced with a number of objectives that cannot be simultaneously optimized, or in other words, improvement in one objective leads to the worsening of the others. Multi-objective optimization itself is a growing research area because of its proximity to the background of real-world problems that are inherently multi-objective. The downside is that it is far more complex than the conventional single-objective optimization that it prevents exact approaches to be developed for the solution method. Researchers are turning to meta-heuristics for that purpose and evolutionary algorithms are one class in meta-heuristics that are suitable for this type of problems (Deb, 2008).

To conclude this section, the problem definition of this research is stated as follows. The intensifying future competition in the shipping industry will force shipping companies to find ways to improve their operations. One possible approach is via collaboration among companies. The studies of maritime logistics collaboration, particularly in the segment of liner shipping, however, are lacking of the quantitative approaches. This area needs to be enriched by further exploring the how-to and methodologies of the collaboration activities. In addition, the real-world problems contain many facets and solution in only one dimension of the problem may not suffice to represent the best solution. Approaching the problem in liner shipping collaboration, therefore, should also consider more than one objective to bring the solution closer to the reality.

1.3 Research Questions

Taking into account the background, rationale, and problem definition as discussed in the first two sections, this research aims to fill the gap in the field of maritime logistics collaboration. To be more specific, the following research questions will be answered:

1. Realizing that real-world problems are inherently multi-objective and given a scope of collaboration in the liner segment, what are the objectives to be optimized that can represent the stakeholders' preferences resulting from the collaborative activities?
2. How such collaboration in (1) should be formulated into a mathematical model, solved with a quantitative approach, and translated in operational details?
3. What will be the properties of the developed quantitative model in (2) with regard to computational complexity and sensitivity to the model parameters?

1.4 Research Objectives

The objectives of this research are as follows:

1. To introduce the idea of maritime logistics collaboration, particularly in the segment of liner shipping, with emphasis on multi-objective optimization to capture the mutual interests from the collaborating parties.

2. To formulate a mathematical model for liner shipping collaboration as described in (1), using means of a generated case study.
3. To develop a solution methodology for (2) with an evolutionary algorithm approach and to investigate the properties of the proposed methodology.

1.5 Research Scope

Research in liner collaboration has grown satisfactorily at a steady rate in the last two decades. In anticipation of a more intense future competition in shipping business as a result from the mismatch in supply and demand, more in-depth studies are called for in this area. As of today, the literature rests heavier on the input side (investigation on motives for collaboration, etc.) and mainly adopts qualitative approaches (surveys, interviews, etc.). Figure 1.1 displays this situation with the scope of this dissertation highlighted in the sections of quantitative and process-output. Logically, research on process cannot stand on itself because whatever method to be applied, the outputs must be measurable to gauge its effectiveness and efficiency. Therefore, the scope in Figure 1.1 encompasses both the process and output grids.

Maritime logistics offers a number of topics that can be studied in these sections. Some examples are written in the lower box of Figure 1.1 (will be revisited in chapter two with more details). A related branch in the study of these topics is the what-so-called vehicle routing problem (VRP) including its variants (time windows, pickups and deliveries, split deliveries, and so on) (Toth and Vigo, 2002). VRP studies have gained considerable attention in the academic world owing to their usefulness in real-life applications. This research demonstrates the VRP applications in maritime logistics by extending it into a ship routing problem (SRP).

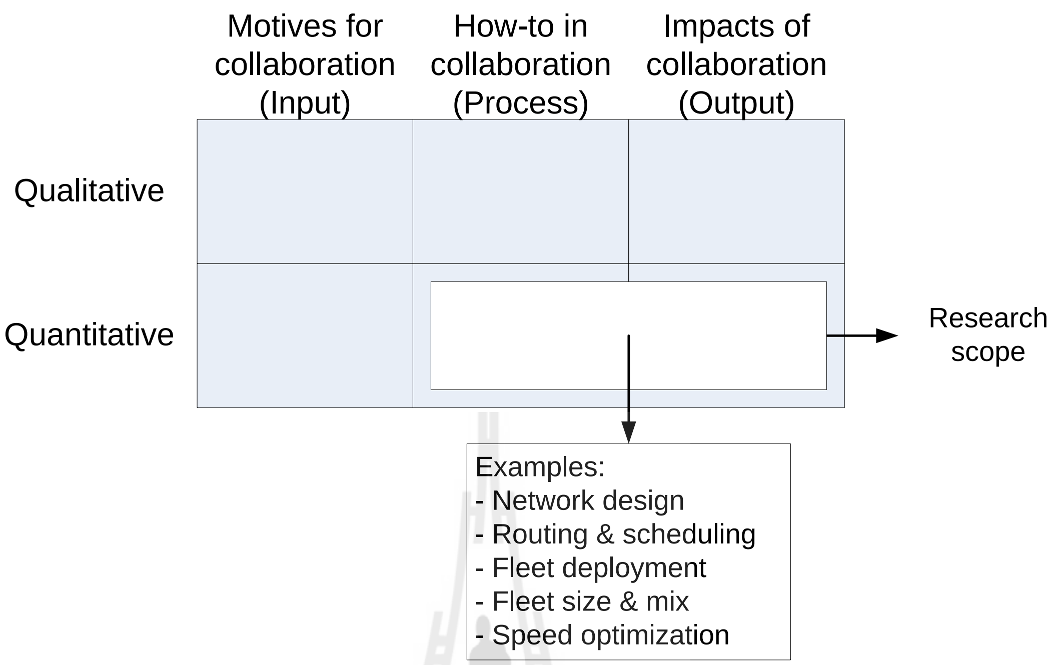

Figure 1.1 Research scope

From the perspective of methods, multi-objective optimization will be in the central theme and since network/routing problems belong to the class of hard combinatorial optimization, meta-heuristic approach will be employed, particularly the branch of evolutionary algorithm. The idea behind this is to accommodate the involvement of more dimensions of the problem resulting from the collaborative activities.

Finally, numerical examples will be needed for model validation and therefore a case study with data as close as possible to reality will be utilized. For this purpose, Indonesian archipelago will be used as the data background. The archipelago, consisting of more than 17,500 islands, is the largest in the world but maritime research on this country can hardly be found.

1.6 Organization of Dissertation

Chapter one presents the background, rationale and problem definition of the research, followed by formulation of research questions and objectives. A general discussion on research scope provides an outline of research areas and its boundaries.

Chapter two extensively reviews the related literature. Subjects discussed include the general concept of supply chain/logistics to highlight the research positioning, overview of maritime logistics with emphasis given on liner network design, collaboration issues in the segment of liner shipping, and in the sections of methods: vehicle routing problem and multi-objective optimization. The chapter concludes with identification of the research gap.

Chapter three discusses the research methodology that includes the research framework and research stages. Two preliminary models are proposed to introduce the research idea on maritime logistics collaboration with multiple objectives.

Chapter four builds an improved version of genetic algorithm that is suitable for a routing problem of a liner shipping company. The model used is based on vehicle routing problem that considers heterogeneous vessels, time windows, and fixed cost. Some or all of these attributes are usually not considered in land-based logistics, but all are important for a problem involving a liner shipping company.

Chapter five extends the work of chapter four by combining the principles of effective and efficient genetic algorithm already developed in chapter four with one elitist multi-objective evolutionary algorithm (MOEA). The resulting methodology is a novel contribution of this research and its application on maritime logistics collaboration involving multiple objectives is demonstrated.

Finally, in chapter six, summary and conclusions of the research are outlined and research contribution is highlighted. Future research directions are also discussed.

1.7 Chapter Summary

Maritime logistics is the backbone of international trade and a key factor driving the globalization. In the last decade, international shipping faces challenges due to the mismatch in supply and demand. Given such a background, collaboration, partnership, and forging alliances are some possible paths that could be pursued by shipping companies to achieve more efficient operations.

Among other shipping services, liner shipping is a segment most responsible for the global seaborne trade. A liner company deals with containers and serves many shippers, so it needs to publish its schedule and routing in advance. Network design is therefore an important strategic decision for such company. The theoretical ground related to this field is called the vehicle routing problem, where its studies and applications are scant in maritime logistics. This research intends to enrich that area.

If collaboration is seen as a system of input-process-output, the process and output sides are still vast research ground to be explored, more specifically those using quantitative approaches. Also, since collaboration will involve more than one stakeholder, potentially there will also be more than one objective representing different preferences of each stakeholder. Multi-objective optimization (MOO) is therefore one research agenda in this dissertation. The complexity of MOO prohibits the use of exact approaches to solve the problem and this calls the adoption of meta-heuristics. One emerging class in this field is called the evolutionary algorithms.

CHAPTER II

LITERATURE REVIEW

2.1 Logistics vs. Supply Chain Management

Much has been said about logistics and supply chain management (SCM). Authors have been debating on their similarities, differences, and functions within an organization. Its terminology is sometimes even more obscured from the amalgamation of the two terms, for example 'supply chain logistics' (Liu, 2012) or 'supply chain logistics management' (Bowersox *et al*, 2013). Some authors argue that SCM is a broader function than logistics management (Lambert *et al*, 1998). This argument is backed up by Long (2003) stating that "*SCM is logistics taken to a higher level of sophistication.*" In contrast, Waters (2003) argues that both terms refer to exactly the same function, and arguments over their differences are largely semantics rather than real differences in practice.

In an effort to establish a unity of views for both terms, The Council of Supply Chain Management Professionals (CSCMP, formerly The Council of Logistics Management), has set forth a definition for each term (CSCMP, 2014). Many authors refer to CSCMP definitions that are more in favor of putting SCM in a larger context than logistics (Lambert *et al*, 1998; Long, 2003; Wisner *et al*, 2008; Langley, Jr. *et al*, 2009), although the exact wordings are different at the time of publications due to the continuous updates in the CSCMP website.

Table 2.1 Definition of logistics and supply chain management from various sources

Author(s) (year)	Term	Definition/quote	Remarks
Bowersox *et al* (2013)	Logistics	The work required to move and geographically position inventory.	
	Supply chain management	Consists of firms collaborating to leverage strategic positioning and to improve operating efficiency.	
Christopher (2005)	Logistics	The process of strategically managing the procurement, movement and storage of materials, parts and finished inventory (and the related information flows) through the organization and its marketing channels in such a way that current and future profitability are maximized through the cost-effective fulfillment of orders.	
	Supply chain management	The management of upstream and downstream relationships with suppliers and customers to deliver superior customer value at less cost to the supply chain as a whole.	
Council of Supply Chain Management Professionals (2014)	Logistics management	That part of supply chain management that plans, implements, and controls the efficient, effective forward and reverses flow and storage of goods, services and related information between the point of origin and the point of consumption in order to meet customers' requirements.	
	Supply chain management	Encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third party service providers, and customers.	
Harrison and Van Hoek (2005)	Supply chain	A group of partners who collectively convert a basic commodity (upstream) into a finished product (downstream) that is valued by end-customers, and who manage returns at each stage.	
	Logistics	The task of coordinating material flow and information flow across the supply chain.	
	Supply chain management	Planning and controlling all of the processes that link partners in a supply chain together in order to serve needs of the end-customer.	
Lambert *et al* (1998)	Logistics management	The process of planning, implementing and controlling the efficient, effective flow and storage of goods, services, and related information from point of origin to point of consumption for the purpose of conforming to customer requirements.	Follow CLM (former name of CSCMP)
	Supply chain management	The integration of business processes from end user through original suppliers that provides products, services, and information that add value for customers.	

Table 2.1 Definition of logistics and supply chain management from various sources (continued)

Author(s) (year)	Term	Definition/quote	Remarks
Langley *et al* (2009)	Supply chain	An extended enterprise that crosses the boundaries of individual firms to span the related activities of all the companies involved in the total supply chain.	
	Logistics	That part of the supply chain process that plans, implements, and controls the efficient, effective flow and storage of goods, services, and related information from point of origin to point of consumption in order to meet customer requirements.	Follow CSCMP
Long (2003)	Logistics management	That part of the supply chain process that plans, implements, and controls the efficient, effective flow and storage of goods, services, and related information from point of origin to point of consumption in order to meet customer requirements.	Follow CLM (former name of CSCMP)
	Supply chain management	The integration of key business processes from end user through original suppliers that provides products, services, and information that add value for customers.	Follow Lambert *et al* (1998)
Waters (2003)	Supply chain	Consists of the series of activities and organizations that materials move through on their journey from initial suppliers to final customers.	
	Logistics	The function responsible for the flow of materials from suppliers into an organization, through operations within the organizations, and then out to customers.	
Wisner *et al* (2008)	Logistics	The process of planning, implementing and controlling the efficient, effective flow and storage of goods, services, and related information from point of origin to point of consumption for the purpose of conforming to customer requirements.	Follow CSCMP
	Supply chain management	The planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third-party service providers, and customers.	Follow CSCMP

Table 2.1 lists the definition of logistics and SCM from various sources. Despite the variety, few keywords can be discerned from those definitions. Relationships with outside partners, from upstream (suppliers) to downstream (customers/end users), highlights the SCM definition, whereas movement of goods (and information) signifies the definition of logistics.

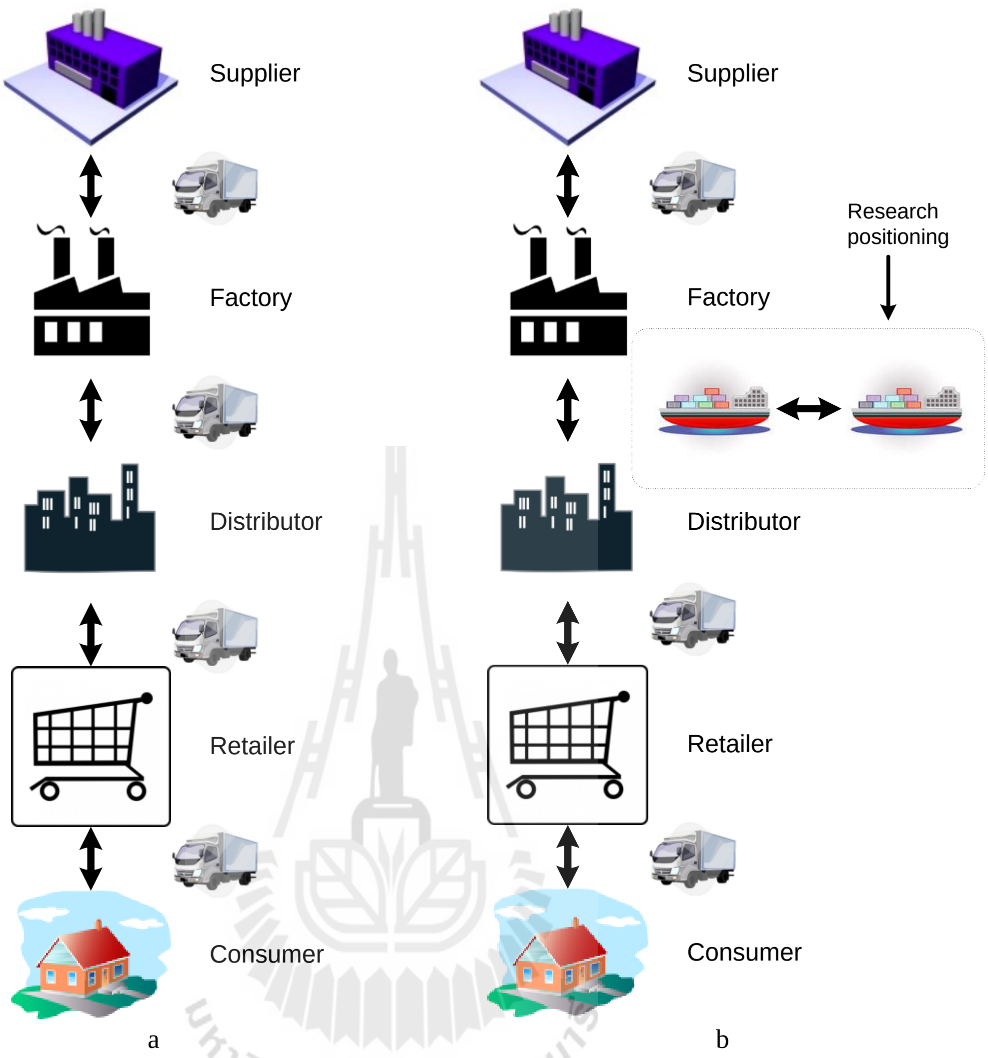

Figure 2.1 Positioning of the research

The purpose of highlighting logistics and SCM definitions is to put in context the positioning of this research. Figure 2.1a displays the common view of SCM concept following many definitions already mentioned. In this figure, the supply chain is shown as the spanning relationships from the supplier all the way to the consumer. The role of logistics can be divided in two types: inbound and outbound. Inbound logistics deals with the transportation of materials within an organization (e.g. material handling in a factory) whereas outbound logistics is the movement of goods between entities in the chain, represented with the truck icons in both figures.

In Figure 2.1b, notwithstanding other outbound logistics role of the chain, factory-to-distributor transportation is used as an example to highlight the research positioning. The central theme of this research is maritime logistics collaboration. Hence, logistics is obviously the key activity. The 'collaboration' part in the research theme entails a partner company collaborating in logistics activities. The involvement of an outside partner in collaboration here should not be confused with the upstream-downstream relationship as in the common SCM concept, since the nature of the relationship is horizontal rather than vertical, involving partner in the same tier of the chain with similar role. Such a positioning is also highly affected by the fact that the organization type being studied is logistics instead of manufacturing companies.

The research positioning outlined in the preceding paragraph serves as a background to look deeper into one of the logistics modes chosen for this research. Various issues in maritime logistics will be discussed in the next section.

2.2 Maritime Logistics

Despite being a subset in the overall logistics literature, research in maritime logistics is abundant and dedicated reviews are needed to provide a general view on its classification and where the trend is going. History of such reviews can be traced back to 1983 in a review by David Ronen, which was then updated by the same author in 1993. Christiansen *et al* (2004; 2013) continued with updated reviews in 2004 and 2013, hence setting a decade interval for a comprehensive review in maritime logistics. Between the last two reviews, a different version of review appeared as a chapter on ‘Maritime Transportation’ in the ‘Handbook in Operations Research and Management Science’ (Christiansen *et al*, 2007). This version of review, being part of a handbook rather than an invited journal article, focuses on descriptive models through the inclusion of in-depth mathematical formulations.

Furthermore, in the 2007 review, the authors grouped shipping services into three types: liner, tramp, and industrial. Liner shipping is akin to bus operations where it has fixed and published schedules. As such, it not only involves high fixed costs but also administrative overhead because the service promises to depart on a predetermined schedule regardless of whether the ship is full. Tramp shipping is more like taxis where ships are usually contracted by specific buyers (cargo owners) to ship their cargo in a rather exclusive setting. Industrial shipping is similar to owning private cars, i.e. both the ships and cargo are owned by the same party. In the 2013 review, tramp and industrial shipping were considered similar in certain aspects and thus merged as one class.

In addition to the types of services, ships can also be classified into these classes based on their physical attributes (Lindstad *et al*, 2011): (a) Bulk vessels which are built for carrying either dry or wet cargoes. Their main commodities include iron ore, coal, grain, alumina and aggregates, while crude oil is the dominant wet bulk commodity. These vessels have typical dead-weights ranging from 40,000 to 300,000 tons and service speeds at 13-16 knots; (b) Container vessels which are employed for the transport of containers filled with a wide range of products and commodities, from high-value items like electronics, to low-value products as well as scrap steel and paper for recycling. The typical dead-weights of these vessels range from 40,000 to 160,000 tons and service speeds are around 25 knots; (c) RoRo (Rollon Roll-off) vessels (multi-deck vessels where the cargo is driven on and off the vessel through a ramp) which are used for the transport of cars, trucks, heavy machines, forest products and project cargo, and typically have dead-weights between 15,000 and 40,000 tons with service speeds around 20 knots.

Today, container shipping constitutes the major segment of liner shipping. Other segment such as RoRo, although expanded remarkably during recent decades, is considered minor. The cargo carrying capacity of the world containership fleet has more than doubled in each of the last three decades. In 2006, the maximum ship size carrying capacity has surpassed the 10,000 TEUs (twenty-foot equivalent unit) milestone (Imai *et al*, 2006). Notteboom and Rodrigue (2009) argue that the future of containerization will be geared by commercial, technological and logistical forces. Given the fast growth of the containership fleet, liner shipping therefore has attracted a large attention in research, particularly on liner network design and related topics.

The volume of research roughly doubles every decade and during the last decade, over a hundred new papers have been refereed. These already exclude specialized problems associated with container line operations, such as berth scheduling, container stowage, containers management, container yard management, and cargo allocation (the left part of Figure 2.2), and papers regarding operation of non-commercial vessels (e.g. naval vessels). General reviews for port/in-land operations can be found in Steenken *et al* (2004) and Stahlbock and Voß (2008). A more specific review on berth allocation and quay crane scheduling problems is reported by Bierwirth and Meisel (2010). Berth allocation is a growing research area as studied by Golias (2011) and Zhen and Chang (2012), both using bi-objective approach. Other topics in this part, for example, include port selection (Lam, 2010;

Tran, 2011; Talley and Ng, 2013) and the impact of inland transport times on container fleet sizing (Dong and Song, 2012).

The right part of Figure 2.2 is the substance of review in Christiansen *et al* (2013). A total of 132 papers are cited in that review. This number already excludes working papers, conference proceedings, theses, dissertations, and technical reports, and also port/in-land operations as mentioned earlier. While tramp/industrial shipping is an important part of the review, liner network design and its related topics are given wider coverage due to the fast growth of the containership fleet. Also included in the review are topics with increasing attention, such as maritime inventory routing (MIR), liquefied natural gas (LNG) transportation, offshore supply vessels (OSV), decision support systems (DSS), and sailing speeds/environmental impact. Table 2.2 provides the statistic of papers classification, reproduced from Christiansen *et al* (2013).

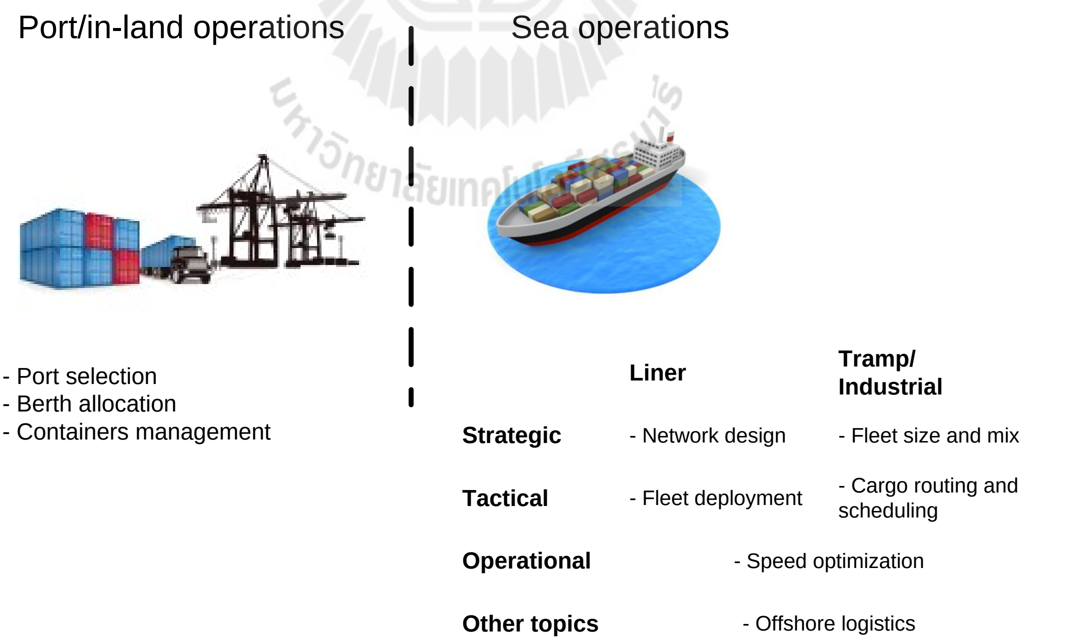

Figure 2.2 Grouping of research topics in maritime logistics

Table 2.2 Statistic of maritime papers classification

Publication year	Total * (all modes)	Liners						General
		Net. design	Size & mix	Routing & sch.	Deploy-ment	Speed	Other	
2007-2011	104	10	4	13	8	9	5	3
2002-2006	26			6	1		1	3
1997-2001	28		3		3			3
1992-1996	11			1			1	2

Publication year	Tramp and Industrial							
	Size & mix	Routing & sch.	Speed	MIR	LNG	OSV	DSS	Other
2007-2011	1	16	7	11	6	5	3	6
2002-2006		4		5			1	6
1997-2001	4	9	2	5		1		1
1992-1996	2	4		2				1

* A paper may address more than one topic.

Source: Christiansen *et al* (2013)

2.2.1 Tramp and industrial shipping

Although tramp/industrial shipping is not the segment to be studied in this research, few points worth addressing here. At the strategic level, fleet size and mix (or composition) is an important issue in tramp/industrial shipping. Hoff *et al* (2010) provided a literature survey on fleet composition and routing. They included both road-based and maritime transportation in the review and discussed their industrial aspects. Pantuso *et al* (2014) provided a more specific review on fleet size and mix by focusing on maritime problems, but the scope is on all segments and not limited to tramp/industrial. Both papers agree on one thing: most papers under their reviews did not consider the stochastic aspects which are obviously present in reality, especially given the long time-frame of planning at the strategic level. Further, three papers proposed the use of decision support systems for strategic planning in maritime transportation: Cheng and Duran (2004) developed a decision support system using discrete event simulation and stochastic optimal control for world-wide crude oil transportation; Fagerholt (2004) promoted TurboRouter, a decision support system for fleet scheduling; and Fagerholt *et al* (2010a) designed a decision support methodology that combines Monte Carlo simulation and optimization.

At the tactical level in tramp/industrial shipping, the focus of attention shifts from fleet size and mix to routing and scheduling. Brønmo *et al* (2010) and Korsvik and Fagerholt (2010) discussed ship scheduling problems with flexible cargo sizes/quantities. The former used a column-generation approach, whereas the latter developed a tabu-search heuristic. The difference between the two papers is regarding the spot cargoes in its relation to cargo-size flexibility. In Brønmo *et al* (2010), such flexibility is treated outward, i.e. some of the cargoes are offered on the spot market, whereas Korsvik and Fagerholt (2010) treated it inward, i.e. to allow spot cargoes to be carried to improve profit. A similar research is reported by Korsvik *et al* (2011) where the authors introduced the concept of split loads to break the restriction that each cargo can only be transported by one ship. Split-loads consideration is common in land-based routing (split delivery vehicle routing problem), but not in ship routing and scheduling as argued by the authors. A large neighborhood search (LNS) heuristic was used in this paper and good solutions were obtained for all test cases. The authors also reported that their LNS heuristic will be integrated in the above-mentioned prototype DSS called TurboRouter.

For liquid bulk cargoes, reference can be made to these papers. Jetlund and Karimi (2004) discussed routing and scheduling for multi-compartment chemical tankers. The authors argued that their mixed-integer linear programming formulation can improve profit when compared to the actual plan used by a chemical shipping company. For crude oil transportation, Hennig *et al* (2012) proposed a path flow model for a split pickup and split delivery oil tanker routing and scheduling problem and Nishi and Izuno (2014) recently suggested a column-generation heuristic, also for oil tanker routing and scheduling problem with split deliveries. A different business sector in liquid bulk cargoes is liquefied natural gas (LNG). Halvorsen-Weare *et al* (2013) studied ship routing and scheduling in this area, dealing with uncertainty such as in sailing times and production rates.

Other specific areas in tramp/industrial shipping can be found in the following papers. Andersson *et al* (2011) studied a special segment in tramp shipping called project shipping, where a cargo can be part of a process facility, hence deliveries of the cargo and different parts of the facility might need synchronization within some time windows. Pang *et al* (2011) studied a ship routing problem with a focus on coordination for loading and unloading of cargoes at pickup and delivery locations by multiple vessels, so to avoid berthing time clash. Finally, Stålhane *et al* (2014) introduced a vendor managed inventory (VMI) service in tramp shipping that may potentially be a better way to substitute the contract agreement that has for decades been a standard approach between a tramp shipping company and a charterer. These novel developments can pave new directions for future research in tramp/industrial shipping.

2.2.2 Liner shipping

The strategic scope in tramp/industrial shipping is on determining the fleet size and mix to serve the contracted buyers (realized demand). Afterward, the tactical scope then determines the route and schedule of such a service. Different from this structure, in liner shipping, the network of services should first be established before any consideration for vessel allocation. This owes to the fact that a liner company works with a larger number of shippers than a tramp company does. As explained, liner operations are similar to bus operations with published schedules for their customers to adhere to (anticipating future demand). A liner company therefore needs to assess the feasibility of the ports-of-call it plans to serve, in terms of various aspects such as market potential, port “friendliness”, government regulations in that city, etc. The service network consists of ship routes, i.e. the sequence of port-of-calls to be visited by a given fleet of ships. This sequence generally rotates in the same cycles over a certain planning horizon. A liner company needs to also determine the sailing frequency on those routes to maintain the integrity of its schedule. Such a network of a liner company is usually utilized for several years before a review, although the frequency of sailings may change seasonally. Upon establishment of the network, comes the tactical planning in fleet deployment. In this phase, the sailing frequency will dictate the number of ships to be deployed on the service routes.

Confusion may arise from the literature as to the separation of strategic and tactical scopes in liner operations as described above. For example, Agarwal and Ergun (2008) consider the fleet size and mix of liner operations falls in the strategic phase and network design in the tactical phase, but Christiansen *et al* (2013) regard otherwise. However, a closer look suggests that Agarwal and Ergun (2008) view the fleet size and mix from the perspective of a start-up liner company. In this case, the decision of acquiring how many ships and the resources needed is indeed a strategic one. On the other hand, the classification from Christiansen *et al* (2013) assumes a given fleet size hence the network design phase shifts up to the strategic decision-making area. In the subsequent discussion, the latter point of view will be used.

In the specific section on liner network design, Christiansen *et al* (2013) classify the models from published research papers into four categories below:

1. Models with a single route or sets of routes without transshipment.
2. Models with hub and feeder routes where each feeder port is connected to a single hub port.
3. Models where some ports are classified as hub ports without any constraints on the number of hub and non-hub ports a route may visit.
4. Models with multiple routes without any separation of hub and non-hub ports.

A hub port is a major transit port where supply/demand is accumulated before distributed to the smaller ports (usually called “spoke”). This process of accumulation and distribution is known as “transshipment”. The route connecting hub ports is the main route whereas the routes between a hub port and its spokes are called the feeder routes. A hub-and-spoke network configuration is shown in Figure 2.3.

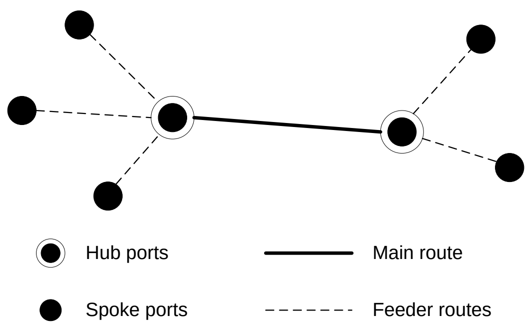

Figure 2.3 A hub-and-spoke network configuration

The above classification from Christiansen *et al* (2013) only groups the references based on one element, i.e. network characteristics. It lacks classification from other factors that are equally important and regularly found in practice, such as issues of empty-container repositioning, demand uncertainty, transshipment, etc. A classification that is composed of a number of factors is called taxonomy. An example of research taxonomy in liner operations can be found in Kjeldsen (2011). In the article, the author reviewed 24 papers regarding ship routing and scheduling problems from 1969 to 2010. The taxonomy has 18 elements, which is somewhat excessive considering the low number of papers reviewed. Some of the elements are not critical, for example number of starting points and number of routes for ship. Determining the starting point is often a more critical problem, while number of routes per ship is more relevant for RoRo shipping. Other elements are less significant based on the author's self arguments, for example whether or not demand is allowed to be split or satisfied partially. These two elements are common in land-based logistics but rarely found in liner shipping. The elements of port-related considerations such as port precedence requirement and ship-port compatibility also have little value if the focus of review is not on port operations. Cruising speed is another element lacking of relevance in liner network design since it is more suitably considered as an operational problem.

Therefore, the following review intends to also use a taxonomic approach with a few improvements: (1) the taxonomy elements from Kjeldsen (2011) will be filtered based on the above evaluation and also to make it more concise. The result is 5 elements reflecting the issues of empty-container handling, nature of demand, transshipment, time windows, and fleet composition; (2) new elements will be added, including network classification from Christiansen *et al* (2013), and other elements related to the scope of activity, collaboration, and a variable element describing the number of ports in the research. This last element will be useful to gauge the complexity of the model studied in the papers. A total of 26 papers will be reviewed under the newly developed taxonomy, dated from 2003 to 2014. Compared to Kjeldsen (2011), the range of years of the selected papers is more recent. The inclusion of recently published papers that have not been discussed in Kjeldsen (2011) and Christiansen *et al* (2013) will enhance the quality of the review. Below are explanations of the taxonomy elements followed by the review.

1. Characteristics of the network

This element follows the work of Christiansen *et al* (2013). The papers will be classified based on the four network categories as explained earlier and the network model will labeled as *1*, *2*, *3*, and *4* accordingly.

2. Scope of activity

This element consists of three options: network design (*ND*), fleet deployment (*FD*), and network design and fleet deployment (*NF*). While the majority of the papers discuss network design activity exclusively, there are papers studying network design and fleet deployment problems simultaneously, and some other papers deal with just fleet deployment problem by assuming a given network (*a priori* known and not to be designed).

3. Empty-container handling

In Kjeldsen (2011), this element is labeled as *Ships required to be empty* with two options: *Yes* indicates no empty containers are involved, and *No* otherwise.

Here, it is rephrased as above with two options: *Considered* and *Not considered*. Such a rewording is more straightforward in its articulation.

4. Nature of demand

Nature of demand is also an element taken from Kjeldsen (2011), although here the option *Dependent of service* is omitted, which leaves two remaining options: *Deterministic* and *Stochastic*. The rationale for omitting the third option is due to its rare applications.

5. Cargo transshipment

Cargo transshipment is an element from Kjeldsen (2011) and along with its options (*Allowed* and *Not allowed*), are used here as is.

6. Time windows

This element was formulated in Kjeldsen (2011) as *Scheduling constraints at the port* with three options: *Time of service fixed in advance*, *Time windows*, and *No restrictions*. The first element appeared only in a 1969 publication and is never revisited for its lack of relevance. As a matter of fact, time of service is difficult to be fixed and some allowance must be given to obtain a robust schedule. Therefore, only two options are used in this element: *Restricted* and *Not restricted*.

7. Fleet composition

Similar to *Cargo transshipment*, this element is taken from Kjeldsen (2011) as is with its two options *Homogenous* and *Heterogeneous*.

8. Collaboration scheme

Collaboration scheme is an important element added to the present taxonomy. It will be used to highlight that only a few papers address this important issue, despite the competitive background faced by many shipping companies today. The options of this element are: *Collaboration*, *Competition*, and *Not discussed*.

9. Number of ports in the network

The number of ports used in the case study of the papers reflects the complexity of the models and their algorithmic solutions. The options of this element are: *1-10, 11-20, 21-50, > 50*.

There are 26 papers included in the following review. To ease the readability of the review, the network classification from Christiansen *et al* (2013) is used as a main structure in dividing the papers.

1. Models with a single route or sets of routes without transshipment

Chu *et al* (2003) studied a pendular route consisting of 8 ports with the objectives to determine the cycle time of the route and the number of vessels needed to serve that route. In this sense, the scope of their model can be considered an NF (both network design and fleet deployment problems are considered concurrently). Once the cycle time is determined, the number of vessels needed for weekly service is known, and chartering is left as an option if the company's fleet cannot meet up this requirement (hence fleet composition is not mentioned). Time windows are included in the model formulation but are imposed for a cycle of a route rather than at the ports. Sambracos *et al* (2004) analyzed and proposed the use of small containers as a new technology for the coastal freight shipping in the Aegean Sea in Greece. Many papers in the field of liner network design build a mixed-integer linear programming formulation from scratch. However, this one makes use of the existing vehicle routing problem (VRP) formulation and adapts it to its case study consisting of 13 ports and 25 sea links.

Shintani *et al* (2007) can be considered as one of the pioneers in modeling a liner network by incorporating empty-container repositioning. They argue that the deployment of ships and containers are key and inter-related issues that are usually treated separately in the earlier models. Empty containers occur as a result of trade imbalances and its handling is a multi-billion dollars business. It is certainly a promising research area in the future. In their paper, the problem is tackled in two stages: first, the lower problem identifies the optimal calling sequence of ports for a specific group of calling ports; and second, the upper problem is reduced to the Knapsack problem and chooses the best set of calling ports that associate to the calling sequence found in the lower problem. A heuristic based on genetic algorithm (GA) is used. Another positive area in this paper, which is often cited in the other papers, is related to the detailed formulation of the cost functions.

Boros *et al* (2008) studied the optimization of cycle time between a shipping company and a port operator. In this research, it is assumed that a shipping company would prefer a longer cycle time as that would allow its vessels for slow steaming to reduce fuel consumption. On the other hand, a port operator would prefer a shorter cycle time as more ships berthing translates to more profit. The conflicting preference of these two parties is modeled as conflicting objectives. However, since both take the same dimension, i.e. time, the objective function is aggregated and modeled into a single-objective optimization. The search for an optimized cycle time for both logistics actors in this study can be considered as a collaborative endeavor. In addition, the authors extend the vessel-scheduling problem to container-yard capacity optimization problem.

Chuang *et al* (2010) use the fuzzy genetic approach for the routing of container ships taking into account uncertainty in demand, voyage time, and berthing time. Meng and Wang (2011a) discuss long-term ship fleet planning (10 years in their case study) as they argue that the fleet size, mix and ship-to-route allocation should be adjustable period-by-period, since the container shipment demand is period-dependent. Stochastic demand is considered and a scenario-based dynamic programming using a tree structure is employed. Since the routes are fixed, this paper is oriented more on the fleet size and mix instead of network design. Finally in this category, Plum *et al* (2014) discuss single liner shipping service design (SLNSSD) that possesses similarities with the traveling salesman problem with pickup and deliveries. A branch-and-cut-and-price algorithm is proposed and shown that it can solve problems with up to 25 nodes (ports).

2. Models with hub and feeder routes where each feeder port is connected to a single hub port

An example of a multi-objective approach in maritime logistics is proposed by Hsu and Hsieh (2007). Their research involves routing, ship size, and sailing frequency under the hub-and-spoke environment with transshipment. Two objectives being traded off are shipping costs and inventory costs in order to obtain Pareto optimal solutions. Minimizing shipping costs is the objective pursued by a shipping company, whereas minimizing inventory costs is the shipper’s objective. This follows a similar pattern as in Boros *et al* (2008) in two ways: firstly, each objective represents a different interest of each logistic actor; secondly, both objectives are measured in the same units. However, they differ in the approach used, i.e. single vs. multi-objective optimization. After lengthy and detailed costs formulation, the authors prove that the objectives are conflicting, thus justifies the multi-objective approach.

The papers of Karlaftis *et al* (2009) and Takano and Arai (2009) have one thing in common, they both use genetic algorithm (GA) approach. Karlaftis *et al* (2009) extend the work of Sambracos *et al* (2004) by adding transportation from the islands to the mainland and incorporating delivery time limits. These added complexities call for meta-heuristics approach that is represented by GA. Since Sambracos *et al* (2004) use a VRP formulation, the model extension in Karlaftis *et al* (2009) is developed based on a variant of VRP called VRP with pick-ups and deliveries and time windows (VRPPDTW). Takano and Arai (2009) did not formulate any time restriction in their model. They also use two types of ships, different from the homogenous fleet in Karlaftis *et al* (2009). The number of nodes in Karlaftis *et al* (2009) is 26, including one depot, although it should be noted that the remaining 25 nodes actually refer to islands in the Aegean Sea instead of ports. On the other hand, Takano and Arai (2009) use a case study consisting of 18 ports with two of them are hub ports in Los Angeles and Rotterdam.

Two papers from Gelareh *et al* (2010) and Gelareh and Nickel (2011) address a different perspective from other common network design problems. While they can still be classified as network design problems, the issue at hand is how to locate the hub ports among the other ports in the network to increase the overall efficiency of operations. These are commonly referred to as hub-location problem

(HLP). More specifically, Gelareh *et al* (2010) coined the term a competitive hub location problem (CMPT-HLP) for their model, as it addresses the competition between a newcomer liner service provider and an existing dominating operator, both operating on hub-and-spoke networks. Gelareh and Nickel (2011) compared general Public Transport (PT) model to Hub Location Problem for Public Transport (HLPPT) and showed that HLPPT is more efficient in terms of the number of variables and constraints than the PT. Further, the authors suggest that the model can also be applied to urban transport network in addition to liner network design. Gelareh *et al* (2010) use a MILP formulation with Lagrangian, whereas Gelareh and Nickel (2011) use Benders decomposition.

Meng and Wang (2011b) present an unconventional problem in their research. The problem still belongs to hub-and-spoke network design, but involving multiple stakeholders and multiple types of containers. The stakeholders include the sea, rail, and road links, and the problem is called an intermodal hub-and-spoke network. A hybrid GA was employed.

3. Models where some ports are classified as hub ports without any constraints on the number of hub and non-hub ports a route may visit

Gelareh and Pisinger (2011) studied the hub-location problem by simultaneously considering network design and fleet deployment activities. Their model aims to locate the hub ports on a circular hub route then assign/connect the spoke ports to those hub ports. Assignment of optimal vessel type, arrival frequency to each spoke link, and determination of the fraction of demand to be fulfilled are subsequent problems to be answered (the latter problem implies that the demand is elastic). Since general-purpose MIP solvers had difficulties to solve small problem instances (up to 10 ports), Benders decomposition was proposed to solve larger instances. Similar to this research, Reinhardt and Pisinger (2012) combined network design and fleet assignment problems, with a difference that their study is on butterfly routes. A branch-and-cut algorithm was used to efficiently deal with the model involving transshipment factor, heterogeneous fleet, and route-dependent capacities. In both papers, time windows are imposed over a schedule period but not at the ports.

Meng and Wang (2011c) combined multi-port-calling (MPC) and hub-and-spoke (H&S) into an integrated model by considering empty-container repositioning, and compared it to pure MPC and pure H&S networks. They demonstrate that large cost-savings can be expected by integrating both the MPC and H&S networks and empty-container repositioning at the network design stage. Heterogeneous fleet is also considered and time windows are observed through berth occupancy times at the ports.

Two recent papers in this category appear in 2014 and they were not discussed in Christiansen *et al* (2013). First, Lin and Tsai (2014) introduced a new operational model called “daily frequency”. The sensitivity analyses on idle cost, cargo due date, and delay cost, confirm the potential use of this new model. Homogenous fleet is considered and time constraints are imposed for container shipment in a case study on 22 ports along the Pacific Rim. A MIP formulation was developed and solved with Lagrangian and local search. Second, Mulder and Dekker (2014) combined and solved the fleet-design, ship-scheduling, and cargo-routing problems simultaneously. The case considered is with limited availability of ships.

When discussing the fleet design problem, the authors follow the framework of Agarwal and Ergun (2008) regarding the strategic level of planning in a liner company, i.e. the optimal composition of the fleet (the number and size of the ships) as a factor to be determined first. In the ship-scheduling problem (tactical level), the service network has to be designed. Such a network consists of a set of ship routes and the allocation of ships to the routes. In cargo-routing problem (operational level), the shipping company decides which demands it accepts and which routes are used to transport the cargo. The authors also discuss the determination of optimal speed in servicing a certain route. Stochastic demand is generated between 80% and 120% of the actual demand from the reference network.

4. Models with multiple routes without any separation of hub and non-hub ports

Agarwal and Ergun (2008) discussed ship scheduling and cargo routing problems by considering transshipment, stochastic demand, time constraint on the operated routes, and heterogeneous fleet of vessels. Their case study was based on published cycles of major liner shipping companies, but the experiment data were randomly generated. The demand sizes were randomly generated from the interval 0.1 to 1.0 times the capacity of the largest ship, while the three ship sizes (2000 TEU, 4000 TEU, and 8000 TEU) used in the study were defined arbitrarily. The authors also show the dominance of Benders decomposition based algorithm over the greedy heuristic and the column generation based algorithm. The same authors, Agarwal and Ergun (2010), extend the work by discussing the design of large scale networks as a result of integrating the service networks of different carriers in the alliance. They also discuss the allocation of limited capacity on a transportation network among the carriers in the alliance. Inverse programming and game theory are the methods used to design a mechanism to guide the alliance members to allocate the whole cargo for the overall benefits of the alliance. The model complexity, however, is slightly reduced by the use of homogenous fleet.

Imai *et al* (2009) compared multi-port calling by conventional ship size to hub-and-spoke by mega ships. The authors have earlier justified the economies of scale from the deployment of container mega-ships (over 10,000 TEU) in Imai *et al* (2006). In their latest study, they consider empty-container repositioning and conclude that neither network is superior in all cases in terms of the container management costs (CMC). Optimality of each network depends on the shipping line. The role of CMC, however, is very important since whether or not it is considered will affect the network choice.

Wang and Meng (2010) studied a fleet deployment problem involving transshipment, multiple routing options, and uncertain demand. The network used in their study is known *a priori* and not part of problem formulation therefore it is considered as a fleet deployment and not a network design problem. The stochastic nature of the demand is formulated as a stochastic program and solved by the sample average approximation method, through which the expected value model (EVM) is transformed to the approximating deterministic model (ADM). A case from real-world problems is efficiently solved to 1% of relative optimality gap at 95% confidence level. Another research in this area where the network is given is by Wang (2013), where the author discussed a fleet deployment problem that incorporates five elements concurrently, i.e. slot-purchasing, integer number of containers, multi-type containers, empty container repositioning (ECR), and ship repositioning. The author's arguments are based on practical insight, that two twenty-feet equivalent containers and one forty-feet equivalent container, although occupy the same space, have different handling costs. Using a MILP formulation, the results demonstrate that slot-purchasing and empty-container repositioning have the largest impact on tactical planning decisions and relaxing the numbers of containers as continuous variables has little impact on the decisions.

Song and Dong (2012) studied the cargo routing and empty-container repositioning in multi-routes. Their proposed methods divide the solution algorithm in two stages: first, cargo-route planning is tackled by finding the shortest paths (no time windows involved); then second, an integer programming problem is solved for laden container assignment and empty-container repositioning in the dynamic situation. Two methods are evaluated (both are based on integer programming formulation): (1) shortest-path based method; (2) heuristic-rule based method. It is shown that for a large-scale real case study, the SPBM has difficulty to deal with computational complexity, but such is not the case with the HRBM. The performance of both methods, however, is insensitive to demand variations.

Wang and Meng (2013) proposed a reversing-port-direction model as an alternative to revamping an existing network. The authors collaborated with a real global liner shipping company and according to the authors, the company concurs that such an alternative is more feasible than revamping the network due to many factors (dedicated container terminals, joint shipping services with alliances, direct call at ports adjacent to major customers, container handling contracts with port operators, and locations of the ships to be deployed all affect the flexibility of changing the shipping network). The purpose is to improve the network without dramatic changes. Their model can also partially reverse and optimize the already-established network.

Wang and Meng (2014) studied liner shipping network design problem with deadlines (LSNDPD). Although the problem characteristics possess similarities with its counterpart in land-logistics model, i.e. vehicle routing problem with time windows (VRPTW) or vehicle routing problem with pickups-deliveries and time windows (VRPPDTW), they authors argue for their differences for several reasons: (1) split delivery may be allowed in container shipping; (2) each port, including that in the middle sequence, can be an origin port; (3) the port time is a function of the number of containers handled at the port; (4) a fixed weekly service frequency has to be maintained. In their model, the time windows are derived from the transit time and container handling time. The authors also demonstrate that the LSNDPD is NP-hard and it can be formulated as a mixed-integer non-linear non-convex programming model. Column generation based heuristic is used.

To conclude this section, the taxonomy of research in liner shipping network design is presented in Table 2.4. For readability, the papers are numbered as shown in Table 2.3.

There are other papers concerning pure fleet deployment that cannot be categorized in the above taxonomy. For example, Gelareh and Meng (2010) discussed fleet deployment problem (FDP) for a short-term planning horizon. Wang *et al* (2011) later reformulated the model in Gelareh and Meng (2010) and remedied some of the constraints. Other papers by Meng and Wang (2012) and Wang and Meng (2012) discussed FDP with different varieties.

Table 2.3 List of the papers reviewed in liner shipping network design

Model	No.	Author(s) (year)	Model	No.	Author(s) (year)
	1	Chu *et al* (2003)		14	Gelareh & Pisinger (2011)
	2	Sambracos *et al* (2004)		15	Meng & Wang (2011c)
	3	Shintani *et al* (2007)	3	16	Reinhardt & Pisinger (2012)
1	4	Boros *et al* (2008)		17	Lin & Tsai (2014)
	5	Chuang *et al* (2010)		18	Mulder & Dekker (2014)
	6	Meng & Wang (2011a)		19	Agarwal & Ergun (2008)
	7	Plum *et al* (2014)		20	Imai *et al* (2009)
	8	Hsu & Hsieh (2007)		21	Agarwal & Ergun (2010)
	9	Karlaftis *et al* (2009)	4	22	Wang & Meng (2010)
2	10	Takano & Arai (2009)		23	Song & Dong (2012)
	11	Gelareh *et al* (2010)		24	Wang (2013)
	12	Gelareh & Nickel (2011)		25	Wang & Meng (2013)
	13	Meng & Wang (2011b)		26	Wang & Meng (2014)

Table 2.4 Taxonomy of research in liner shipping network design

No.	Taxonomy element	Options	Papers
1	Characteristics of the network	1	1-7
		2	8-13
		3	14-18
		4	19-26
2	Scope of activity	ND	3, 5, 7-13, 15, 19-21, 23, 25, 26
		NF	1-2, 14, 16-18
		FD	4, 6, 22, 24
3	Empty-container handling	Considered	3-4, 15, 19-20, 23-24
		Not considered	1-2, 5-14, 16-18, 21-22, 25-26
4	Nature of demand	Deterministic	1-4, 7-17, 20-21, 23-26
		Stochastic	5-6, 18-19, 22
5	Cargo transshipment	Allowed	2, 8-19, 21-26
		Not allowed	1, 3-7, 20
6	Time windows	Restricted	1, 4, 9, 14-17, 19, 26
		Not restricted	2-3, 5-8, 10-13, 18, 20-25
7	Fleet composition	Homogenous	2, 5, 9, 17, 20, 21
		Heterogeneous	3, 6, 8, 10, 14-16, 18-19, 22-26
8	Collaboration scheme	Collaboration	4, 21
		Competition	11, 12
9	Number of ports in the network	1-10	1, 4-5, 8, 21
		11-20	2-3, 10-11, 14, 16, 19-20, 24, 26
		21-50	6-7, 9, 12-13, 15, 17, 22-23, 25
		> 50	18

As earlier mentioned, one of the emerging research areas in maritime logistics is concerning the empty-container repositioning. There exists research in this field that is not related to network design problem. For example, Choong *et al* (2002) studied the effect of planning horizon length on empty-container management for intermodal transportation networks involving truck, rail, and barge, and found that inexpensive and slow-speed barges are the key factor in the management of empty containers; Jula *et al* (2006) simulated the reuse of empty containers to reduce cost and congestion in port areas; Li *et al* (2007) discussed the imbalances of international trade activities that are causing an oversupply of empty containers in the Middle East but a shortage of empty containers in Hong Kong. Their study aims to formulate a strategic empty-container allocation policy between multi-ports with specific emphasis on the repositioning of surplus empty containers and the leasing of additional empty containers; Song and Dong (2011) developed point-to-point (P2P) and coordinated balancing mechanisms to reposition empty containers. The first leads to a P2P repositioning policy and the second leads to a coordinated repositioning policy. Neither policy is best for all scenarios. Each policy is highly influenced by demand uncertainty and route topological structure; Long *et al* (2012) approached the problem of stochastic empty-container repositioning with the sample average approximation and scenario decomposition methods. The stochastic nature of their problem lie in the demand, supply, residual ship space capacity, and residual ship weight capacity factors; finally, Di Francesco *et al* (2013) also investigated stochastic empty-container problems but focusing in port disruptions, modeled as partial disruptions (only seaside operations are hampered) and complete disruptions (both seaside and landside operations are prohibited).

2.2.3 Speed optimization

Apart from the demand and supply mismatch, global economic uncertainty and geopolitical tensions, international shipping is also facing a pressing agenda in the matters of climate change and environmental sustainability. Despite positive developments on a number of fronts, the world is not yet on track to limit the average global temperature rise to 2°C (UNCTAD, 2013). Without adequate and proper precautionary actions from all involved parties including the shipping companies, port authorities, and legislation bodies, the potential negative impacts (e.g. extreme weather events and rising sea levels) are actually in a close distant to badly affect the whole international seaborne operations.

To respond to such problems, energy efficiency in shipping industry is an attractive research topic nowadays as summarized in a survey by Psaraftis and Kontovas (2013). The survey result in this review shows that international shipping accounts for 2.7% CO_2 emissions. Among the other transport modes, this figure comes second to the road transport (21.3%) and is higher than aviation (1.9%), domestic shipping and fishing (0.6%), and rail (0.5%) (Figure 2.4). Containerships are the top-category maritime emitters of CO_2. Corbett *et al* (2009) suggest that compared to bulk shipping, crude oil tankers, and general cargo ships, CO_2 emissions from containerships are 1.3, 2.2 and 2.5 times greater, respectively. Different from road transport that cannot avoid traffic congestion, a ship can travel on seas and oceans relatively uncontested and it is limited only by its speed design and, to some extent, weather conditions. Faster speed burns more fuel in a quadratic (Fagerholt *et al*, 2010b) or cubical (Corbett *et al*, 2009) relationship and increases gas emissions. CO_2

is a type of greenhouse gases (GHGs) and together with methane (CH_4) and nitrous oxide (N_20), their emissions are accountable for the global warming phenomenon. In addition to the GHGs, ships also emit non-greenhouse gases (NGHGs) such as sulfur oxides (SO_x) that are responsible for acid rain and deforestation, and nitrogen oxides (NO_x) that can cause undesirable health problems. In 2008, the Sulfur Emissions Control Areas (SECAs) is enacted in the Baltic Sea, the North Sea, and the English Channel. In 2010, the entire US-Canadian coastal zone is designated as an Emissions Control Areas (ECAs). Regulation for the GHGs came a bit late in 2011.

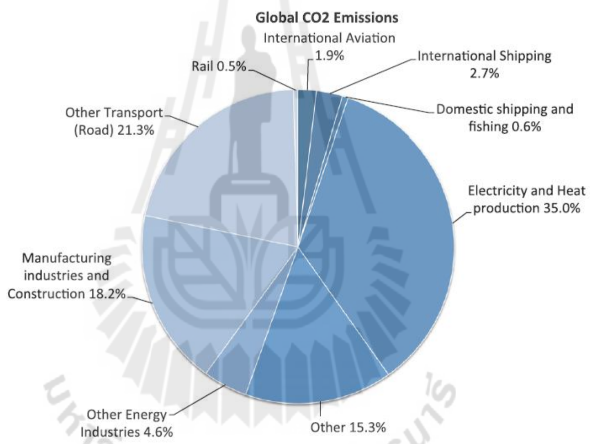

Figure 2.4 Survey on energy efficiency on shipping industries

Source: Psaraftis and Kontovas (2013)

In light of the above, speed reduction has been a strategic theme in shipping operations, not just from the perspective of vessels' owners, but also port authorities. The benefit of this strategy is obvious especially during the times when fuel prices are high, such as the peaks in 1979 and 2008 where they rose to US$116 and US$135, respectively (inflation adjusted in 2014 dollars). This practice can be achieved at two levels: by building ships with smaller engines thus reducing their maximum speed; and by reconfiguring the engine so that a ship can sail at speeds lower than its maximum speed design (Psaraftis and Kontovas, 2010). The former is a more strategic and future-oriented approach, while the latter is more tactical/operational and can be executed with the current available fleet. Lindstad *et al* (2011) conducted an analysis to prove that lower speeds can reduce GHGs emissions for bulk, RoRo, or container vessels. Their calculation show that 50% speed reduction in bulk vessels, 59% in RoRo, and 67% in container ships, can lead to 35%, 46%, and 62% emission reduction from each class, respectively. The authors further argue that given today's oversupply of vessels, there is no need to build additional vessels. In fact, shipbuilding activities will also create emissions and such a factor should be accounted in future analysis.

Gas emissions and fuel consumption in shipping are determined by one key variable: sailing speed. Speed optimization is therefore a viable path to pursue to arrive at overall efficiency in shipping operations. This includes but not limited to speed reduction strategy. Speed reduction strategy can be achieved in many ways such as instituting speed limits or designing more efficient propeller systems for the ships (therefore, demolitions of older ships is a necessity for the industry so that better ships replace the older and less efficient ones). It is understood that slow steaming might reduce service levels to the shippers; however, environmentally-driven concerns suggest this must be pursued whenever possible.

Despite its importance, speed optimization in shipping still receives less attention from researchers. Psaraftis and Kontovas (2013) proposed taxonomy for speed models for researches done in this area. From 1981 to present, as few as 41 papers are found in this topic, with majority are dated within the last decade. This proves that the research in this area albeit few but is growing. Some of the papers mentioned in the review will be briefly discussed below.

In the perspective of GHGs, Corbett *et al* (2009) examined a database of over 90,000 records involving US ports and ships in foreign commerce and found that a 50% speed reduction translates to 70% reduction in emissions across the board of the shipping industry. Speed reduction is naturally against the profit maximizing behavior of shippers, and therefore it would be neutral if authorities such as the government or multilateral organizations mandate the regulation, for example by tying it up with fuel and carbon taxes.

The recent issue of gas emissions is only a part of the picture. Still in the area of speed optimization, a larger scope is related to the rising oil prices and this leads to fuel optimization strategy. Both fuel consumption and gas emissions have the same merit with regard to speed optimization strategy since fuel consumption follows a quadratic or cubical functions of design and operational speeds of the vessel, and the CO_2 emission is a linear function from the fuel-consumption's function. A number of papers in this area deserve some attention as discussed below.

Lo and McCord (1995) formulated a routing problem to minimize fuel consumption for ships sailing in an ocean, particularly in the Gulf Stream region which was used as their case study. Using a dynamic programming approach, they developed two heuristics to find a path that minimizes fuel consumption by riding favorable currents and avoiding unfavorable ones. They refined their methods by involving a stochastic element in the ocean currents by formulating current changes as state transition probabilities with 5 categories of magnitude changes and 9 categories of direction changes, bringing 45 combination of states overall, and mapped over 15 × 15 km grids of Gulf Stream region (Lo and McCord, 1998).

Unfortunately in liner shipping, schedule unreliability is largely caused by events at the ports rather than in the seas. When a ship is behind schedule, it has to recover it by fast steaming on its next leg to the next port of call. By so doing it will burn more fuel and ultimately will deteriorate its cost performance. To maintain higher schedule integrity, a possible way is to add more time buffers in port operations but it is undesirable from the shippers' point of view. Another way is to assess the possibility to add more vessels to service a certain route such as studied by Ronen (2010) and Notteboom and Vernimmen (2009). Both studies found that when fuel prices rise above USD 150, an option to reduce speed and add another vessel (to maintain service frequency) is in fact more favorable in term of total costs. Ronen (2010) cited that bunker fuel may constitute more than 75% of vessel's operating costs (approximately USD 100,000 per day for a large ship) and reducing the cruising speed by 20% can reduce the bunker cost by 50%.

Both studies by Ronen (2010) and Notteboom and Vernimmen (2009) were carried on deterministic settings. Complexity arises when stochastic elements play part such as in Qi and Song (2012). In their paper, uncertainties are modeled in the port times. This research has more potential for the fuel optimization strategy than modeling uncertainties in the seas. Three models are discussed in the paper: (1) deterministic with 100% service level; (2) stochastic with 100% service level; and (3) stochastic without 100% service level. Non-linear programming formulations were constructed with rigorous proof of propositions to validate the optimality conditions for the first two models, whereas the last model used a simulation-based stochastic approximation approach. A case study was used to compare the results of the original problem against model 2 and 3.

2.3 Liner Shipping Collaboration

The history of formal collaboration among liner shipping companies stretched back to 1875 when the U.K.-Calcutta Conference was established. Afterward, development of other conferences quickly followed. In these conferences, liner companies fix cargo rates and members' quotas. This practice can actually be considered as cartels, and in Europe the industry had been sheltered by the Council Regulation 4056/86 that exempted conference practices from competition law. The regulation, however, has been repealed since 2008. In the USA, The Ocean Shipping Reform Act of 1998 changed the treatment of conferences under American antitrust law, by mandating secret and independent action to the members. In the absence of these immunities, evidence show that conferences are gradually being displaced by alliances (Sjostrom, 2009). Unlike conferences, alliances do not fix rates, but they enlarge service coverage by taking advantage of the economies of scale.

Since owning an asset, such as an airplane or a ship, involves large capital investment (millions of US dollars), the cost of idling an asset runs in tens of thousands of dollars per day. Liners therefore collaborate and form alliances to share capacity on assets and infra-structural setup and capital costs. From the academic point of view, however, more research is still needed to establish sound and proven analytical evaluation on the benefits of alliance formation. Agarwal and Ergun (2010) argue that only a few references on qualitative study on liner shipping alliances are available, but a rigorous quantitative study is missing. Of the 17 papers concerning liner alliance literature surveyed by Panayides and Wiedmer (2011), only 5 (29%) can be considered as quantitative studies. Not only the total number is minimal, but the percentage also favors the qualitative studies.

This section intends to develop further the work carried out by Panayides and Wiedmer (2011) in analyzing the literature related to liner alliance. Figure 1.1 will be used as a basis in qualifying the reviewed articles. This will also enhance the previous review where the articles are outlined briefly on account of the findings and the methods used. The axes in Figure 1.1 are: (1) the input-process-output (IPO) perspective; (2) the approach, either qualitative or quantitative.

The IPO perspective classifies the literature based on the following arguments. An article is tagged as “input” if it concerns to answer the “why” question, mostly in this case, why carriers embark on collaborative activities. The “process” tag serves to describe the “how” question, or in other words, to explain the technicality of the collaboration schemes. The last tag, the “output”, is used for articles that put emphasis on observing the impacts of collaboration. Naturally, one cannot discuss a process without mentioning the results. All articles grouped in this category, therefore, actually encompass both the process and output dimensions. However, for the sake of mutually-exclusive grouping, the leading aspect is considered outweighing the lagging one. Only when an article clearly focuses on studies such as impact assessment, outcome verification, etc., it will be classified in the output group. The other axis, qualitative vs. quantitative, is pretty much self-explanatory. Qualitative studies use methods such as survey, interview, descriptive statistics, empirical investigation, etc., whereas quantitative studies deal with model development, analytical investigation, etc. Table 2.5 depicts the classification result for articles on collaboration between carriers, and Table 2.6 does so for articles on collaboration between carrier and port.

Table 2.5 Classification result for articles on collaboration between carriers

	Input (Why)	Process (How)	Output (Impact)
Qualitative	Alix *et al* (1999) Evangelista & Morvillo (2000) Heaver *et al* (2000) Yeo (2013)	Lu *et al* (2006) Sjostrom (2009)	
Quantitative	Alexandrou *et al* (2014) Bergantino & Veenstra (2002) Czerny & Mitusch (2005) Lam & Van de Voorde (2011)	Ding & Liang (2005) Lei *et al* (2008) Pierre (2000)	Yang *et al* (2011)

Table 2.6 Classification result for articles on collaboration between carrier and port

	Input (Why)	Process (How)	Output (Impact)
Qualitative	Heaver (2002)	Heaver *et al* (2001)	
Quantitative		Álvarez -SanJaime *et al* (2013) Asgari *et al* (2013) Boros *et al* (2008)	

The collection of articles in Table 2.5 and 2.6 is not a copy of the articles reviewed by Panayides and Wiedmer (2011). Some articles are omitted, but other recent articles are added. These articles are reviewed below.

Alix *et al* (1999) used CP Ships, a liner company in Canada, as their case study. The company had grown from a series of periodic acquisition and based on that fact, the authors argue that forming an alliance is not the only path to survival. Such an argument, however, is largely questionable as witnessed in 2005 when CP Ships was purchased by Hapag Lloyd. Evangelista and Morvillo (2000) presented a descriptive model for the various forms of cooperative relations undertaken by shipping lines. They used a database survey for their methodology and the survey result showed a polarization of operations around two main groups: contractual agreements and equity agreements (joint-ventures and minority stakes). The former group outweighs the latter by a big percentage gap with the ratio of 79:21. A specific attention was also given to survey the cooperation forms of Italian shipping lines. Heaver *et al* (2000) also studied the rationale behind cooperation in the shipping industry. They categorized four market players in this industry: shipping companies, stevedores, hinterland transport, and port authorities. These players can interact to setup collaborative agreements, but collaboration between shipping companies and shipping companies has the most variety compared to the other combinations. The authors further argue that initiative for cooperation strategies is almost always taken by shipping companies, e.g. Maersk pushed dedicated terminal in Rotterdam, and the same case with MSC in Antwerp. They finally conclude that reasons for cooperation are to improve efficiency and to increase entry barriers for new players to enter the market. The last paper in this group is by Yeo (2013), who studied the patterns of mergers and acquisitions (M&As) in the industry. The author found two underlying factors behind M&As. First, the geographical distance, i.e. the longer the distance is, the less likely a target will be acquired. Second, contrary to the existing literature that financially underperforming firms are more likely to be targeted, it turn out that smaller and unquoted public firms are more vulnerable to M&As.

Lu *et al* (2006) used the Delphi method in a qualitative survey to CKYH alliance members to investigate the motives for alliance and found that to extend the service coverage and to provide more service frequencies are the top two reasons.

Sjostrom (2009) firstly presented the evolving trend of liner shipping competition and cooperation from a historical perspective, then used the models of monopoly and perfect competition to explain the extend of competition in the shipping market. In the concluding remarks, the author stated that "*in liner shipping… research on strategic alliances remains largely descriptive*."

Alexandrou *et al* (2014) studied all shipping M&As from 1984 to 2011 and found that, contrary to evidence reported in general M&A studies, acquirers realize positive abnormal returns. Bergantino and Veenstra (2002) investigated the evolution of forms of cooperation in liner shipping, in particular of global strategic alliances, from the perspective of network theories. Quantitative analysis is given on the model of alliance formation and evolution and the model is used to illustrate the rationale for network integration in the liner shipping industry. The authors caution that under certain circumstances, the benefits for joining an alliance might be offset by the coordination costs. Czerny and Mitusch (2005) presented a logical argument that the existence of conferences (with open membership) leads to higher average prices and more uncertainty with respect to entry and investment decisions. This is a very interesting argument as it seems to bear a paradoxical loop: conferences are presumed to stabilize supply, but in actual fact, the presence of a conference induces market instability; if such instability is observed, liners would tend to reinforce their support and making things worse. Given such conclusion, the authors proposed for the abolishment of liner conferences. Lam and Van de Voorde (2011) demonstrated the approach of scenario analysis in empirical examinations of the world's top 30 container shipping lines. They mapped these top liners based on their strategies into four quadrants: high integration, partner-focused, low integration, and activity-focused. They conclude that market situations favor those scenarios representing higher level of supply-chain integration.

The last four papers in Table 2.5 are characterized by sound quantitative analysis. Ding and Liang (2005) used a fuzzy multi-criteria decision making approach to setup criteria and model in selecting partners for strategic alliances. A hypothetical problem was designed to demonstrate the computational process of the algorithm. Lei *et al* (2008) compared three management policies in liners partnership: the non-collaborative policy, the slot-sharing policy, and the total-sharing (the total collaboration) policy. In each policy, a mixed integer programming model is employed and the results are then compared to arrive at a conclusion that the sharing policies have lots of potential to offer. Pierre (2000) developed an allocation model for ship owners involved in strategic alliances. The author argues that achieving the economies of scale in an alliance might not necessarily be an automatic outcome since each alliance member (ship-owner) is constrained by the limited number of vessels. A classical transportation problem was used as the background in model development. Finally, Yang *et al* (2011) investigated the influence of increasing ship size to the stability of alliance. They applied the core theory (co-operative game theory) to study the economic performance and stability of liner shipping alliance. In general, they conclude that the alliance's stability is significantly related to the structure of member's demands and joint-ship's capacity. Unlike the former three papers, this study is classified in the output box for its stronger emphasis on the impacts of collaboration than the collaboration process itself.

Five studies appear in Table 2.6 concerning collaboration between carrier and port operator. Heaver (2002) studied the economics behind vertical integration in liner business. The author inferred the integration strategies from liner’s three types of services: (a) with port terminals; (b) with intermodal transport; and (c) with logistics services. Heaver *et al* (2001) observed the response of port authorities to the changing market environment. Their descriptive statistics shows that the port authorities responded well to these changes. New companies with new strategies emerged in container terminal management and they became better counterpart for shipping lines in establishing long-term mutual cooperation. In the quantitative section, Álvarez-SanJaime *et al* (2013) focused their study on partnership between a shipping line and a terminal operator, particularly in investigating whether it is strategically profitable for a shipping line to own a dedicated terminal. Two scenarios were studied assuming a liner owns a terminal: (1) deviating part of its own traffic to the open terminal; (2) supply its terminal services to the other shipping lines. Admitting that no generalization can be made to the whole population of ports and container terminals, the authors suggest that non-exclusivity is a better way to capture more market share and gain control over the rivals. Asgari *et al* (2013) investigated the competition and cooperation strategies among three parties: two major container hub-ports and the shipping companies. Three scenarios were studied: (1) perfect competition between the hub-ports; (2) perfect cooperation between the hub-ports; and (3) cooperation among all as a whole. The model was tested on two Asian hub-ports, Singapore and Hong Kong, and the authors found that the objective value of shipping companies is conflicting with the objective value of the hub-ports. Non-dominated solutions were then sought. Lastly, Boros *et al* (2008) has been discussed in Section 2.2.2 and no further remarks are added here.

Other academic papers discussing collaboration and/or competition but not involving shipping companies are also available. For example, Hoshino (2010) discussed competition and collaboration with specific attention to Japan ports. Kim (2011) developed the appraisal criteria to assess the likelihood for a port to become The Premier Port (not necessarily a hub-port but basically means “mega port” that can handle more than 20 million TEUs). The proposed criteria are geographical advantages, scale of container volumes, cost advantage, and national port policy. Musso *et al* (2013), similar to the previous two authors, also discussed the variables of port competition that are expected to provide insights to port competitiveness. They used a case study from Italian seaports. Finally, Panigrahi and Pradhan (2012) used qualitative methodology to reflect the competitive maritime policies for seaports in India.

Before concluding the whole discussion on maritime logistics, two final remarks are worth to be pointed out. Firstly, collaboration platforms in shipping business are numerous, and depending on the chosen platform, some academic papers reviewed above confirm the benefits, but others caution against the potential pitfalls. Secondly, a number of papers address special geographical attention focusing on certain countries, such as Greece, Italy, Japan, and India, but no reference is found on maritime studies in Indonesia. This is quite a striking fact considering the country is the largest archipelago in the world with over 17,500 islands. Research with particular attention to this country will contribute to the overall big picture in maritime logistics studies and its practical applications.

2.4 Vehicle Routing Problem and Its Variants

Dantzig and Ramser (1959) first introduced "The Truck Dispatching Problem" that was since more popularly referred to as the Vehicle Routing Problems (VRP). The problem generalizes the Travelling Salesman Problem (TSP) and is therefore NP-hard, thus their more complex variants such as VRP with time windows (VRPTW) or VRP with pickups and deliveries (VRPPD) are also NP-hard (Cordeau *et al*, 2007). The VRP literature grows in an almost perfectly annual exponential rate at 6.09% between 1956 and 2005 (Eksioglu *et al*, 2009) and therefore it would be nearly impossible to cite all progresses unless in a dedicated review. However, several review papers are worth mentioning in the need to trace back the latest advances to their origins. In addition to the general reviews by Cordeau *et al* (2007) and Eksioglu *et al* (2009), specific reviews can be found in Bräysy *et al* (2005) for evolutionary algorithms for VRPTW; Gendreau *et al* (2008) for meta-heuristics VRP; Josefowiez *et al* (2008) for multi-objective VRPs; El-Sherbeny (2010) for VRPTW; Vidal *et al* (2013) for heuristics for multi-attribute VRP; and Lin *et al* (2013) for a survey of trends in green VRP.

In this section, the basic formulation of VRP will be presented. The capacitated VRP (CVRP) is often considered as the basic version of VRP (Toth and Vigo, 2002) so these two terms are used interchangeably. The following sub-sections further detail the mathematical model formulation of the well-known VRP variants particularly those that are relevant to this research.

A CVRP model can be described as a complete undirected graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ with a node set $\mathcal{N} = \{0, 1, \dots, N\}$ and an arc set $\mathcal{A}$. Node 0 is the depot and the remaining nodes $\mathcal{C} \in \mathcal{N}\backslash\{0\}$ represent the customers, each with a non-negative demand. Each arc $(i, j) \in \mathcal{A}$ has a non-negative travel cost $c_{i,j}$ associated with it and corresponds to the cost incurred for traversing from node i to node j. If the relationship $c_{i,j} = c_{j,i}$ holds, the problem is called a symmetric CVRP (SCVRP); one which is usually assumed in many VRP studies. On the other hand, if $c_{i,j} \neq c_{j,i}$, then it is called asymmetric CVRP (ACVRP). The CVRP problem consists of determining a set of vehicle trips to minimize the total travel cost, such that: (1) each vehicle starts from and ends at the depot, (2) each customer is visited exactly only once, and (3) the total demand in each trip does not exceed the vehicle capacity. Define set $\mathcal{V}$ as the set of the vehicles, indexed by v, and each vehicle has a capacity K^v. The demands to be satisfied in $\mathcal{C}$ are represented by d_i. The simplest CVRP formulation is then as follows.

$$\text{Min.} \sum_{v \in \mathcal{V}} \sum_{(i,j) \in \mathcal{A}} c_{i,j} . x_{i,j}^{v} \tag{2.1}$$

Subject to:

$$\sum_{v \in \mathcal{V}} \sum_{j \in \mathcal{N}} x_{i,j}^{v} = 1 \qquad \forall i \in \mathcal{C} \tag{2.2}$$

$$\sum_{i \in \mathcal{C}} d_i \sum_{j \in \mathcal{N}} x_{i,j}^{v} \leq K^v \qquad \forall v \in \mathcal{V} \tag{2.3}$$

$$\sum_{j \in \mathcal{C}} x_{0,j}^{v} = 1 \qquad \forall v \in \mathcal{V} \tag{2.4}$$

$$\sum_{i \in \mathcal{N}} x_{i,k}^{v} - \sum_{j \in \mathcal{N}} x_{k,j}^{v} = 0 \qquad \forall k \in \mathcal{C}; v \in \mathcal{V} \tag{2.5}$$

$$\sum_{i \in \mathcal{C}} x_{i,0}^{v} = 1 \qquad \forall v \in \mathcal{V} \tag{2.6}$$

$$x_{i,i}^{v} = 0 \qquad \forall i \in \mathcal{N}; v \in \mathcal{V} \qquad (2.7)$$

$$x_{i,j}^{v} \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}; v \in \mathcal{V} \qquad (2.8)$$

The objective function (2.1) minimizes total cost. Each node can only be visited by one vehicle (2.2) and demands are satisfied by considering vehicles' capacity (2.3). Constraints (2.4) state that all vehicles must provide a service (leave the home node); constraints (2.5) are the flow constraints, i.e. any incoming arc in one node must be followed immediately by an outgoing arc from that node; and constraints (2.6) ensure that a vehicle will return to the home base. Constraints (2.4)-(2.6) are commonly referred to as a multi-commodity flow structure. Vehicles cannot start and end at the same node (2.7) and finally, constraints (2.8) are the binary requirements for the decision variables ($x_{i,j}^{v} = 1$ if vehicle v traverses arc (i,j) and $x_{i,j}^{v} = 0$ otherwise).

In addition to the above basic formulation, the following constraints can be added to ensure that the number of routes is not more than the number of the vehicles, in other words no vehicle can take up more than one route.

$$\sum_{v \in \mathcal{V}} \sum_{j \in \mathcal{C}} x_{0,j}^{v} \leq V \qquad (2.9)$$

Some authors (for example, El-Sherbeny, 2010) use constraints (2.4)-(2.6) for the flow structure. Others (for example, Baños *et al*, 2013) use constraints (2.10) to replace the above three sets of constraints, however it should be noted that constraints (2.10) does not require that all vehicles must leave the depot.

$$\sum_{k \in \mathcal{C}} x_{0,k}^{v} - \sum_{k \in \mathcal{C}} x_{k,0}^{v} = 0 \qquad \forall v \in \mathcal{V} \qquad (2.10)$$

Heterogeneity of the vehicles plays a critical role. If the costs $c_{i,j}$ are not the same for each vehicle traversing arc (i,j) (hence, denoted by $c_{i,j}^{v}$), then the requirement that all vehicles must go must be relaxed to allow the model to choose vehicles with smaller cost. In this case, the following sub-tour breaking constraints (2.11) must be added to the model. Define $\mathcal{Q}_n$ as all subsets of size 2 or larger of $\mathcal{C} = \{1,2,\dots,N\}$ with $n_{\max} = \sum_{r=2}^{N} C_r^N$. Then, for example, if $N = 5$, $\mathcal{Q}_1 = \{1,2\}$; $\mathcal{Q}_2 = \{1,3\}$; ...; $\mathcal{Q}_{10} = \{4,5\}$; $\mathcal{Q}_{11} = \{1,2,3\}$; ...; $\mathcal{Q}_{n_{\max}} = \mathcal{Q}_{26} = \{1,2,3,4,5\}$. The sub-tour breaking constraints formulation is as follows (Cordeau *et al*, 2002).

$$\sum_{i \in \mathcal{Q}_n} \sum_{j \in \mathcal{Q}_n} \sum_{v \in \mathcal{V}} x_{i,j}^{v} \le |\mathcal{Q}_n| - 1 \qquad n = 1,2,\dots,\sum_{r=2}^{N} C_r^N \qquad (2.11)$$

2.4.1 Vehicle routing problem with time windows

In a vehicle routing problem with time windows (VRPTW), a customer i has to be visited within a certain time frame $[e_i, l_i]$ where e_i is the earliest time and l_i is the latest time a visit is allowed. In practice, a single-sided time window where $e_i = 0$ and $l_i > 0$ is equivalent to imposing a due-date to the service. Many real-life routing applications require this additional constraint, making this variant of VRP one of the popular ongoing research areas. Especially in liner shipping where schedule is the most important part of the service, due dates or estimated arrival times at the ports of call are the key feature of the process for the customers.

The formulation of time windows is obtained by introducing variables $s_i^v, i \in \mathcal{N}, v \in \mathcal{V}$ that represent the time vehicle v starts to service customer i. In the basic CVRP model described earlier, the costs $c_{i,j}^v$ are assumed in linear relationship with $t_{i,j}^v$ (the travel time of vehicle v from node i to node j), thus either of the two sets of parameters are considered valid representation in the minimization of the objective function. Since that is not always the case, it would actually be more accurate to use both parameters in the model. Also, when time dimension is such of a paramount factor as in the VRPTW formulation, defining the time parameters explicitly is nothing but a necessity. The constraints representing the time windows are as follows.

$$s_0^v = 0 \qquad \forall v \in \mathcal{V} \qquad (2.12)$$

$$x_{i,j}^v.\left(s_i^v + t_{i,j}^v - s_j^v\right) \leq 0 \qquad \forall (i,j) \in C; v \in \mathcal{V} \qquad (2.13)$$

$$e_i \leq s_i^v \leq l_i \qquad \forall i \in \mathcal{N}; v \in \mathcal{V} \qquad (2.14)$$

$$s_i^v \geq 0 \qquad \forall i \in \mathcal{N}; v \in \mathcal{V} \qquad (2.15)$$

If $x_{i,j}^v = 1$, constraints (2.13) state that vehicle v cannot arrive at customer j before $s_i^v +$ (travel time from customer i to customer j). These constraints are non-linear and require the following transformation.

$$s_i^v + t_{i,j}^v - M.(1 - x_{i,j}^v) \leq s_j^v \qquad \forall (i,j) \in C; v \in \mathcal{V} \qquad (2.16)$$

The parameter M is a large number, such that when $x_{i,j}^v = 0$, the constraints will become redundant. Some authors (Cordeau *et al*, 2007; El-Sherbeny, 2010) generalize (2.13) by having $(i,j) \in \mathcal{N}$ and omitting (2.12), but this requires node $N+1$ as the last sinking node for all the departing vehicles. This can be the same depot from where all vehicles depart ($i=0$), only indexed differently. Finally, constraints (2.15) suggest that s_i^v are continuous decision variables and change the pure-binary CVRP into a mixed-integer programming VRPTW.

One interesting aspect to observe in the VRPTW model is that the sub-tour breaking constraints (2.11) are no longer required due to the time windows.

Proposition 1. Time windows in (2.12) to (2.15) eliminate sub-tours.

Proof. Suppose we have $N>3$ and, for any vehicle v, if the set of routes contains a sub-tour where $x_{1,2}^v = x_{2,3}^v = x_{3,1}^v = 1$, then $s_1^v \leq s_2^v \leq s_3^v$ and clearly $s_3^v \nleq s_1^v$ and the sub-tour cannot be formed due to the relations of s_i^v established by (2.13). However, it is still possible for vehicle v to form a tour $x_{0,1}^v = x_{1,2}^v = x_{2,3}^v = x_{3,0}^v = 1$ and to have $s_0^v = 0 \leq s_1^v \leq s_2^v \leq s_3^v$ and s_3^v is not restricted to be $\leq s_0^v$.■

In reality, strict due dates are hardly encountered. Mild late arrival of orders, in most cases, are still tolerated but at certain penalty costs. In this case, both the lower and upper bounds of the time windows can be utilized as due dates with e_i being the minimum and l_i being the maximum. The minimum due date e_i serves as a point where lateness is measured after this point, but is still accepted up to the point of l_i. On the other hand, l_i is a hard constraint where lateness is absolutely prohibited. This can be a point where customers cannot accept late deliveries (for example fresh products such as vegetables or fruits) and the distribution company will have to compensate for such lateness (Figure 2.5).

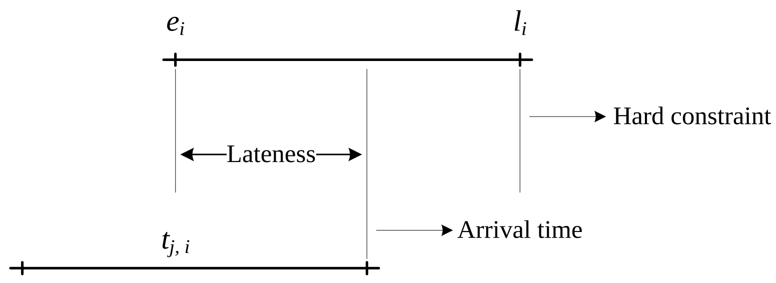

Figure 2.5 Time windows as minimum and maximum due dates

Another possibility for due dates formulation related to time windows is to assign penalty costs beyond, but not inside, the time windows. In other words, early deliveries before e_i are penalized, in addition to late deliveries over l_i. This is also common in reality with regard to warehouse management from the customer's point of view. Fagerholt (2001) discussed this issue with various penalty cost functions.

2.4.2 Vehicle routing problem with pickups and deliveries

Another popular variant of VRP is called the VRP with pickups and deliveries (VRPPD). In this variant, the source node for goods to be delivered is not restricted to a single depot. Other nodes can serve the same function as the depot, i.e. becoming locations where goods are to be picked up and delivered. This variant has a high degree of relevance in maritime logistics applications since it is possible that a vessel, after transporting goods in one port of call, can pick up other goods from that port to be delivered to the next port of call. What can be considered as classes of VRPPD are (Wassan and Nagy, 2014): (1) VRP with backhauling (VRPB), where all deliveries must be served before pick-ups can begin; (2) VRP with mixed pick-ups and deliveries (VRPMPD), where pick-ups and deliveries are allowed to occur in any order along the vehicle route; and (3) VRP with simultaneous pick-ups and deliveries (VRPSPD), where pick-ups and deliveries are made in the same locations. Further, the VRPTW discussed in the previous section can be generalized in this variant as the VRPPD with time windows (VRPPDTW) (Desaulniers *et al*, 2002). Due to its distinct characteristics involving timetable and the likelihood of transshipment in its operations, liner shipping has a large potential to benefit from research in VRPPDTW. An example of VRPPDTW application in maritime routing problem is demonstrated by Karlaftis *et al* (2009) that is solved using a hybrid genetic algorithm.

The formulation of VRPPDTW as presented in Desaulniers *et al* (2002) is rewritten below, with simplification by assuming that all vehicles can serve all destinations. This does not change the key aspects in the formulation, but only to generalize the notations. In this formulation, the nodes are divided into two sets: set $\mathcal{P}$ for the nodes where pick-up is to be made, and set $\mathcal{D}$ for the nodes that will receive delivery. There are n requests of pick-up and delivery to be satisfied in the problem and each request i is identified by a pair of nodes, i and $n+i$, corresponding to the pick-up node and delivery node, respectively. Note that the identification of nodes is no longer based on the geographical separation (e.g. customer or city), but on the pick-up and delivery pair of request, i.e. $\mathcal{N} = \mathcal{P} \cup \mathcal{D}$. Let $u_i = d_i$ and $u_{n+i} = -d_i$ if request i consists of transporting d_i units from i to $n+i$. It is further assumed that each vehicle will depart from its origin, node $o(v)$, and will finish its tour on node $d(v)$. Lastly, variables L_i^v denote the load of vehicle v after the service at node i.

$$\text{Min.} \sum_{v \in \mathcal{V}} \sum_{(i,j) \in \mathcal{A}} c_{i,j}^{v} . x_{i,j}^{v} \tag{2.17}$$

Subject to:

$$\sum_{v \in \mathcal{V}} \sum_{j \in \mathcal{N}} x_{i,j}^{v} = 1 \qquad \forall i \in \mathcal{P} \tag{2.18}$$

$$\sum_{j \in \mathcal{N}} x_{i,j}^{v} - \sum_{j \in \mathcal{N}} x_{j,n+i}^{v} = 0 \qquad \forall v \in \mathcal{V};\ i \in \mathcal{P} \tag{2.19}$$

$$\sum_{j \in \mathcal{P}} x_{o(v),j}^{v} = 1 \qquad \forall v \in \mathcal{V} \tag{2.20}$$

$$\sum_{i \in \mathcal{N}} x_{i,k}^{v} - \sum_{j \in \mathcal{N}} x_{k,j}^{v} = 0 \qquad \forall k \in \mathcal{N}; v \in \mathcal{V} \tag{2.21}$$

$$\sum_{i \in \mathcal{D}} x_{i,d(v)}^{v} = 1 \qquad \forall v \in \mathcal{V} \tag{2.22}$$

$$s_{o(v)}^{v} = 0 \qquad \forall v \in \mathcal{V} \tag{2.23}$$

$$s_i^v + t_{i,j}^v - M.(1 - x_{i,j}^v) \leq s_j^v \qquad \forall (i,j) \in \mathcal{A}; v \in \mathcal{V} \tag{2.24}$$

$$e_i \leq s_i^v \leq l_i \qquad \forall i \in \mathcal{N}; v \in \mathcal{V} \tag{2.25}$$

$$s_i^v + t_{i,n+i}^v \leq s_{n+i}^v \qquad \forall i \in \mathcal{P}; v \in \mathcal{V} \tag{2.26}$$

$$x_{i,j}^v . \left(L_i^v + u_j - L_j^v\right) = 0 \qquad \forall (i,j) \in \mathcal{A}; v \in \mathcal{V} \tag{2.27}$$

$$u_i \leq L_i^v \leq K^v \qquad \forall i \in \mathcal{P}; v \in \mathcal{V} \tag{2.28}$$

$$0 \leq L_{n+i}^v \leq K^v - u_i \qquad \forall n+i \in \mathcal{D}; v \in \mathcal{V} \tag{2.29}$$

$$L_{o(v)}^v = 0 \qquad \forall v \in \mathcal{V} \tag{2.30}$$

$$x_{i,j}^v \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}; v \in \mathcal{V} \tag{2.31}$$

$$s_i^v, L_i^v \geq 0 \qquad \forall i \in \mathcal{N}; v \in \mathcal{V} \tag{2.32}$$

The objective function (2.17) minimizes total travel cost. Constraints (2.18) and (2.19) warrant each request to be served once and by the same vehicle. Constraints (2.20)-(2.22) are the multi-commodity flow so that each vehicle starts from its origin depot and ends at its destination depot. As in the previous section, constraints (2.23)-(2.25) are the time windows constraints. For each request, a vehicle must visit the pick-up node before the delivery node (2.26). Constraints (2.27) regulate the feasibility of vehicle loads with respect to the routes the vehicle traverses. The linearization of these constraints is given in (2.33) and (2.34). Next, constraints (2.28) and (2.29) are the vehicle dependent capacity intervals at pick-up and delivery nodes, and constraints (2.30) set the initial vehicle load at its origin node. Finally, constraints (2.31) and (2.32) are the binary and non-negativity requirements, respectively, for the corresponding decision variables.

$$L_i^v + u_j - L_j^v \leq \left(1 - x_{i,j}^v\right).M \qquad \forall (i,j) \in \mathcal{A}; v \in \mathcal{V} \qquad (2.33)$$

$$L_i^v + u_j - L_j^v \geq 0 \qquad \forall (i,j) \in \mathcal{A}; v \in \mathcal{V} \qquad (2.34)$$

Other formulation of VRPPD can be found, for example, in Nagy and Salhi (2005). In their paper, the authors assume that the commodities to be transported are generic and they can be supplied from all depots instead of certain origins. This type of formulation clearly does not resemble liner shipping operations, as in liner shipping, containers to be shipped have specific origin and destination ports.

2.4.3 Meta-heuristics for the VRP

There are still other VRP variants in the VRP literature than the previously described VRPTW and VRPPD. One possible variant that is highly applicable in maritime logistics is the VRP with stochastic demand (VRPSD) (Tan *et al*, 2007). In reality, the nature of demand is stochastic, and deterministic treatment in many studies is catered mainly to reduce problem complexity. Another variant is the Site-dependent VRP (SDVRP) (Pisinger and Ropke, 2007) where a customer may only be serviced by a given subset of the vehicles. This can be because the access paths to the node do not allow certain type of vehicles to pass, or because specific facilities are demanded in the vehicles. The access-dependent situation is frequently encountered in shipping, for example, not all ports can handle mega ships. Specific facilities, e.g. a freezing compartment, are also common in many ships. Split-delivery VRP (SDVRP) (Archetti and Speranza, 2008) is another possible variant to be accommodated in maritime routing problems, particularly in tramp shipping. Note that due to the richness of the subject, it is difficult to gain consensus among authors in abbreviating the VRP variants and different variants may appear with the same abbreviations in the literature.

Although the VRP models belong to hard combinatorial problems, their applications in maritime routing problems are scant. Part of the reasons is their unique structure that is inflexible to cope with different kinds of route in maritime transportation (e.g. pendulum route, butterfly route, etc.). For example, the VRPPDTW formulation from Desaulniers *et al* (2002) above cannot be used for the butterfly route as illustrated in Reinhardt and Pisinger (2012). However, when the case is relatively small such as in Sambracos *et al* (2004) (13 ports including a depot port, and 25 sea links), VRP can still be applied.

The complexity of VRP calls for meta-heuristic approaches, e.g. Gambardella *et al* (1999) and Silva, Jr. and Leal (2011) who developed multiple ant colony system and Baños *et al* (2013) who proposed a hybrid meta-heuristic, all dealing with multi-objective VRPTW. Gendreau *et al* (2002) suggest that meta-heuristics for CVRP outperform classical heuristics in terms of solution quality, and sometimes now in terms of computing time. However, algorithm such as Clarke and Wright remains popular because it can be easily adapted to other variants of VRP and is easy to implement. They also conclude that tabu search is the most effective approach compared to genetic algorithms (GA), neural networks, simulated/deterministic annealing, and ant systems, but also further argue that while GA is not competitive on general VRPs, it is still considered promising on VRPTW.

In contrast to the above argument, however, Prins (2004) presented a simple and effective hybrid GA and reported that it is able to outperform most published tabu search heuristics on some well-known instances. The author's GA uses tour-splitting procedure, dispersal mechanism, and local search mutation (the latter two components are usually referred as memetic algorithm and the reason why the algorithm is classified as hybrid). Each of these components has its own role in enhancing the algorithm's performance: the tour-splitting procedure (called *Split*) partitions and forms feasible and optimal/near-optimal trips from the chromosome under evaluation; the dispersal mechanism maintains the population such that no identical chromosomes (or *clones*) can co-exist in the population, hence improving the quality of the search; and the local search mutation increases the search speed by performing methodical swaps of cities in the same or different trips (e.g. the well-known 2-Opt).

Split is a novel procedure of the above GA and its effectiveness makes it stand out among other similar approaches ever developed. To illustrate how it works, consider the following VRP example, reproduced from Prins (2004), consisting of one depot (**0**) and five cities (***a*** to ***e***) as shown in Figure 2.6a. The distances between cities (including from and to the depot) are shown adjacent to the arrows connecting the cities, and the figures inside the brackets are the demands of the corresponding city. The vehicles are identical with capacity of 10 units each. *Split* does not work on the original graph of the problem, but it transforms the graph in Figure 2.6a to an auxiliary minimum-cost path graph as shown in Figure 2.6b. The auxiliary graph translates the problem more lucidly: which paths should be traversed from **0** to ***e*** that yields the minimum cost? Algorithms described in Prins (2004) can answer this question and the solution with minimum cost 205 is shown in bolded paths in Figure 2.6b. The corresponding solution consisting of three trips is shown in Figure 2.6c.

Progressing further from this groundbreaking work, Prins (2009) developed a GA for heterogeneous VRP (HVRP). The problem is obviously much more complex than CVRP owing to the heterogeneity of the vehicles involving different capacities and different fixed and/or variable costs. Dynamic programming is employed as part of the algorithm and despite an issue with the *Split* procedure that can sometimes produce infeasible splitting, the algorithm is shown very competitive compared to other meta-heuristics when tested on equivalent known instances. The test instances used, however, do not consider fixed costs.

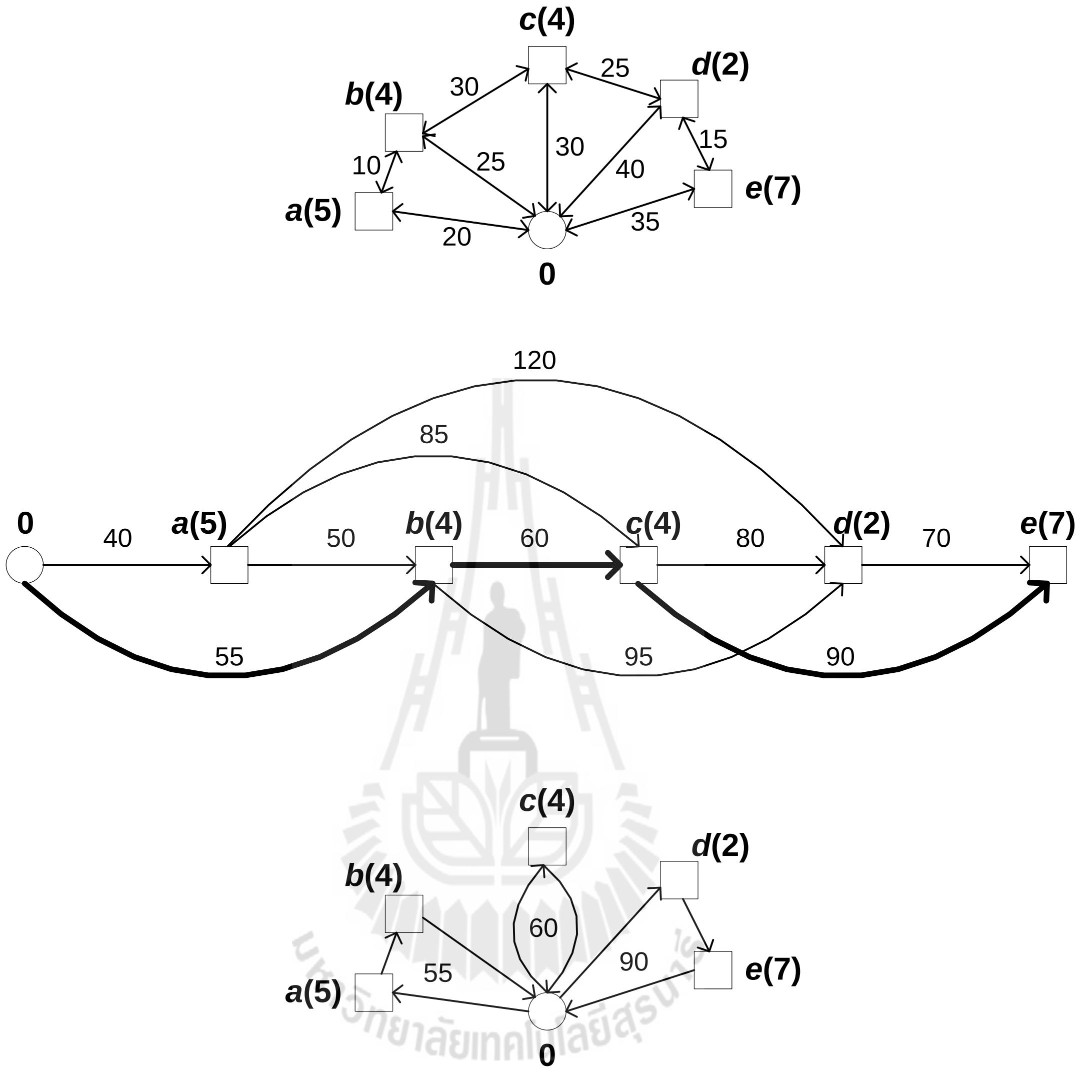

Figure 2.6 (a) Original graph; (b) Minimum-cost path auxiliary graph; (c) Solution with three partitioned trips

Other works on GA for VRP include the following. Chang and Chen (2007) extend the work of Prins (2004) by formulating time-window constraints (GA for VRPTW) in their model. Their work, however, still assumes homogeneous vehicles. The approach for heterogeneous vehicles appears in Liu *et al* (2009) for unlimited number of vehicles, in addition to Prins (2009) for both unlimited and limited number of vehicles as has been described earlier. The version with unlimited number of vehicles is referred by many names such as fleet size and mix vehicle routing problem (FSMVRP), vehicle fleet mix problem (VFMP), or fleet size and composition vehicle routing problem (Renaud and Boctor 2002), but the general notion of application is for a start-up company involving strategic decisions to procure an optimal number of vehicles that have unlimited availability in the supply market. Sub-variants of this branch concern whether or not fixed and/or variable costs are considered. When the number of the heterogeneous vehicles is limited, the problem is called the heterogeneous fleet VRP (HFVRP or HVRP). HVRP is more complex than VFMP, for example, in the trip feasibility of a VFMP, one only needs to check if the trip at least can be served by the largest-capacity vehicle. Reassignment of vehicles with the cheapest ones is also a simple way to test if the objective function can be improved, since these cheapest vehicles are assumed always available. This is not true for HVRP due to limited availability of each vehicle type. Because HVRP arises in tactical planning phase, it implies that the problem will be more frequently encountered.

Contrary to the rapid growth in the VRP studies, the literature on HVRP is relatively scarce. Imran *et al* (2009) outlined 22 papers found between 1984 and 2007 that address this VRP variant. Among these is Li *et al* (2007) who proposed a record-to-record travel metaheuristic that performs well on a number of HVRP benchmark instances. For detailed discussion on these 22 papers, readers can refer to Imran *et al* (2009). The following review will focus on papers published beyond that period that are obtainable, summarized in Table 2.7.

Table 2.7 Latest HVRP studies

Authors	Year	Problem type	Method	Test benchmark
Belfiore and Yoshizaki	2009	HVRPTWSD	Scatter search	Known; generated; real case
Imran *et al*	2009	HVRP	VNS	Known; generated
Li *et al*	2010	HVRP	MAMP + TS	Known; generated
Subramanian *et al*	2012	HVRP	ILS + SP	Known
Leung *et al*	2013	2L-HVRP	SA + LS	Known
Jiang *et al*	2014	HVRP	TS	Known; generated
Wang *et al*	2014	HVRPTW-ILC	Ruin-recreate + TS	Known; real case

Belfiore and Yoshizaki (2009) proposed a scatter-search metaheuristic for a HVRP that considers time windows and split deliveries, and applied it in a real case study on 519 outlets and also compared the method on modified instances from the literature by changing the demands to accommodate split deliveries. Authors who work on pure HVRP include the following. Imran *et al* (2009) developed two variants of variable neighborhood search heuristics and tested the methods on two classes of data sets. The first class of data set is taken from the literature as is, and the second class involves a larger number of customers and modified with regard to vehicle capacity and costs. Li *et al* (2010) used a multi-start adaptive memory programming supported by a modified tabu search. Their benchmark is on instances from the literature with 50-100 customers and generated instances with 50-200 customers. Subramanian *et al* (2012) suggested a hybrid form of heuristic by combining an iterated local search and set-partitioning based algorithm. The set-partitioning problems are solved by mixed-integer programming and the solutions interactively called the local search procedure for improvement. Various test instances from the literature with up to 360 customers are used as test benchmark. The latest in this group is Jiang *et al* (2014) who extended the existing tabu search procedure and implement it on known and generated HVRP instances. Papers with rather different focus from the ones previously discussed are the next two studies that incorporate loading constraints. First, Leung *et al* (2013) combined the routing problem with loading constraint by means of simulated annealing and heuristic local search. Their test benchmark is on instances from 2L-CVRP studies. Second, Wang *et al* (2014) formulated ruin-recreate heuristic and threshold tabu search for a HVRP with time windows and incompatible loading constraint. In addition to comparing their method on known instances, the authors also applied it on a real problem of supermarket chain.

The above review on HVRP indicates not only scarcity on the overall subject, but also on each category with respect to problem type, method, and scope of application. On problem type, most studies look on the general class of HVRP and very few discuss specific variant such as time windows etc. Heuristics and metaheuristics dominate the proposed methods, but evolutionary/population-based algorithm such as GA is rarely encountered. To show the strength and robustness of the newly-developed models, the majority of studies also focuses on benchmarking against common instances rather than showcase their field application. In particular with HVRP studies, benchmark instances in the literature ignore fixed costs (Prins 2009). Reducing complexity is acceptable for the purpose of model testing, but clearly is unrealistic in actual application, especially in maritime logistics where the fixed costs of using a vessel are high.

The subset between maritime logistics and HVRP (or general VRP, for that matter) is even much a smaller domain. Most authors develop LP-based formulation rather than borrow the VRP model because of the uniqueness in maritime routing problems (for example, hub-and-spoke environments). Only few authors discuss problems whose structure are suitable to the adoption of the VRP model, for example Sambracos *et al* (2004), Karlaftis *et al* (2009) and Takano and Arai (2009) (see sub-section 2.2.2 on liner shipping). Also, Agra *et al* (2013) utilized a VRPTW model with uncertain travel times in a maritime transportation problem. In terms of shipping service, their study can be classified in tramp/industrial rather than liner shipping, since ship capacities are not part of their model.

HVRP is probably the closest VRP model that can be adopted for maritime logistics problem since many shipping companies, unlike, for example, trucking companies, usually own heterogeneous vessels. For liner shipping, the model should be extended to HVRP with time windows (HVRPTW) given the paramount importance of schedule/due dates in liner services. The GA principles from Prins (2009) can be borrowed as a starting point in model development, bearing in mind that the fixed costs of operating the vessels should be taken into considerations.

2.5 Single-Objective vs. Multi-Objective Optimization

Real world problems are not only complex, but also contain many perspectives from where the problems can be approached. When an operational problem is optimized only on one dimension (the most common objective is profit maximization or cost minimization), it is carried out under the assumption that other things are negligible or can safely be ignored. This is hardly a fact and such an assumption is made mainly for the purpose of model simplification. The advantage of this approach is to provide decision makers with a clearer picture by pointing out just the important factors of the problem. The disadvantage, however, is a high probability that the problem's solution might deviate from the best solution, or even worse, is impractical.

Logistics and routing problems are no exception from such a syndrome. They are not always cost driven. For example, in a vehicle routing problem, suppose one solution arrives at a minimum cost, but imbalance loads are assigned to the vehicles. In practical terms, some drivers need to work harder than the other drivers to achieve that solution. Clearly this will be an issue in the real world application that demands further thoughts. Other examples relate to situations involving qualitative measures, e.g. customer satisfaction, brand image, safety, etc. What if, for example, total cost is minimized but at the expense of service level (late deliveries to some customers)? Some would argue that such a solution may not be the best solution after all since it does not put emphasis to the future sustainability of the company. To cater for this argument, one possible way is to formulate the other factor as constraints, e.g. the loads deviation in the first example must not be higher than a certain figure, or late deliveries in the second example must have an upper bound value. This approach, however, suffers from a drawback that that other equally-important factor can only be maintained from derailing against certain parameters, but not optimized. Another way is to model all objectives into the same unit so they can be aggregated. If this task can be accomplished without much difficulty, then the problem is solved. However, more often than not what happens is the opposite: how to turn loads imbalance into a cost function? Or how can customer satisfaction level be transformed into profit/cost? All these difficulties lead to the need for a different and better approach that is called multi-objective optimization (MOO).

The next sub-sections provide an introduction to MOO, followed by a review on MOO research studies in routing problems, and conclude with a brief note on a robust approach in multi-objective evolutionary algorithms called *elitism*.

2.5.1 An introduction to multi-objective optimization

In a single-objective optimization with decision variables $\boldsymbol{x}$ (a decision vector) and an objective function z to be maximized, a solution $\boldsymbol{x^1}$ is better than another solution $\boldsymbol{x^2}$ if and only if $z_1 = f(\boldsymbol{x^1}) > z_2 = f(\boldsymbol{x^2})$. In a multi-objective optimization, there are more than one z to be optimized, i.e. $\boldsymbol{z}$ becomes a solution vector. In this case, the situation of comparing two solutions $\boldsymbol{x^1}$ and $\boldsymbol{x^2}$ is more complex. Suppose two objective functions z_1 and z_2 are both to be maximized, and z_1^1 and z_2^1 are the solutions of $\boldsymbol{x^1}$ for z_1 and z_2, respectively, and z_1^2 and z_2^2 are the solutions of $\boldsymbol{x^2}$ for z_1 and z_2, respectively. Here, it is said that $\boldsymbol{x^1}$ dominates $\boldsymbol{x^2}$ if at least one component of $\boldsymbol{z^1}$ is greater than the corresponding component of $\boldsymbol{z^2}$ and none is smaller. If, for example, z_1^1 is greater than z_1^2 but z_2^1 is smaller than z_2^2 (or z_1^1 is less than z_1^2 but z_2^1 is greater than z_2^2), no solution dominates the other and these are referred to as the Pareto or non-dominated set of optimal solutions (Zitzler *et al*, 2003).

Further, let $\boldsymbol{x} = x_1, \ldots, x_n \in \mathbb{R}^n$. In a single-objective optimization, because there is only one objective function f, a space of $\mathbb{R}^{n+1}$ suffices to represent together the vector of variables and the objective. However, when multiple objectives $f_1, \ldots, f_k$ are involved, the mapping of decision variables to the objective function values is made easier by the representation of a decision space $\mathbb{R}^n$ and an objective space $\mathbb{R}^k$. Figure 2.7 shows an example with $n = 2$ and $k = 2$.

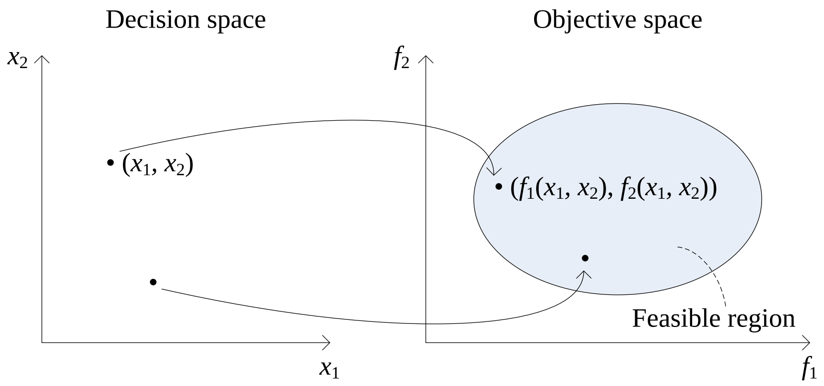

Figure 2.7 The mapping of decision space to objective space

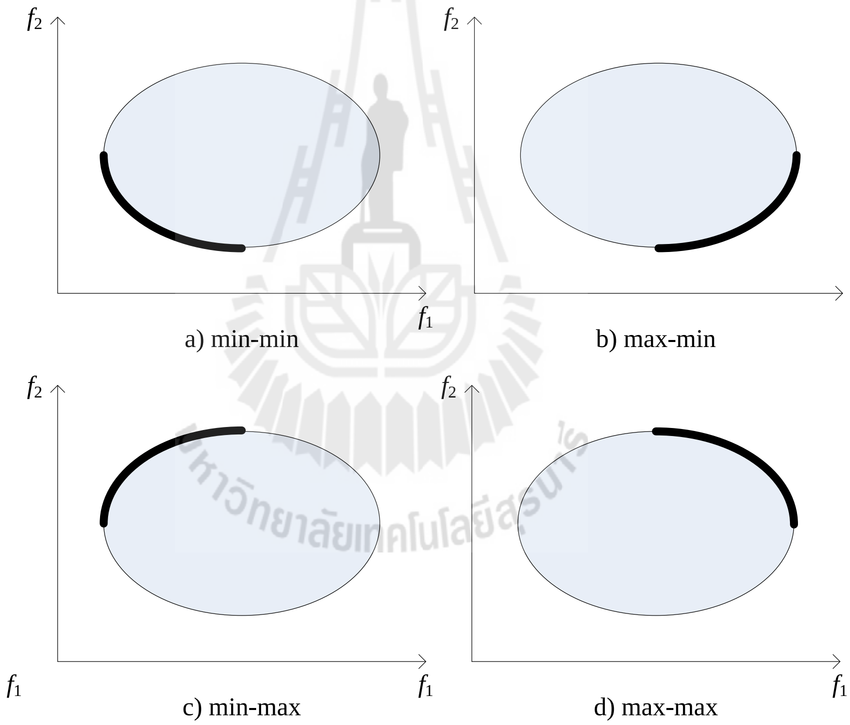

Figure 2.8 Pareto front based on objectives relationship

Two approaches commonly used in solving multi-objective problems are: (1) by assigning a weight vector to the objectives so they can be aggregated into a single value; (2) by searching the Pareto set of non-dominated solutions and letting the decision maker(s) to exercise higher-level considerations to arrive at a desired solution. The latter approach is often considered more practical since weight vector assignment is not an easy process even for experienced users in the field.

To obtain the Pareto set, the nature of the objectives to be optimized will determine the frontier of the set. Figure 2.8 describes the resulting Pareto front in different combinations of a multi-objective problem involving two objectives. In (a) where the two objectives are to be minimized, the front lies in the bottom-left part of the feasible region; in (b) where the first objective is to be maximized and the second is to be minimized, the front lies in the bottom-right; and so on.

2.5.2 Multi-Objective Optimization in Routing Problems

Research in routing problems using multi-objective approach was first encountered in a 1986 study from Park and Koelling concerning routing of perishable products involving several objectives: minimization of the traveled distance, maximization of the realization of urgent queries, maximization of the station of conditional dependence, and minimization of the merchandise deterioration (Josefowiez *et al*, 2008a, 2008b). Ever since, the subject has attracted a growing research interest in various settings and applications.

Bowerman *et al* (1995), Corberán *et al* (2002), and Pacheco and Marti (2006) discussed MOO for school-bus routing problem. Five objectives appear in Bowerman *et al* (1995), mainly on route minimization but include ‘student walking distance’ as one of the objectives, which is an important but a conflicting objective to the minimization effort. The objectives are weighted to form an aggregate measure. Corberán *et al* (2002) and Pacheco and Martí (2006) formulated two objectives, minimization of the number of buses and minimization of the maximum time in the bus. The former used scatter search method while the latter employed a tabu search to explore the non-dominated frontier.

Giannikos (1998) used goal programming for a MOO problem in hazardous product transportation. Four objectives are considered in this study. Lacomme *et al* (2006) experimented with a multi-objective evolutionary algorithm (MOEA) method called Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) in a capacitated arc routing problem. They concluded, however, that the algorithm could not efficiently solve the problem. Doerner *et al* (2007) presented a MOO case on a healthcare facility tour planning in developing countries. In this unique case, in addition to minimization of tour length as one objective, they also formulated 'coverage of population to the facilities' as the other objective. Three meta-heuristics in the form of evolutionary algorithms are investigated in this problem: Pareto-Ant Colony Optimization (P-ACO), Vector Evaluated Genetic Algorithm (VEGA), and Multi-Objective Genetic Algorithm (MOGA).

Specifically in VRPTW applications with multi-objective setting, the following research can be mentioned. Hong and Park (1999) used goal programming for a MOVRPTW involving two objectives: minimization of total vehicle travel time and minimization of customer wait time. Zografos and Androutsopoulos (2004) studied a MOVRPTW application for hazardous materials distribution problem by minimizing total travel time and total transportation risk. They also developed their own algorithm to search for the non-dominated solutions. Ombuki *et al* (2006) employed MOGA for a VRPTW minimizing total cost (distance) and the number of vehicles. Tan *et al* (2006) proposed a Hybrid Multi-Objective Evolutionary Algorithm

(HMOEA) combining specialized genetic operators, variable-length representation, and local search heuristic, for what the authors referred to as the Trucks and Trailers Vehicle Routing Problem (TTVRP). As explained by the authors, this class of problem does not exactly belong to the VRPTW family, but closely related. Two objectives are formulated: routing cost and number of trucks used. Ghoseiri and Ghannadpour (2010) combined goal programming and genetic algorithm in a MOVRPTW with minimization of total fleet size and total traveling distance. The goal programming is used in the formulation to minimize the deviations from the decision maker's aspiration levels, whereas the genetic algorithm is used for exploring the Pareto front. Lastly, Melián-Batista *et al* (2014) proposed two alternative versions of scatter search meta-heuristic that are compared and proven better than the NSGA-II. Two objectives in their VRPTW model are the total traveled distance and the workload of the drivers.

Several important facts can be discerned from the above review. Firstly, the method of finding the Pareto or non-dominated set of solutions appears in references from the year 2006 onwards. Meta-heuristics in the form of evolutionary algorithms such as VEGA, MOGA, and NSGA-II, being the tools for exploring the Pareto front, also have spurred together in the same period. This indicates that the methods are still relatively new and offer much research ground to uncover. Secondly, unlike in earlier studies where the number of objectives could amount to four (Giannikos, 1998) or five (Bowerman *et al*, 1995), research dealing with Pareto-front exploration usually accounts for two objectives (with minimization of total cost/distance often being the main and other such as minimization of vehicles used being the secondary). A possible deduction from this pattern is that Pareto-front exploration is a challenging task for researchers that require them to devote more attention on this part of the studies. On the other hand, having many objectives that are then weighted and aggregated into one final objective value is not a difficult process. What should be cautioned in the latter approach is the process in obtaining the weights that is a subject of research on itself. Thirdly, while maritime logistics has a close association with routing problems, research dealing with MOO in maritime logistics is very few in number, as opposed to the same topic in land logistics.

2.5.3 Elitist Multi-Objective Evolutionary Algorithms

A number of multi-objective evolutionary algorithms (MOEA) have been mentioned in the previous sub-section and the reviews of these and other MOE algorithms can be found in Coello Coello *et al* (2007) and Deb (2008). Basically, MOEAs can be classified into two main groups: *non-elitist* and *elitist*. Elitist MOEAs are considerably better than their non-elitist counterparts due to the use of an elite-preserving mechanism that prevents good solutions from being discarded by the genetic operators during the search iterations. Two competitive elitist MOEAs today are SPEA2 (Strength Pareto Evolutionary Algorithm 2) (Zitzler *et al*, 2002) and NSGA-II (Elitist Non-Dominated Sorting Genetic Algorithm) (Deb *et al*, 2000). SPEA2 is an improvement from the earlier version SPEA (Zitzler and Thiele, 1999). Likewise, NSGA-II is the elitist version from the earlier non-elitist NSGA (Srinivas and Deb, 1994). According to Zitzler *et al* (2002), both SPEA2 and NSGA-II are equally good except in higher dimensional objective spaces where SPEA2 seems to have advantages. On the other hand, NSGA-II is more easily coded, therefore a better preference for a problem with not more than two objectives.

To illustrate the basic principles of NSGA-II, consider a min-min problem with feasible solution space as shown in Figure 2.9. The true Pareto front of this problem, as indicated in Figure 2.8a, is the curve line *A*-*B*. The objective of the algorithm is, thus, to explore the solution space until it finds solutions as close as possible to the line *A*-*B*. As the name implies, NSGA-II sorts the population based on non-dominated principles. Given eight solutions [*a*, *b*, *c*, *d*, *e*, 1, 2, 3] in the population, the algorithm groups these solutions into two non-dominated fronts [*a*, *b*, *c*, *d*, *e*] and [1, 2, 3], and sorts them by assigning a higher rank to the set of solutions [*a*, *b*, *c*, *d*, *e*] due to its proximity to the true Pareto front. In other words, solutions *a*-*e* are non-dominating to each other (and so are solutions 1-3 to each other), but solutions *a*-*e* dominate solutions 1-3.

The algorithm then progresses by considering the ranking of these fronts. The elitism principle plays a critical part in choosing the solutions to be carried to the next iterations. For example, if the number of population is set at 5, solutions *a*-*e* will go through and perform the usual genetic procedures (crossover and mutation), and solutions 1-3 in the second front will be discarded. If the number of population is, for example, set at 4, then the selection becomes a bit more complicated and another measure called *crowding distance* is involved. This measure basically weighs solutions with less neighboring solutions for a better spread of population. In this case, solution *d* is better than solution *b*, thus the four solutions that will advance to the next iteration are *a*, *e*, *d*, and *c*.

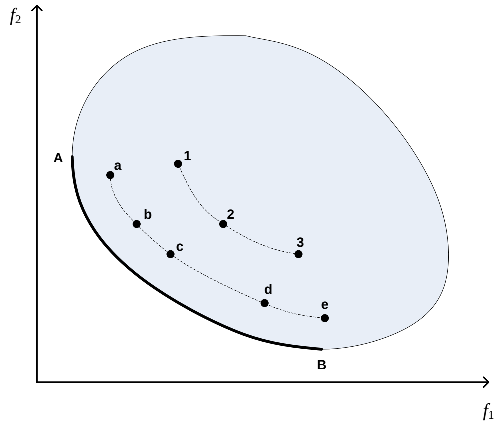

Figure 2.9 Illustration of NSGA-II basic principles

2.6 Research Gap Identification

This section highlights the research gap viewed from two perspectives: scope and method. The scope-wise analysis (Table 2.8) is a closer look on maritime logistics research papers that have been reviewed in the previous sections. These papers are tagged in a taxonomy using four attributes: collaboration, VRP class, objective, and meta-heuristic. The papers listed come from section 2.2 (liner shipping; in particular sub-section 2.2.2 on liner shipping network design) and section 2.4 (liner shipping collaboration). The papers that do not address these two main topics, or any of the attribute in the taxonomy, are automatically screened out.

The method-wise taxonomy has six attributes: scope of logistics, VRP class, objective, meta-heuristic, nature of vehicles, and whether or not fixed costs are considered (Table 2.9). The papers listed mainly come from sections 2.4 and 2.5 on the discussion of VRP and MOO, respectively.

It is clear from both perspectives in the research gap that a research on multi-objective maritime logistics collaboration, with emphasis on liner shipping, utilizing a heterogeneous VRPTW that considers fixed cost, and a meta-heuristic approach, has never been studied. This research aims to fill this gap and contribute in the overall literature of maritime logistics studies. To shorten the abbreviation from HVRPTW-F so to emphasize the uniqueness of this research, the problem is named as the ship routing problem (SRP).

Table 2.8 The research gap: scope-wise

Author(s) (year)	Main topic	Theme			
		Collaboration	VRP class	Objective	Meta-heuristic
Agarwal & Ergun (2010)	Net. design	Yes[1]	-	Single	-
Asgari *et al* (2013)	Collaboration	Yes[2]	-	Multiple	-
Boros *et al* (2008)	Net. design	Yes[3]	-	Multiple	-
Hsu & Hsieh (2008)	Net. design	No	-	Multiple	-
Karlaftis *et al* (2009)	Net. design	No	VRP	Single	GA
Lei *et al* (2008)	Collaboration	Yes[1]	-	Single	-
Sambracos *et al* (2004)	Net. design	No	VRP	Single	LBTA[4]
Takano & Arai (2009)	Net. design	No	-	Single	GA
This research	Collaboration	Yes[1]	VRPTW	Multiple	GA

[1] Between-carrier collaboration
[2] Between-carrier and Carrier-Port collaboration
[3] Carrier-Port collaboration
[4] LBTA (list-based threshold acceptance)

Table 2.9 The research gap: method-wise

Author(s) (year)	Scope of logistics	VRP class	Objective	Meta-heuristic	Nature of vehicles	Fixed costs
Baños *et al* (2013)	General	VRPTW	Multiple	Hybrid	Identical	-
Gambardella *et al* (1999)	General	VRPTW	Single	MACS[1]	Identical	-
Karlaftis *et al* (2009)	Maritime	VRP	Single	GA	Hetero.	No
Melián-Batista *et al* (2014)	General	VRPTW	Multiple	Scatter search	Identical	-
Ombuki *et al* (2006)	General	VRPTW	Multiple	GA	Identical	-
Prins (2004)	General	VRP	Single	GA	Identical	-
Prins (2009)	General	HVRP	Single	GA	Hetero.	No
Sambracos *et al* (2004)	Maritime	VRP	Single	LBTA	Identical	-
Silva, Jr. & Leal (2011)	General	VRPTW	Multiple	MACS[1]	Identical	-
Takano & Arai (2009)	Maritime	-	Single	GA	Hetero.	Yes
This research	Maritime	SRP	Multiple	GA	Hetero.	Yes

[1] Multiple ant colony system

2.7 Chapter Summary

In this chapter, an extensive literature review on a number of subjects is presented. The chapter starts with a discussion on logistics and supply chain management definitions for the purpose to highlight the research positioning, i.e. collaboration between logistics actors in the same tier of the chain. Overview of maritime logistics is then provided with emphasis given on liner shipping. In particular, the section builds taxonomy of research in liner shipping network design. Other issues such as tramp/industrial shipping and speed optimization are briefly discussed. Next, a section on liner shipping collaboration is outlined. The important outcome of this section is the classification of research in liner collaboration under the following clusters: qualitative vs. quantitative, input-process-output perspective, and carrier-carrier or carrier-port collaboration. Vehicle Routing Problem and its variants are then discussed and the mathematical models for CVRP, VRPTW, and VRPPD, as well as discussion and an example of a meta-heuristic approach for CVRP are presented. The next section discusses single-objective vs. multi-objective optimization. An introduction to the subject is given, followed by a review on the progress of research development in this area and a brief outline of one elitist MOEA. Finally, the chapter concludes with identification of the research gap viewed from the perspectives of scope and method.

CHAPTER III

RESEARCH METHODOLOGY

This chapter outlines the research methodology. The research framework is firstly described to show how all the issues and related concepts are bound and linked together in a structured way to form a coherent view. The research stages are then elaborated and these detail the step-by-step planned approach, including the proposed four models, to undertake the research. The first two models are the preliminary models built with the purpose to introduce the idea and scope of this research, i.e. maritime logistics collaboration, and these will be discussed in the third section.

3.1 Research Framework

In chapter two, a literature review has been carried out on a number of subjects in the fields of maritime logistics, liner shipping collaboration, vehicle routing problem and its variants, and multi-objective optimization. The subjects discussed can be grouped in three big blocks. The first block discusses the scope of research in general. From wide-ranging logistics/supply chain operations, maritime logistics is chosen. Based on the types of service in maritime logistics, the general scope is narrowed down to liner shipping. Liner shipping deals with containers and container ships, and as pointed out in Panayides (2006), maritime logistics as a concept in this field applies to the transportation of containerized cargoes rather than bulk cargoes.

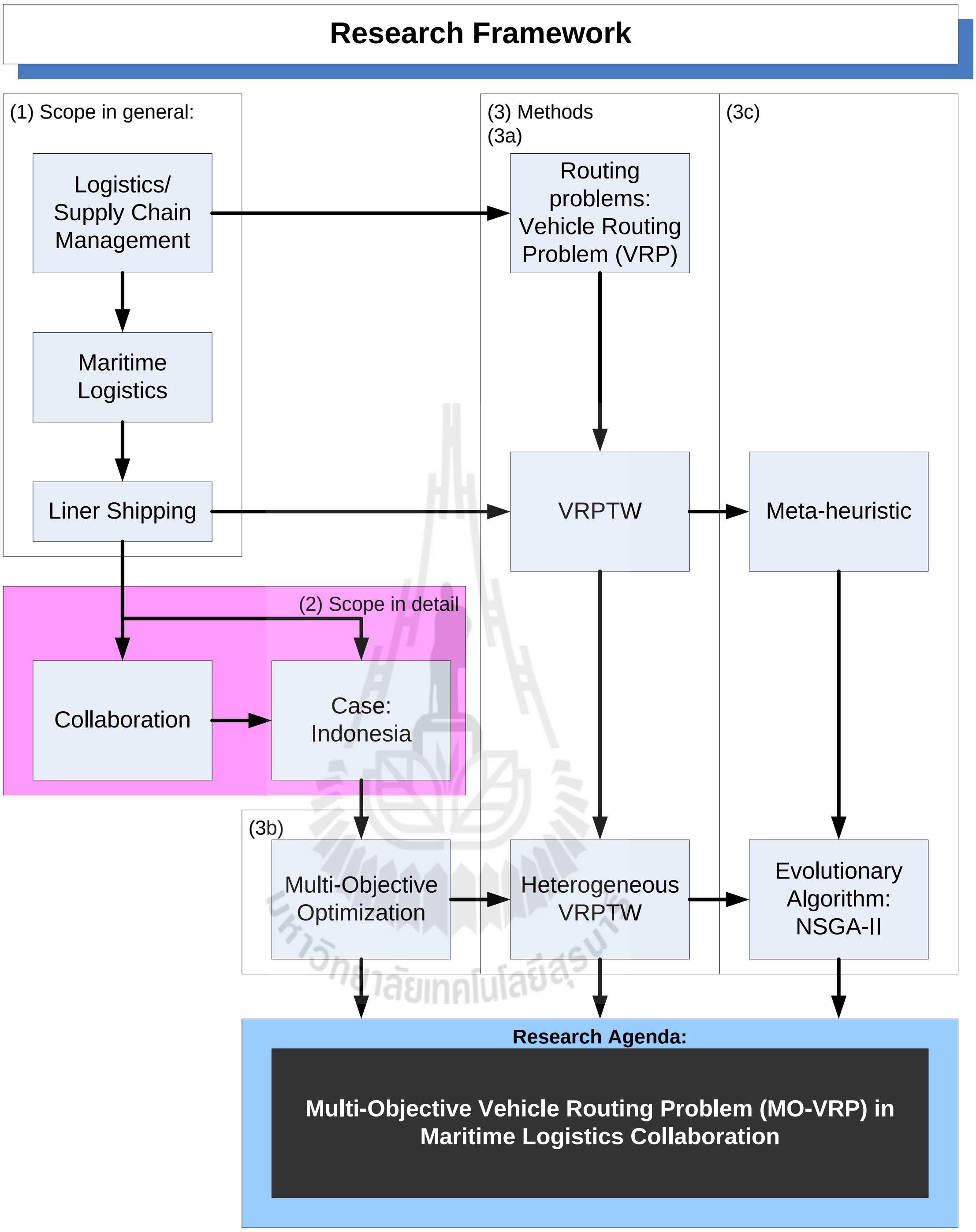

Figure 3.1 Research framework

The second block details the scope further. Liner shipping collaboration is given focus here considering the relatively minimum number of studies in this area.

Further, to be able to demonstrate the proposed model, numerical examples are required. Thus, case studies that can provide data as close as possible to the real-world shipping practice needs to be built. Indonesian archipelago will be used as the data background for this purpose. Despite the fact of being the largest archipelago in the world with over 17,500 islands, to the best of our knowledge, there is no record found on studies in Indonesian maritime cases.

The third block relates to the methods of this research. Since liner operations have a close relation to routing problems with time constraints, the heterogeneous VRP with time windows (HVRPTW) is selected as the model for the final case. Multi-objective optimization is another concept to be utilized due to its more realistic representation of real-world problems. Finally, acknowledging that routing problems are hard combinatorial problems, a meta-heuristic approach in the form of evolutionary algorithm is used, with a particular selection on a method called the elitist non-dominated sorting genetic algorithm (NSGA-II).

3.2 Research Stages

The first stage in undertaking this research is to define its scope. This comes from personal preferences and expertise, and also considers the research potentials in terms of benefits and contributions that the research can offer, both in the theoretical development and practical applications. Maritime logistics and liner shipping collaboration are the topics emerged from this stage. Literature review then follows to establish a foundation upon which the research gap can be identified. The review encompasses both the defined scope and various research methods. Research questions and contributions are then formulated and together with the research gap identification they formalize the research problem.

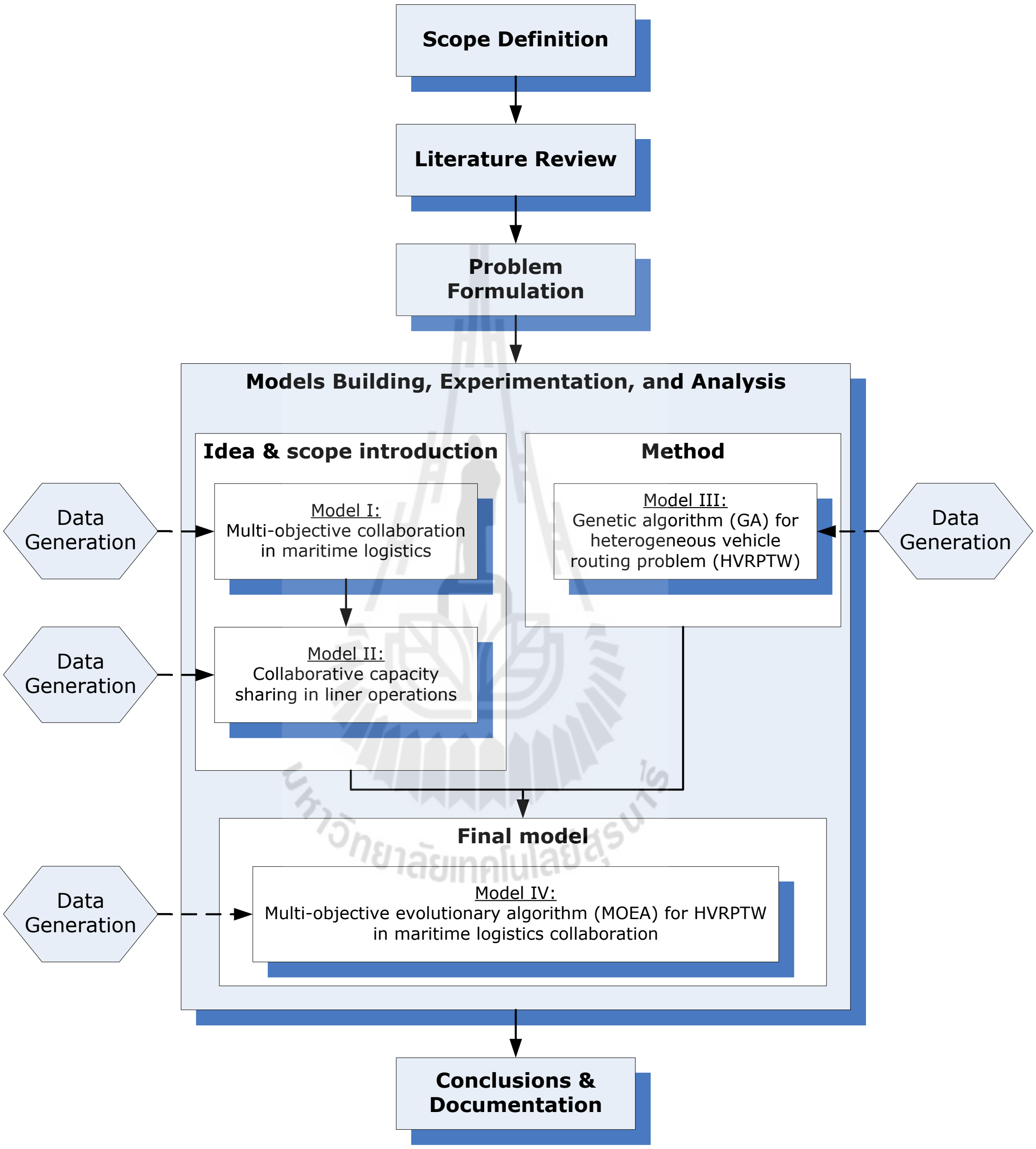

Figure 3.2 Research stages

Models building comes in the next stage and a total of four models are developed, experimented, and analyzed. The first two models introduce the idea and scope of maritime logistics collaboration. Model I is a multi-objective assignment problem and Model II is an extended VRPTW, both are applied on liner shipping case studies. One underlying method, the genetic algorithm for HVRP (Prins, 2009), is introduced in Model III and extended to HVRPTW that also considers fixed costs. This extension is an important adjustment for problems involving liner companies. Next, the last model integrates all the preceding models and becomes the final model of this research. In this final model, the idea of maritime logistics collaboration and GA for HVRPTW are combined with a multi-objective evolutionary algorithm called NSGA-II. Throughout these four models, data are obtained and generated based on the Indonesian archipelago to produce numerical instances. Some of the data are secondary (e.g. company profiles and distances, obtained from websites) and others (e.g. demands) are generated based on published reports. The experiment results are analyzed with regards to the outcomes and also the models' properties. Finally, conclusions are derived and all processes are documented. The research stages are illustrated in Figure 3.2.

3.3 Preliminary Models Building

In this section, two preliminary models are built with numerical examples to demonstrate the idea of multi-objective optimization in liner shipping collaboration. The degree of complexity between the two models varies. The first model is formulated as a multi-objective assignment problem where vessels and ports are paired (indicating services) without considering the possibilities of any vessel routed to more than one port. The approach of assignment is considered adequate for a small case with only 5 ports and 10 vessels operating in relatively short distances. The focus of attention is on the dual objectives formulation and their resulting properties.

In the second model, the case is enlarged with added vessels and ports. Two cases differing in size are introduced: the small case with 6 vessels and 8 ports, and the large case with 9 vessels and 13 ports. Using the VRPTW formulation, routing possibilities are considered. Given the complexity, a single-objective optimization approach is used and what is targeted as a second objective is shifted as a set of constraints. The approaches used in the two models are varied to generate as many angles as possible of the problem. The second model is termed the extended VRPTW and both cases use the Indonesian archipelago as a background for the data setup.

3.3.1 Multi-objective Collaboration in Maritime Logistics[1]

The problem description in this model is stated as follows. Two liner shipping companies (carriers) are operating a heterogeneous fleet of vessels and serving a number of ports from the same home-base port (depot). Given today's norm in the shipping business where supply is larger than demand, these two carriers would like to join forces by sharing their capacities to serve their joint demands. Two objectives are formulated in the model: (1) minimization of total fuel costs, and (2) minimization of total sailing time. It should not be difficult to infer that these two objectives are conflicting because faster sailing speed minimizes the sailing time, but at the same time burns more fuels and increases the fuel costs. These conflicting objectives warrant the approach of multi-objective optimization. The possibility of

[1] Materials of this sub-section have been presented as a paper at *The 2013 International Conference on Logistics and Maritime Systems* (LOGMS 2013), National University of Singapore, Singapore.

fast-steaming is also considered in the model to distinguish it from other typical models in land logistics.

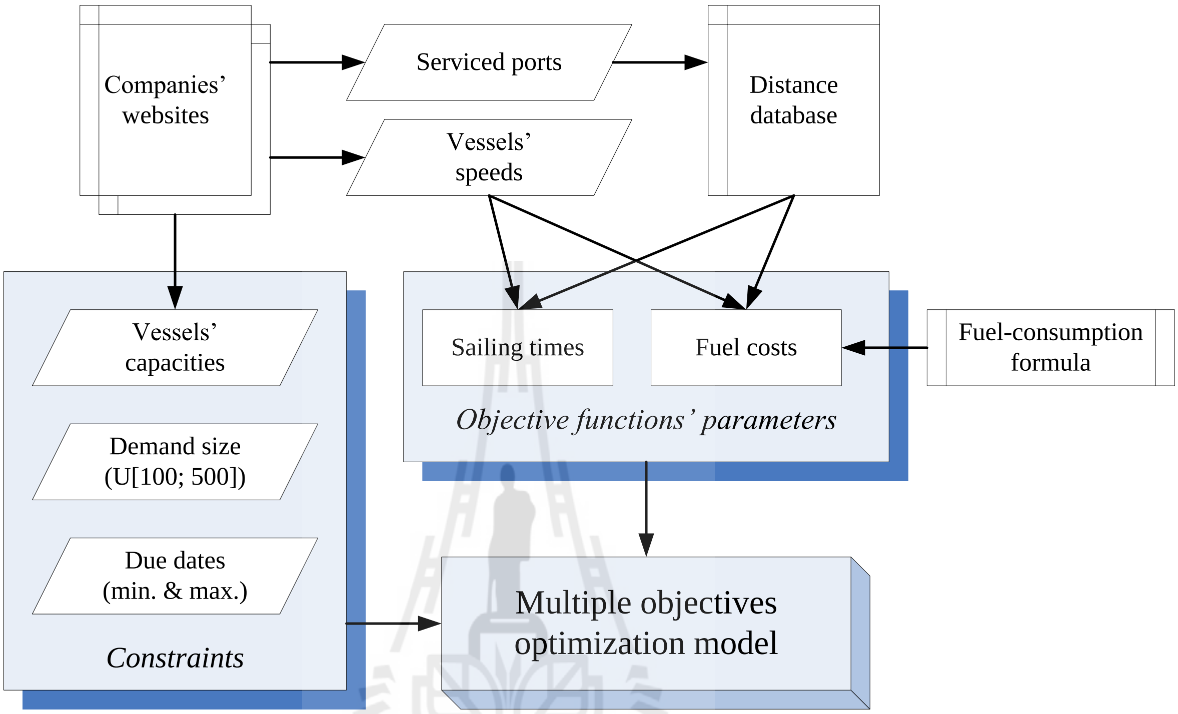

Figure 3.3 Data generation schematic for Model I

The two companies used in this case are typically alike in terms of fleet capacity and serviced ports. Data are obtained from companies' websites (www.meratusline.com and www.tantonet.com). These include the vessels' particulars (capacities and speeds) and ports to be serviced. Since at this stage it is not possible to replicate the whole operations of the two companies, only subsets of the data are used. This results in 7 vessels for each carrier (a combination of homogeneous and heterogeneous) and 5 ports to be serviced. Vessels' capacities range in 224-1024 TEUs and their speeds range in 12.5-19.2 knots. In addition, distances are calculated using distancecalculator.globefeed.com. From the home-base port to the serviced ports, distances range between 500 and 1140 nautical miles. Fuel costs and sailing times are then estimated from distances and speeds. Further, fast-steaming speeds are assumed 30% faster than the normal speeds. Demands (in TEUs) are generated in each port for each carrier using the uniform distribution U[100; 500]. Attached to these demands are the due dates (in hours). Two sets of due dates, minimum and maximum, are tested to examine the model sensitivity to these parameters. The data generation process is described in Figure 3.3 and the data are listed in Appendix A.

In the absent of any search mechanism, obtaining the non-dominated set of solutions is carried out by optimizing the model separately vis-à-vis each objective function, however, both objective functions' values are calculated in each run. By combining the two objective functions with binary fast-steaming decisions and two sets of due dates, eight scenarios are produced and optimized. Fast-steaming decision is formulated as binary variables rather than a function although the latter is also possible, at least at a discrete level. However, for short trips (in domestic seas) it is more of a strategic rather than a tactical decision, and formulating it as a continuous function might have limited practicality.

The following notation is used to describe the mathematical model. Subscript i is used as an index for the vessels and subscript j is used as an index for the ports. To ease the readability of the notations, the sets for each carrier are separated, in terms of the set for the vessels and the decision variables. The pure-binary programming model for the problem is presented after the notation.

$\mathcal{N}$ Set of ports, excluding the depot

$\mathcal{V}^a$ Set of vessels of carrier a

$c_{i,j}$ Cost of vessel i if goes to port j

$c_{i,j}^{+}$ Cost of vessel i if goes to port j with fast steaming

$t_{i,j}$ Sailing time of vessel i if goes to port j

$t_{i,j}^{+}$ Sailing time of vessel i if goes to port j with fast steaming

K_i^a Vessel i capacity of carrier a

d_j^a Demand size of carrier a at port j (in TEUs)

D_j^a Due date of demand of carrier a at port j (in hours)

$x_{i,j}$ Binary decision variables, 1 if vessel i of carrier 1 goes to port j, 0 otherwise

$y_{i,j}$ Binary decision variables, 1 if vessel i of carrier 2 goes to port j, 0 otherwise

$g_{i,j}$ Binary decision variables, 1 if vessel i of carrier 1 goes to port j with fast steaming, 0 otherwise

$h_{i,j}$ Binary decision variables, 1 if vessel i of carrier 2 goes to port j with fast steaming, 0 otherwise

$$\text{Min.} \sum_{i \in \mathcal{V}^1} \sum_{j \in \mathcal{N}} x_{i,j}\left[g_{i,j}.c_{i,j}^{+} + \left(1 - g_{i,j}\right)c_{i,j}\right] + \sum_{i \in \mathcal{V}^2} \sum_{j \in \mathcal{N}} y_{i,j}\left[h_{i,j}.c_{i,j}^{+} + \left(1 - h_{i,j}\right)c_{i,j}\right] \tag{3.1}$$

$$\text{Min.} \sum_{i \in \mathcal{V}^1} \sum_{j \in \mathcal{N}} x_{i,j}\left[g_{i,j}.t_{i,j}^{+} + \left(1 - g_{i,j}\right)t_{i,j}\right] + \sum_{i \in \mathcal{V}^2} \sum_{j \in \mathcal{N}} y_{i,j}\left[h_{i,j}.t_{i,j}^{+} + \left(1 - h_{i,j}\right)t_{i,j}\right] \tag{3.2}$$

Subject to:

$$\sum_{i \in \mathcal{V}^1} x_{i,j}.K_i^1 + \sum_{i \in \mathcal{V}^2} y_{i,j}.K_i^2 \geq d_j^1 + d_j^2 \qquad \forall j \in \mathcal{N} \tag{3.3}$$

$$x_{i,j}.g_{i,j}.t_{i,j}^{+} + x_{i,j}(1 - g_{i,j})t_{i,j} \le \min(D_j^1, D_j^2) \qquad \forall i \in \mathcal{V}^1;\ j \in \mathcal{N} \tag{3.4}$$

$$y_{i,j}.h_{i,j}.t_{i,j}^{+} + y_{i,j}(1 - h_{i,j})t_{i,j} \le \min(D_j^1, D_j^2) \qquad \forall i \in \mathcal{V}^2;\ j \in \mathcal{N} \tag{3.5}$$

$$\sum_{j \in \mathcal{N}} x_{i,j} \le 1 \qquad \forall i \in \mathcal{V}^1 \tag{3.6}$$

$$\sum_{j \in \mathcal{N}} y_{i,j} \le 1 \qquad \forall i \in \mathcal{V}^2 \tag{3.7}$$

$$g_{i,j} \le x_{i,j} \qquad \forall i \in \mathcal{V}^1;\ j \in \mathcal{N} \tag{3.8}$$

$$h_{i,j} \le y_{i,j} \qquad \forall i \in \mathcal{V}^2;\ j \in \mathcal{N} \tag{3.9}$$

$$\sum_{i \in \mathcal{V}^1} \sum_{j \in \mathcal{N}} x_{i,j} \ge 1 \tag{3.10}$$

$$\sum_{i \in \mathcal{V}^2} \sum_{j \in \mathcal{N}} y_{i,j} \ge 1 \tag{3.11}$$

The first objective is to minimize the total fuel costs and the second objective is to minimize the total sailing time. The fuel costs are calculated using the fuel-consumption formula from Fagerholt *et al* (2010b) with oil price assumed at US$100/barrel.

$$f(s) = 0.0036s^2 - 0{,}1015s + 0{,}8848 \tag{3.12}$$

Constraints (3.3) are the demand size constraints. Each carrier has customers of its own and these customers generate the demand. Total demand in each port must be satisfied by a group of vessels going to that port, which can be a combination of the fleets from both carriers. The demands are generated such that total demand of both carriers in all ports is less than total capacity of both carriers.

Constraints (3.4) and (3.5) are the due-date constraints for vessels of carrier 1 and carrier 2, respectively. Constraints (3.6) and (3.7) are the flow constraints to ensure that one vessel can only go to one port. Constraints (3.8) and (3.9) are related to the fast-steaming decision where such a decision can only take place behind the go/no-go decision for each vessel sailing to a port. Lastly, constraints (3.10) and (3.11) are set up so that each carrier must serve at least one port so that it still maintains a shipping activity rather than just being a brokerage firm.

Since products of decision variables present in the model, the model is not linear and needs the following transformation (Chen *et al*, 2010). Let $z^1_{i,j} = x_{i,j}.g_{i,j}$ for carrier 1, $z^2_{i,j} = y_{i,j}.h_{i,j}$ for carrier 2, and these constraints are added:

$$z^1_{i,j} \leq x_{i,j} \qquad \forall i \in \mathcal{V}^1;\ j \in \mathcal{N} \qquad (3.13)$$

$$z^1_{i,j} \leq g_{i,j} \qquad \forall i \in \mathcal{V}^1;\ j \in \mathcal{N} \qquad (3.14)$$

$$z^1_{i,j} \geq x_{i,j} + g_{i,j} - 1 \qquad \forall i \in \mathcal{V}^1;\ j \in \mathcal{N} \qquad (3.15)$$

$$z^2_{i,j} \leq y_{i,j} \qquad \forall i \in \mathcal{V}^2;\ j \in \mathcal{N} \qquad (3.16)$$

$$z^2_{i,j} \leq h_{i,j} \qquad \forall i \in \mathcal{V}^2;\ j \in \mathcal{N} \qquad (3.17)$$

$$z^2_{i,j} \geq y_{i,j} + h_{i,j} - 1 \qquad \forall i \in \mathcal{V}^2;\ j \in \mathcal{N} \qquad (3.18)$$

The combination of two objective functions, binary fast-steaming decisions, and two sets of due dates, produces eight scenarios calling for optimization. All eight scenarios are optimized and the results are reported in Table 3.1. In scenarios 1 to 4, all fast-steaming decision variables are set to zeros. The 'Solution' column in Table 3.1 refers to the decision variables with value 1. It can be inferred from these results that only scenario 2 does not belong to the non-dominated set of solutions. The other 7 scenarios fall into this set and in fact some of them are duplicates, bringing only 4 distinct non-dominated solutions in the set. The difference in solutions with equal objective functions' values, e.g., $x_{6,3}$ in model 3 and $x_{5,3}$ in model 4 is due to the homogeneity of the vessels. Figure 3.4 displays the Pareto-front chart for the results obtained in Model I.

The results in Table 3.1 suggest two important findings: Firstly, when the objective to be minimized is the total costs, the objective functions' values vary. On the contrary, when it is the total sailing time, the same results are obtained, irrespective of fast-steaming decisions and sets of due dates used. Despite the fact that the solutions from this objective belong to the Pareto set, this could indicate that sailing time may not be a critical objective. Secondly, within the subset of total costs objective, due dates play an important role. Longer due dates imply 'no rush' and therefore the vessels can safely slow-steam (reflected in all fast-steaming variables equal to zero) and burn less fuel, at the expense of sailing time. Stricter due dates produce different results, i.e. fast-steaming is required to reach the Pareto front and when it is not allowed (scenario 2) the solution fails to reach that front.

In light of the above findings, a consideration for model extension is in order. That sailing time may not be a critical objective prompts a search for other better one(s). It is also noted that efficient search methods such as evolutionary algorithms are required to further discover the Pareto front.

Table 3.1 Optimization results for Model I

No.	Objective (min.)	Fast speed	Due date	Solution	Total costs (US$)	Total time (hours)
1	Cost	No	Max.	x63, x72; y21, y44, y65	72.306	235
2	Cost	No	Min.	x51, x73; y44, y65, y72	79.374	221
3	Sailing time	No	Max.	x63; y41, y55, y64, y72	81.487	214
4	Sailing time	No	Min.	x53; y41, y55, y64, y72	81.487	214
5	Cost	Yes	Max.	x63, x72; y21, y44, y65	72.306	235
6	Cost	Yes	Min.	x41 (g41), x63, x72 (g72); y45, y54	77.733	218
7	Sailing time	Yes	Max.	x53 (g53); y45 (h45), y54 (h54), y61 (h61), y72 (h72)	170.590	164
8	Sailing time	Yes	Min.	x63 (g63); y41 (h41), y55 (h55), y64 (h64), y72 (h72)	170.590	164

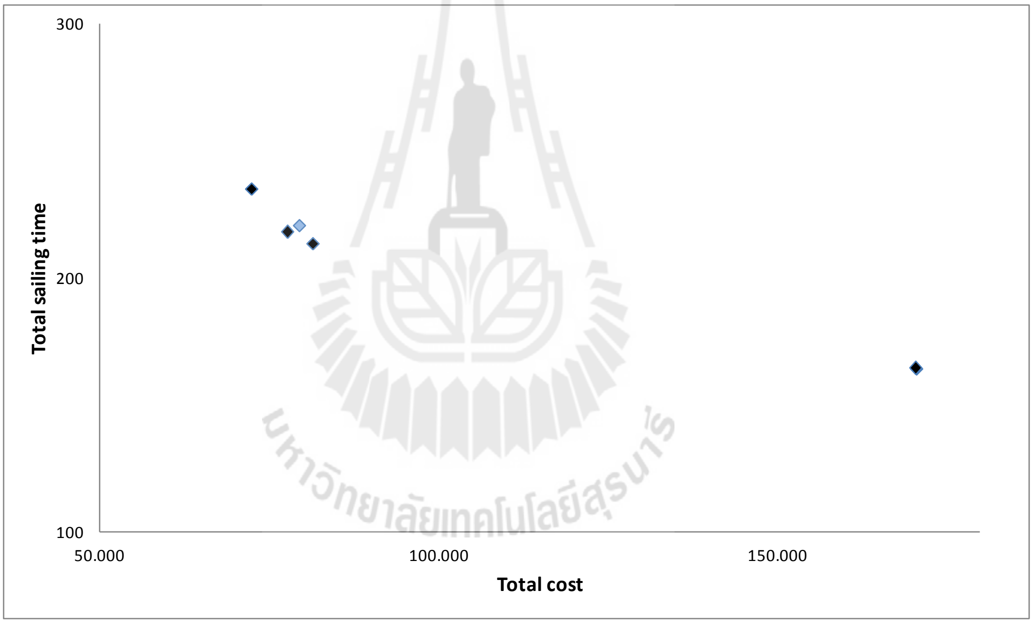

Figure 3.4 Pareto front for Model I

3.3.2 Collaborative Capacity Sharing in Liner Operations[2]

The problem description of Model II is stated as follows: two liner shipping companies (two carriers of different size) are operating a heterogeneous fleet

[2] Materials of this sub-section are part of a paper that has been accepted for publication at *The International Journal of Logistics Systems and Management* (In Press).

of vessels and serving a number of ports from the same depot. Given today's norm in the shipping business where supply is larger than demand, these two carriers would like to collaborate by sharing their capacities. This strategy allows one carrier to fill its unused capacities with orders from the other carrier going to the same destination, and reciprocally send its cargoes to the under-capacity vessels of the other carrier. Using this approach, carriers can avoid operating their under-utilized fleet. The objective is to minimize total fuel consumption.

Model II borrows the VRPTW as the basis to develop a new model with two extensions. Firstly, concerns for a greener environment have prompted maritime actors to seek better ways of operations, for example by slow steaming to reduce gas emissions. In this model, this factor is taken into account by formulating it as decision variables. Secondly, an investigation is carried out with regard to the distribution sharing of operational burdens measured in fuel consumption. More specifically, three different sharing policies will be evaluated:

1. open policy, where there is no restriction to the sharing requirement
2. proportionate-sharing policy, where the sharing is set in proportion to the size of the carriers
3. equal-sharing policy, where the sharing is set equal, or fifty-fifty, regardless of the carriers' size.

The following sets, parameters and variables are defined below.

$\mathcal{C}$ Set of carriers, indexed by a

$\mathcal{V}_a$ Set of vessels of carrier a, indexed by v

$\mathcal{A}$ Set of arcs (i,j) denoting a flow from port i to port j

$\mathcal{N}$ Set of all ports $\mathcal{N} = \{1, 2, \ldots, n\}$; $\{1\}$ is the home-base port

$\mathcal{P}$ Set of ports-of-call, or $\mathcal{N} \setminus \{1\}$

$c_{i,j}^{a,v}$ Fuel consumption of vessel v of carrier a if it sails from port i to port j

$c_{i,j}^{a,v,-}$ Fuel consumption of vessel v of carrier a if it sails from port i to port j with slow steaming

$t_{i,j}^{a,v}$ Sailing time of vessel v of carrier a if it sails from port i to port j

$t_{i,j}^{a,v,-}$ Sailing time of vessel v of carrier a if it sails from port i to port j with slow steaming

$C^{a,v}$ Capacity of vessel v of carrier a

D_i Total demand of both carriers at port i (in TEUs)

T_i Due date at port i (in hours)

p_i Service time at port i

M Big M

a, b Minimum and maximum deviations of fuel-consumption sharing between the two carriers

$x_{i,j}^{a,v}$ Binary variables for vessel v of carrier a in arc (i,j); $x_{i,j}^{a,v} = 1$ if the vessel traverses arc (i,j) and equals 0 otherwise

$f_{i,j}^{a,v}$ Binary slow-steaming variables for vessel v of carrier a in arc (i,j); $f_{i,j}^{a,v} = 1$ if the vessel traverses arc (i,j) with reduced speed and equals 0 if it uses normal speed

$s_i^{a,v}$ Time window for vessel v of carrier a at port i

The extended VRPTW model can then be formulated as follows:

$$\text{Minimize} \sum_{a\in\mathcal{C}} \sum_{v\in\mathcal{V}_a} \sum_{i,j\in\mathcal{A}} x_{i,j}^{a,v}.\left[f_{i,j}^{a,v}.c_{i,j}^{a,v,-} + \left(1-f_{i,j}^{a,v}\right).c_{i,j}^{a,v}\right] \tag{3.19}$$

Subject to:

$$\sum_{a\in\mathcal{C}} \sum_{v\in\mathcal{V}_a} \sum_{i,j\in\mathcal{A}} x_{i,j}^{a,v}.C^{a,v} \geq D_i \qquad \forall\, i\in\mathcal{P} \tag{3.20}$$

$$\sum_{i\in\mathcal{P}} D_i \sum_{j\in\mathcal{N}} x_{i,j}^{a,v} \leq C^{a,v} \qquad \forall\, a\in\mathcal{C};\ v\in\mathcal{V}_a \tag{3.21}$$

$$\sum_{i\in\mathcal{N}} x_{i,k}^{a,v} - \sum_{j\in\mathcal{N}} x_{k,j}^{a,v} = 0 \qquad \forall\, k\in\mathcal{P};\ a\in\mathcal{C};\ v\in\mathcal{V}_a \tag{3.22}$$

$$x_{i,i}^{a,v} = 0 \qquad \forall\, i\in\mathcal{N};\ a\in\mathcal{C};\ v\in\mathcal{V}_a \tag{3.23}$$

$$\sum_{j\in\mathcal{P}} x_{1,j}^{a,v} \leq 1 \qquad \forall\, a\in\mathcal{C};\ v\in\mathcal{V}_a \tag{3.24}$$

$$f_{i,j}^{a,v} \leq x_{i,j}^{a,v} \qquad \forall\, i,j\in\mathcal{A};\ a\in\mathcal{C};\ v\in\mathcal{V}_a \tag{3.25}$$

$$s_i^{a,v} \leq T_i \qquad \forall\, i\in\mathcal{P};\ a\in\mathcal{C};\ v\in\mathcal{V}_a \tag{3.26}$$

$$s_i^{a,v} + \left[f_{i,j}^{a,v}.t_{i,j}^{a,v,-} + \left(1-f_{i,j}^{a,v}\right).t_{i,j}^{a,v}\right] + p_i - M\left(1 - x_{i,j}^{a,v}\right) \leq s_j^{a,v} \qquad \forall\, i\in\mathcal{N};\ j\in\mathcal{P};\ a\in\mathcal{C};\ v\in\mathcal{V}_a \tag{3.27}$$

$$\begin{aligned} a \leq & \sum_{v\in\mathcal{V}_1} \sum_{i,j\in\mathcal{A}} x_{i,j}^{1,v}.\left(f_{i,j}^{1,v}.c_{i,j}^{1,v,-} + \left(1-f_{i,j}^{1,v}\right).c_{i,j}^{1,v}\right) \\ & - \sum_{v\in\mathcal{V}_2} \sum_{i,j\in\mathcal{A}} x_{i,j}^{2,v}.\left(f_{i,j}^{2,v}.c_{i,j}^{2,v,-} + \left(1-f_{i,j}^{2,v}\right).c_{i,j}^{2,v}\right) \leq b \end{aligned} \tag{3.28}$$

$$x_{i,j}^{a,v}, f_{i,j}^{a,v} \in \{0,1\} \qquad \forall\, i,j\in\mathcal{A};\ a\in\mathcal{C};\ v\in\mathcal{V}_a \tag{3.29}$$

$$s_i^{a,v} \geq 0 \qquad \forall\, i \in \mathcal{N};\ a \in \mathcal{C};\ v \in \mathcal{V}_a \qquad (3.30)$$

The objective function (3.19) is to minimize total fuel consumption. Note that binary decision variables $f_{i,j}^{a,v}$ are added for whether reduced or normal speed will be used by a particular vessel in a particular arc. An extra summation sign is also present to signify the involvement of more than one carrier. The per-nautical-mile fuel-consumption formula follows the quadratic function from Fagerholt *et al* (2010b) as shown in constraints (3.12) with single variable sailing speed s (in knots). This function is valid for speeds between 14 and 20 knots which will be the case in our study. We consider that fuel consumption is sufficient to reflect the operational burdens of the carriers, thus we avoid converting this figure to monetary values, particularly given the unstable oil prices in the current market and also to reduce too many approximations from other cost-relevant factors.

Constraints (3.20) to (3.24) are the foundation of a VRP formulation, and constraints (3.26) and (3.27) are the addition for a VRPTW. Constraints (3.20) ensure that the demand in each port will be satisfied and constraints (3.21) dictate that such fulfilment by a vessel in several ports will not exceed the vessel's capacity. Constraints (3.22) are the flow equation to balance the incoming and outgoing trips to and from each port. Constraints (3.23) state that a vessel cannot travel inside the same node. Constraints (3.24) prevent a vessel to assume more than one tour. Constraints (3.25) dictate that decision for speed reduction can only be imposed if a vessel sails an arc. The products of binary variables resulting from the introduction of slow-steaming decisions are transformed to maintain the linearity of the model by using the same sets of constraints similar to constraints (3.13) to (3.18). These constraints imply that constraints (3.25) can be omitted from the formulation since if $x_{i,j}^{a,v} = 0$, whatever the value of $f_{i,j}^{a,v}$ will have no effect on the objective function. However, supplying bounds in mathematical programming is helpful to reduce the computation time.

Time windows are observed by constraints (3.26) and (3.27). A single-sided time window T_i reflecting a due date that a vessel must arrive in a port is used as an upper bound of $s_i^{a,v}$. Given port service time p_i and the big M in constraints (3.27), the inequality constraints specify that if a vessel sails from port i to port j, the vessel cannot arrive at port j before $s_i^{a,v} + \text{travel time from port } i \text{ to port } j + \text{service time at port } i$, either with reduced or normal speed. Constraints (3.27) also eliminate sub-tours (see 2.4.1). The model is a mixed-integer program due to the presence of $s_i^{a,v}$.

An important part of the formulation is constraints (3.28) where the deviation of total fuel consumption between two carriers is measured. Parameters a and b serve as the bounds for the fuel-consumption sharing policies to be investigated. The case involves two carriers of different sizes and the collaboration bears a question as to how the division of operational burdens should be assigned to each carrier.

The case study uses data from the Indonesian archipelago. The data are divided into cities and distances, vessels' particulars, demand, and the due dates. For the purpose of benchmark and further studies, all data can be found in this URL: http://ti.ubaya.ac.id/index.php/component/content/article/24-dosen/159-wibisono-jittamai-2014.html

a. Cities and distances

Over 17,500 islands span in the geographical layout of Indonesia between latitudes 6°N and 11°S and longitudes 95°E and 141°W, and cities in all corners of the country are almost equally important in the subjects of trade and economy. The two largest cities, the capital Jakarta situated on West Java and Surabaya on East Java, are both on the southern/south-western part of the archipelago. These two cities are heavily linked to the other regions of the country for various, especially business-related, affairs. In this study, the city of Surabaya is chosen as the depot, and two cases are developed: the small case with six vessels (4:2 for the ratio of fleet size between the two carriers) and eight ports; and the large case with nine vessels (6:3 for the same ratio) and thirteen ports. The small case is basically orientated towards servicing the eastern part of the country. The geography and included ports in the study are illustrated in Figure 3.5. Distances between ports are measured using distancecalculator.globefeed.com, however, since these are Euclidean measures, some adjustments are made with 103% to 180% of the obtained measures maintaining triangular relationships ($c_{i,j} + c_{j,k} \geq c_{i,k}$). For example between Pontianak (West Kalimantan) and Samarinda (East Kalimantan), a ship must travel via the Java Sea which clearly takes a longer distance than if the transport is made over land. Taking into account all possible links, the distances measured fall in the range of 63 to 2,396 nautical miles. The travel times are assumed deterministic based on these distances.

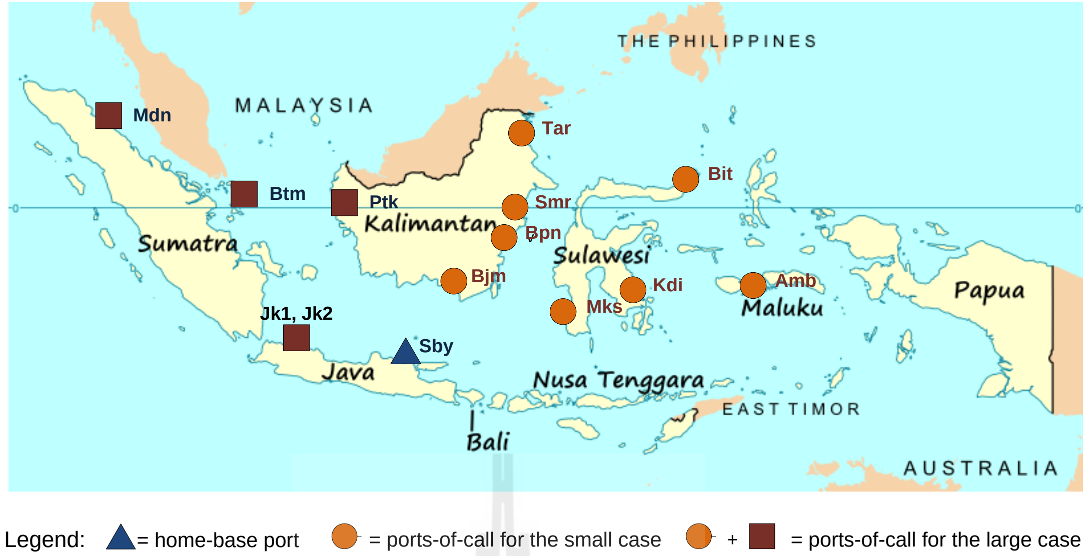

Figure 3.5 Map of Indonesia with cities being studied in Model II

b. Vessels' particulars

Two particulars of the vessels are involved in the data setup. These are: (1) capacities of the vessels, which are generated using a uniform distribution $U[500; 1500]$ TEUs (twenty-foot equivalent); (2) their speeds: a vessel with capacity ≤ 1000 TEUs uses 15 knots and 19 knots for the slow speed and normal speed, respectively, whereas the upper half of the range uses 16 knots and 20 knots for the corresponding speeds. The random generation for capacities is a one-time process and the results are used in all instances of the experiment. Of the six vessels in the small case, two are the slow/low-capacity vessels and four are the fast/high-capacity vessels with the range of capacities between 708 to 1390 TEUs. In the large case, there are five slow/low-capacity vessels and four fast/high-capacity vessels with the range of capacities in 530-1390 TEUs.

The vessels in this case study are assumed homogenous in terms of age and other cost-related factors. This assumption is needed given the variety of cost elements in shipping operations and incorporating all of them could obscure the focus of the study which is to investigate the impacts of sharing policies on fuel consumption. However, one major cost element that cannot be neglected is the fixed cost of running a vessel. In the experiment, it is possible to obtain a result of lower consumption in one policy but by using an extra vessel, and certainly this is not comparable to a result of higher consumption with less number of vessels in the other policy. To deal with this issue, for each instance, we run the experiment twice if the results show there is a policy using a fewer number of vessels. On the second run, constraints (3.31) are imposed on all policies with n being the minimum number of vessels found in the first run.

$$\sum_{j \in \mathcal{P}} x_{j,1}^{a,v} \leq n \qquad \forall\, a \in \mathcal{C};\ v \in \mathcal{V}_a \tag{3.31}$$

c. Demand

Each carrier has customers of its own and these customers generate the demand. Similar to the capacities, the demands are also in TEUs and generated randomly. However, in order to get as close as possible to the reality and avoid blind randomization, we based the generation from the OECD report (OECD, 2012), which provides data for container volumes through Indonesian ports in 2012, both for international and domestic traffic. Several cities are selected from the list of the major ports (the same with those in Figure 3.5 except for Kendari, which is added arbitrarily) and the domestic data are used. Ten percent of the weekly demand is then assumed as the market share of each carrier and $\pm 50\%$ is given for the range of the uniform distribution used in the demand generation. Demands are then generated for twelve instances both for the small and large cases. Table 3.2 summarizes the process. The idea of capacity sharing collaboration is to make one carrier responsible for the demand of its partner carrier and of its own in some ports, and let the partner carrier take care of its demand in the other ports. Therefore during optimization, only the total demand is relevant.

Table 3.2 Demand generation process for Model II

No.	Port	Abbrev.	Domestic traffic 2012 (000 TEUs) [1]	Weekly 10% (TEUs)	Uniform dist.
1	Jakarta	Jk1, Jk2	833	1602	U[801; 2403]
2	Medan	Mdn	278	535	U[267; 802]
3	Makassar	Mks	248	477	U[238; 715]
4	Banjarmasin	Bjm	118	227	U[113; 340]
5	Pontianak	Ptk	99	190	U[95; 286]
6	Samarinda	Smr	95	183	U[91; 274]
7	Bitung	Bit	63	121	U[61; 182]
8	Balikpapan	Bpn	35	67	U[34; 101]
9	Batam	Btm	26	50	U[25; 75]
10	Tarakan	Tar	17	33	U[16; 49]
11	Ambon	Amb	15	29	U[14; 43]
12	Kendari	Kdi	10	19	U[10; 29]

[1] Based on OECD (2012)

The demand of Jakarta is very large and for simplicity we split the demand in this city into two equal sizes and created a duplicate city (both are identified as Jk1 and Jk2 with zero distance) that shares half of the demand. Since only one city has this problem, this approach is preferred to split-delivery formulation in order to reduce model complexity. Note that the total number of ports in the large case is therefore thirteen instead of twelve. Also, since the upper limit of demand in Jakarta still exceeds the upper limit of vessel capacity, some generated instances violating this have to be omitted.

d. Due dates

Since there is no sufficient information for the background of due dates establishment, the due dates are assigned by considering normal sailing time that can be achieved from the depot in Surabaya plus some slack that could allow a vessel to serve several more ports. Leaving the due dates completely open is not a practical approach, as that might produce a long tour for a vessel that is limited only by its capacity to serve as many ports as possible. The due dates for the small case are stricter than those for the large case, but none of the due date exceeds one week since the demand is on a weekly basis. In addition, port service times are set equally for twelve hours for all ports including the initial service at the home port in Surabaya. Rooms for further studies are open for the consideration of probabilistic port service times.

In summary, two cases are developed. The small case consists of six vessels and eight ports, and the large case consists of nine vessels and thirteen ports. In each case, three models in relation to fuel-consumption sharing policies are evaluated: open policy, proportionate policy, and equal policy. Twelve instances are generated, plugged into the model, and run for optimization.

The parameters a and b in constraints (3.28) are determined as follows: first, a few instances were run without these constraints to probe the range of minimized total fuel consumption. The small case has this figure less than 2000 and the large case has it less than 2800, thus we set the upper bound b close to those figures so we have $a = 0$ and $b = 2000$, and $a = 0$ and $b = 3000$, respectively, for the small case and the large case in the open policy. For the proportionate-sharing policy, noting that carrier A offers two times of fleet size (4:2 in the small case and

6:3 in the large case) than carrier B, the fair proportion of fuel consumption consequently should be in 2:1 ratio. We therefore set $a = 600$ and $b = 700$, and $a = 800$ and $b = 900$, respectively, for the small case and the large case in this policy. Finally, in the equal-sharing policy, both carriers are expected to equally share the fuel consumption hence the upper bound b of the equation should be set as minimum as possible and it is set at 100 for both cases in this policy. Table 3.3 summarizes these values for all scenarios. All instances for both cases and the three policies were run for optimization using Lingo 11.0 on an Intel i5-2430M processor at 2.4 GHz and 4 MB of RAM. The running times for the small case reached 15 seconds maximum, whereas for the large case they spread from seconds to five hours.

Table 3.3 Values of a and b for all scenarios

	Small-case Policies			Large-case Policies		
	Open	Proportionate	Equal	Open	Proportionate	Equal
a	0	600	0	0	800	0
b	2000	700	100	3000	900	100

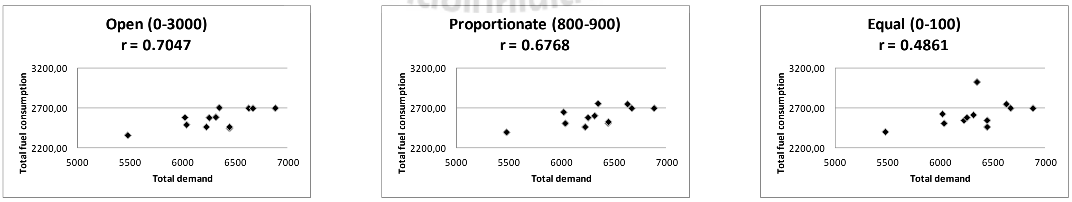

Figure 3.6 Scatter plots of total demand vs. total fuel consumption for the large case

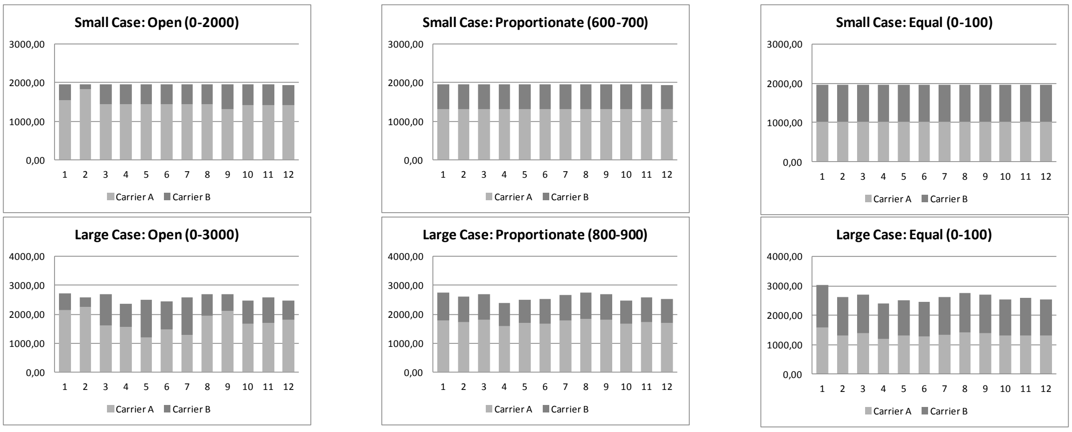

Figure 3.7 Distribution of fuel consumption between two carriers

Table 3.4 Experiment results of the large case for Model II

Instance	# of vessels	Demand (TEU)	Open Policy			Proportionate-sharing Policy				Equal-sharing Policy			
			Carrier A	Carrier B	Total	Carrier A	Carrier B	Total	Gap	Carrier A	Carrier B	Total	Gap
1	8	6347	2131	578	2710	1780	980	2760	1.86%	1563	1469	3032	11.91%
2	8	6314	2236	354	2590	1718	889	2607	0.65%	1310	1307	2617	1.05%
3	9	6880	1617	1085	2702	1799	903	2702	0.00%	1397	1305	2702	0.00%
4	7	5476	1555	806	2361	1599	799	2399	1.59%	1203	1202	2405	1.86%
5	8	6036	1187	1307	2494	1701	810	2511	0.67%	1295	1216	2511	0.67%
6	8	6443	1469	980	2449	1676	838	2514	2.65%	1264	1202	2466	0.68%
7	8	6020	1272	1313	2586	1776	877	2653	2.60%	1316	1313	2629	1.69%
8	9	6627	1939	764	2702	1826	926	2753	1.86%	1425	1328	2753	1.86%
9	9	6667	2124	578	2702	1799	903	2702	0.00%	1397	1305	2702	0.00%
10	8	6223	1667	799	2466	1667	799	2466	0.00%	1306	1243	2549	3.36%
11	9	6251	1704	878	2583	1722	861	2583	0.00%	1303	1280	2583	0.00%
12	8	6445	1812	654	2466	1692	838	2531	2.63%	1306	1243	2549	3.36%
Mean		**6311**			**2568**			**2598**	**1.21%**			**2625**	**2.20%**
Variance		**132,239**			**14,389**			**13,768**				**26,760**	

Results of the small case do not reveal much information and it is very likely due to the excess capacity (6536) than the average demand of the twelve instances (2299). The total fuel consumptions in all instances do not vary except in the last instance of open and proportionate policies. An interesting finding, however, can be seen from the distribution of fuel consumption between the two carriers. For the proportionate-sharing and equal-sharing policies, the distribution does not spread, naturally because the policies dictate so. However, the behavior of such distribution is rather erratic in the open policy where on one instance the ratio is 1836:118 and on the other 1317:637 (Figure 3.7). This finding is reconfirmed in the results of the large case.

The large case comes with total fleet capacity of 8571 and is relatively tighter to the average demand of 6311, compared to the same ratio in the small case. The first analysis concerns the effect of the randomized demand to the optimized fuel consumption. Figure 3.6 presents the scatter plots and the correlation coefficients between the total demand and the resulting optimized total fuel consumption of the three policies. The correlation coefficients of the open policy and the proportionate-sharing policy are statistically significant at 0.52% and 0.78%, respectively. Compared to these two policies, the equal-sharing policy has a weaker coefficient and it is significant at 5.45%. In general, we can assert that the fuel consumption is largely affected by the demand size except in the equal-sharing policy. However, these relationships do not tell the story of the consumption sharing that has to be analyzed separately.

As previously confirmed in the small case, an unclear pattern is observed from the distribution of fuel consumption between carrier A and carrier B in the open policy. On one hand, it is logical since the minimization of total fuel consumption is not restricted by any rule. On the other hand, an important conclusion is obtained that, whenever a sharing policy is imposed, be that proportionate or equal, total fuel consumption shifts from its minimum value. We measure the optimality gap between the open policy and the two sharing policies and the results are presented in Table 3.4 together with the resulting fuel consumption. The gaps are relatively low except for instance #1 on equal-sharing policy that spikes to nearly 12%. This suggests that these gaps are instance-dependent and careful investigation is mandatory prior to utilizing the policy.

Between the two sharing policies, observing that no policy dominates the other, we conducted a statistical test to check the significance level of differences between the policies. Since the data sets (instances) serve as the locking factor, two-tailed paired-t test is used in this case. The calculated two-tailed significance level of 0.2925 indicates that the difference in fuel consumption between these two policies is not significant. Since the underlying factor behind these policies is the ratio of fleet size, it implies that this ratio is not a significant factor affecting the total fuel consumption. Another finding is related to the variances in fuel consumption and it can be inferred from Table 3.3 that the proportionate-sharing policy has the lowest variance than the other two policies.

The slow-steaming decision variables $f_{i,j}^{a,v}$ exhibit certain behaviour that should be addressed. In the open policy, these variables help reduce the fuel consumption by finding combination of segments in a route that can be travelled using the slow speed. However, in the other policies, there are cases where these variables function to satisfy the bounds a and b in constraints (3.28) even if the application makes no sense. For example, a route can safely be serviced with slow steaming, but for the sake of satisfying the bounds, the resulting decision variables are to use the normal speed instead. The implication of this finding is that these variables have proper use only in the open policy.

Table 3.5 Example of one routing result for Model II

Case: Small Policy: Proportionate Instance: #1		
Results: Carrier A consumption = 1317.27 Carrier B consumption = 636.81 Total consumption = 1954.08		
Carrier	Vessel	Routing[1]
A	A1	-
	A2	Sby – Mks – Kdi * Sby
	A3	Sby – Bpn * Sby
	A4	Sby – Amb * Bit * Sby
B	B1	Sby – Smr – Tar * Sby
	B2	Sby * Bjm * Sby
[1] * indicates slow steaming		

Overall, we can conclude that in a collaboration effort such as observed in this study, minimization of operational burdens is a conflicting objective with the policies on how these burdens are to be shared. The minimized fuel consumptions in the open policy are demand-dependent and therefore cannot be predicted, thus the policy is difficult to be used as a basis for planning. For practical purpose, the sharing policies should be preferred. The choice of sharing policy (proportionate or equal) does not significantly affect fuel consumption, but since the proportionate-sharing policy has smaller variance, it is considered more predictable and therefore a better choice as a basis for the carriers to setup their liner route. An example of routing from one instance in the small case with the proportionate-sharing policy is provided in Table 3.5. Note that one vessel of carrier A is not assigned a trip thereby maximizing the utilization of the remaining five vessels.

3.4 Chapter Summary

In this chapter, the research methodology is presented consisting of research framework and research stages. The framework encapsulates various aspects of the research that can be divided in three big blocks: (1) general scope; (2) detailed scope; and (3) methods. Maritime logistics is defined in the general scope and liner shipping collaboration, with case studies in Indonesian archipelago, is selected for the detailed scope. The vehicle routing problem, multi-objective optimization, and evolutionary algorithm, are the components in the methods block. The research stages detail the step-by-step planned approach to undertake the research from the scope definition to conclusions and documentation.

Two preliminary models are then built, experimented, and analyzed with the objective to introduce the idea of multi-objective maritime logistics/liner shipping collaboration. In Model I, a case study is demonstrated showing collaboration between two carriers under a slot-exchange scheme. The model is a multi-objective assignment problem involving 5 ports and 10 vessels. Two objective functions, costs and sailing time, are minimized under various scenarios related to fast-steaming decisions and different sets of due dates. By optimizing each objective function separately, a number of non-dominated solutions are obtained. The optimization results suggest that sailing time is not a critical objective, hence the search for a better secondary objective in this problem continues. It is also noted that an efficient search method such as evolutionary algorithm is required to further discover the Pareto front.

In the second model, the case is enlarged with added vessels and ports. Two cases differing in size are introduced: the small case with 6 vessels and 8 ports, and the large case with 9 vessels and 13 ports. Routing possibilities are considered using VRPTW formulation and the model is extended by incorporating slow-steaming variables and fuel-consumption sharing policies. More specifically, three sharing policies are evaluated: open policy, proportionate-sharing policy, and equal-sharing policy. The objective of Model II is to investigate the impacts of capacity sharing that is reflected in fuel consumption between two collaborating liner shipping companies. To reduce model complexity, a single-objective optimization approach is used and what is targeted as a second objective is shifted as a set of constraints. Twelve instances are generated based on the Indonesian archipelago.

Both the small and large cases exhibit a similar pattern of high unpredictability of fuel-consumption sharing between both carriers when it is minimized without any restriction, i.e. by employing the open policy. This indicates that the best solution does not provide a clear suggestion as to how the operational burdens, reflected in fuel consumption, should be shared. In other words, the optimal results in the open policy are impractical to be used as a basis for route planning in liner shipping since they fluctuate depending on the generated demand. The two sharing policies, the proportionate-sharing and the equal-sharing policies, on the other hand, provide better guidance in operations due to their less erratic pattern of fuel-consumption distribution, although they result in relatively higher (does not minimize) total fuel consumption. Furthermore, the proportionate-sharing policy has a smaller variance than the equal-sharing policy although not statistically significant. If a decision must be made, the proportionate-sharing policy is the most recommended.

Improvement in this study can be made by formulating the problem into a multi-objective model. For example, in addition to minimize fuel consumption, a secondary objective can be added to represent either of the sharing policies (e.g. equal-sharing policy can be formulated as a minimization of deviation in total fuel consumption). This versatile approach can possibly lead to more information on the impacts of collaboration. A more detailed cost structures could also help in providing better picture of bottom-line results.

CHAPTER IV

GENETIC ALGORITHM FOR HETEROGENEOUS VEHICLE ROUTING PROBLEM WITH TIME WINDOWS IN SHORT-SEA SHIPPING[3]

4.1 Introduction

Due to the complexity of VRP and in order to reduce it, most VRP studies are addressed to tackle a specific variant, but to warrant the robustness of the proposed method and to benchmark the strength of a method over another, comparisons are made on the effectiveness of a method in dealing with a large number of cities. Another approach to reduce complexity is by assuming homogeneous fleet of vehicles, in terms of capacity and/or cost structure. For land-logistics applications, such an assumption is still valid, for example, fleet in the trucking companies.

In maritime logistics, however, the assumptions of homogeneous vehicles and hundreds of cities are hardly realistic. Shipping companies are more likely to own heterogeneous vessels servicing dozens port-of-call. This is especially true in domestic shipping, where the problem is characterized by a small number of ports connected in short distances (short seas) and companies operating ships with low, but different, speeds and capacities. Given such background, this chapter will investigate the application of heterogeneous vehicle routing problems with time windows

[3] Materials in this chapter are part of a paper submitted for publication at *The International Journal of Logistics Research and Applications*.

(HVRPTW) in short-sea shipping with an emphasis on routing design, using the Indonesian archipelago for the case-study data. The chosen type of shipping services in this paper is liner shipping that deals with container ships operating with due-date restrictions. Genetic algorithm (GA) will be used as the tool in this study and we will analyze its properties based on several parameters and compare the method to the classical mixed-integer programming optimization. The choice of a metaheuristic approach, in particular GA, is due to its flexibility and potentials to be developed further for more complex problems. The methods discussed here have been proposed by other authors but only in the scope of test instances and, to the best of our knowledge, have never been shown for their actual application in real-world problems. It will be shown later in the experiment results that when applied to a case with some of the data obtained from a real problem, minor but critical tweaking on the methods is needed for improvement. More specifically, the objectives of this chapter are:

1. to demonstrate the real-life application of genetic algorithm for heterogeneous vehicle routing problem with time windows in maritime logistics, particularly in short-sea shipping in Indonesian archipelago, within the scope of liner routing design
2. to improve the GA by proposing simple heuristics to help accelerate its convergence and improving the local search procedure to increase its chance to reach optimality
3. to investigate how the GA parameters affect its properties in terms of the ability to reach optimality and the running time.

4.2 Problem Description

The problem can be described as follows. A liner shipping company operates in domestic shipping using nine heterogeneous feeder vessels with capacities ranging between 400 and 800 TEUs (twenty-foot equivalent unit) and speeds of 13-17 knots. The company operates from one home-base port and serves a number of ports-of-call similar to the case presented in 3.3.2 with the geographical spread of the ports-of-call shown in Figure 3.5. The case study will also be divided into two groups: small and large. This division has a purpose to test the model sensitivity on different scales.

As in 3.3.2, one port of call, Jakarta, has a large demand that cannot be served in one shipment of containers by any of the available vessel, thus the demand of this port is divided into two batches and a dummy city at the same coordinate is created to assume roughly half of the demand. Because there is only one port with this characteristic, this simple approach is opted rather than using split-delivery formulation. To recap, the small case consists of six vessels and eight ports-of-call, whereas the large case involves nine vessels and thirteen ports-of-call. The data of distances can be accessed in the following URL:

http://ti.ubaya.ac.id/index.php/component/content/article/24-dosen/177-wibisono-jittamai-2015.html

The vessels used in the small case are of four different types, and another type is added to the large case. The costs data are extrapolated from those of larger ships in Stopford (2004), without inflation adjustment. The bunker costs are estimated from the speed of 19 knots. A cubical constant is derived from the speed-cost relationship based on this speed, and then it is used to estimate the other bunker costs of different speeds. Details of vessels' particulars are shown in Table 4.1.

Table 4.1 Data of vessels for Model III

Type	Capacity (TEUs)	Speed (knots)	Weekly fixed cost (USD)	Bunker cost per nm (USD)	Small case		Large case	
					Units available	Total capacity	Units available	Total capacity
A	400	13	81,638.20	3.53	-	-	1	400
B	500	14	84,756.00	4.48	3	1,500	3	1,500
C	600	16	87,873.80	6.82	1	600	2	1,200
D	800	14	94,109.40	4.73	1	800	1	800
E	800	17	94,109.40	8.47	1	800	2	1,600
				Total	6	3,700	9	5,500

Table 4.2 Data of ports for Model III

No.	City	Abbrev.	Due date (hours)	Small case		Large case	
				Demand (TEUs)	Port time (hours)	Demand (TEUs)	Port time (hours)
1	Samarinda	Smr	66	335	16.38	90	10.25
2	Balikpapan	Bpn	66	111	10.78	32	8.80
3	Banjarmasin	Bjm	54	260	14.50	102	10.55
4	Kendari	Kdi	90	26	8.65	9	8.23
5	Makassar	Mks	66	753	26.83	149	11.73
6	Ambon	Amb	108	38	8.95	14	8.35
7	Tarakan	Tar	108	53	9.33	10	8.25
8	Bitung	Bit	126	167	12.18	39	8.98
9	Medan	Mdn	126	-	-	254	14.35
10	Pontianak	Ptk	90	-	-	90	10.25
11	Jakarta1	Jk1	78	-	-	456	19.40
12	Jakarta2	Jk2	78	-	-	707	25.68
13	Batam	Btm	102	-	-	28	8.70
			Total	1,743		1,980	

The maximum due dates (that served as upper time windows) in each port are seven days, hence the service can be associated as weekly. This will allow a vessel to visit more than just one port in one trip. The port demands are estimated from OECD report (OECD 2012). For the large case, 15% of weekly total domestic demand is assumed, and 4.5% is assumed for the small case. These numbers are then used as the mean of a uniform distribution to generate one time the port demands as shown in Table 4.2. These demands also affect berthing times. A constant of eight hours plus a fixed 40-container-per-hour unloading times in all ports are assumed for these figures (except in home base port Surabaya where only eight hours service time is assumed).

4.3 Methodology

In this section, the linear-programming formulation of HVRPTW is explained, followed by discussion on various aspects of the GA that are used and will further be developed. The section concludes with details on model development.

4.3.1 Formulation of HVRPTW

The formulation of HVRPTW is similar to that of VRPTW as described in 2.4.1. However, given heterogeneous vessels, costs data must be stated explicitly in terms of fixed cost f^v and variable cost $c^v_{i,j}$. The following are definitions of sets, parameters and variables, and the model formulation.

$\mathcal{V}$	Set of vessels, indexed by v
$\mathcal{A}$	Set of arcs (i, j) denoting a flow from port i to port j
$\mathcal{N}$	Set of all ports $\mathcal{N}$={0, 1, …, N}; {0} is depot port
$\mathcal{C}$	Set of ports-of-call, or $\mathcal{N}\backslash\{0\}$
f^v	Weekly fixed cost of vessel v
$c^v_{i,j}$	Bunker cost of vessel v if it sails from port i to port j
$t^v_{i,j}$	Sailing time of vessel v if it sails from port i to port j
C^v	Capacity of vessel v
D_i	Total demand at port i (in TEUs)
T_i	Due date at port i (in hours)

p_i Service time at port i

M Big M

$x_{i,j}^v$ Binary variables for vessel v in arc (i, j); $x_{i,j}^v = 1$ if the vessel traverses arc (i, j) and equals 0 otherwise

s_i^v Time window for vessel v at port i

$$\text{Minimize} \sum_{v \in \mathcal{V}} \sum_{i,j \in \mathcal{A}} x_{i,j}^v . c_{i,j}^v + \sum_{v \in \mathcal{V}} \sum_{j \in \mathcal{A}} f^v . x_{0,j}^v \tag{4.1}$$

Subject to:

$$\sum_{v \in \mathcal{V}} \sum_{i,j \in \mathcal{A}} x_{i,j}^v . C^v \geq D_i \qquad \forall\, i \in \mathcal{C} \tag{4.2}$$

$$\sum_{i \in \mathcal{C}} D_i \sum_{j \in \mathcal{N}} x_{i,j}^v \leq C^v \qquad \forall\, v \in \mathcal{V} \tag{4.3}$$

$$\sum_{i \in \mathcal{N}} x_{i,k}^v - \sum_{j \in \mathcal{N}} x_{k,j}^v = 0 \qquad \forall\, k \in \mathcal{C};\ v \in \mathcal{V} \tag{4.4}$$

$$x_{i,i}^v = 0 \qquad \forall\, i \in \mathcal{N};\ v \in \mathcal{V} \tag{4.5}$$

$$\sum_{j \in \mathcal{C}} x_{0,j}^v \leq 1 \qquad \forall\, v \in \mathcal{V} \tag{4.6}$$

$$s_i^v \leq T_i \qquad \forall\, i \in \mathcal{C};\ v \in \mathcal{V} \qquad 4.(7)$$

$$s_i^v + t_{i,j}^v + p_i - M(1 - x_{i,j}^v) \leq s_j^v \qquad \forall\, i \in \mathcal{N}; j \in \mathcal{C};\ v \in \mathcal{V} \tag{4.8}$$

$$x_{i,j}^v \in \{0, 1\} \qquad \forall\, i,j \in \mathcal{A};\ v \in \mathcal{V} \tag{4.9}$$

$$s_0^v = 0 \qquad \forall\, v \in \mathcal{V} \tag{4.10}$$

$$s_i^v \geq 0 \qquad \forall\, i \in \mathcal{N};\ v \in \mathcal{V} \tag{4.11}$$

The objective function (4.1) minimizes total cost. Constraints (4.2) and (4.3) guarantee that demands are fulfilled without violating vessel capacity. Constraints (4.4) are the flow balancing equations. Constraints (4.5) prevent a vessel from looping in the same node. Constraints (4.6) regulate a vessel to assume only one tour. Constraints (4.7) and (4.8) are the time windows formulation with M being a large number such that when $x_{i,j}^{v} = 0$, the constraints will become redundant. Finally, constraints (4.9)-(4.11) are the nature of decision variables involved. Note that since s_{i}^{v} are continuous in addition to the binary variables $x_{i,j}^{v}$, the model is a mixed integer programming.

4.3.2 Genetic algorithm for HVRPTW

The concept of genetic algorithms and the idea of using them as optimization tool were first introduced by Holland (1975) but considered popularized by one of his students, Goldberg (1989). The algorithms mimic Charles Darwin's theory of evolution through natural selection where a population, through its natural ability to evolve on the basis of survival-of-the-fittest, will continuously and consistently generate members with better attributes as they are more likely able to survive than members with worse attributes. Over time, better individuals will dominate the population and produce even better offspring, thus advancing the entire population to an overall better state. In optimization problems, population members (or individuals) represent solutions and are encoded in a unique structure called chromosomes. For example, in routing problems, a solution in a form of a trip visiting a series of cities can be encoded as a chromosome reflecting the sequence of that trip and is regarded as one population member. Population members then compete via a certain scheme for a spot to 'mate' with other members and produce another member. These processes in GA terms are labelled 'crossover' and 'reproduction'. Another important process in GA is called 'mutation' that alters the codification of a chromosome to maintain diversity of the population. Although usually given small chance of occurring, this last process is very important for the algorithm to avoid reaching premature convergence at local optima.

The GA developed in this paper will be based on Prins (2004) (for VRP) and Prins (2009) (for HVRP). Basic tenets of these GAs are described in the following points.

a. *Split* procedure

Split is a tour splitting procedure that partitions a chromosome *m* into *T* feasible trips. A chromosome *m* is a permutation of *N* cities/customers in the problem, without trip delimiters, or similar to a giant TSP tour. This giant tour relaxes constraints such as vehicle capacity. The purpose of *Split* is to optimally partition this tour into T trips, subject to available constraints, with each trip served by one vehicle, and also to calculate the fitness value of a chromosome. Specific constraints referring to specific VRP variants can be coded in this procedure as part of feasibility tests, for example, load feasibility in basic CVRP, load and time-windows feasibilities in VRPTW, and so on. *Split* works on an acyclic auxiliary graph $\mathcal{H} = (\mathcal{N}, \mathcal{A})$ that transforms the original distance matrix of cities to a minimum-cost path problem. Sub-section 2.4.3 already provides a general overview of this procedure. For more detailed discussion, interested readers should refer to Prins (2004, 2009).

b. Initial population construction using heuristics

To enhance the performance of the GA in terms of speed, the initial population must be setup by including several good chromosomes (usually two or three good chromosomes are sufficient for a population of size 50). The good chromosomes will help accelerate convergence of the GA while the rest of the population, which are simply randomized, will maintain the diversity. In Prins (2004), three heuristics are included in the initial population construction: Clarke-Wright savings algorithm, Mole-Jameson sequential insertion heuristic, and Gillett-Miller sweep algorithm. This inclusion is possible since these heuristics are tailored for CVRP, thus they are matched with the problem discussed in the paper. In Prins (2009), however, in the absence of reliable heuristics for HVRP, the good chromosomes are obtained by applying local search after they are generated. This is one part of the problem that we aim to improve by proposing two simple heuristics for HVRPTW. As in the other cases, the heuristics need not necessarily be the best ones. It is acceptable to use simple but reliable heuristics since their purpose is mainly to jump start the search, while the task to explore the space and locate the best solution is left to the GA mechanism. Heuristics that are too good not just burden the computation time, but might also run the risk to trap the search in local optima.

c. Population management

The population is managed in such a way that all members are unique and no two identical members (clones) are allowed. Two methods proposed in Prins (2009) are used and tested here. The first one is based on a distance measure in solution space. For two chromosomes *A* and *B*, the distance *d*(*A*, *B*) is the number of pairs of adjacent cities in *A* that are no longer adjacent in *B*. For example, if *A* = (1, 2, 3, 4, 5) and *B* = (3, 5, 4, 1, 2), then (2, 3) and (3, 4) are no longer adjacent in B, thus $d(A, B) = 2$. Given $D(P, C) = \min\{d(A, C) : A \in P\}$ as the minimum distance of a new chromosome *C* to population *P*, *C* is accepted if and only if (4.12) holds, where distance limit *DL* is a non-negative threshold. A well-dispersed population as regulated above is termed *spaced*. During the initialization stage, *DL* is set at 0, and during the GA iterations, *DL* follows (4.12) but the value changes either increasingly or decreasingly, proportionate to the number of iterations. However, an exception for acceptance is given in the iterations stage if the fitness value of the new chromosome is smaller (minimization problem) than the fitness value of the best population member (*n* = number of cities).

$$D(P, C) > DL \qquad\qquad DL \in \{1..0.5 \times (n-1)\} \qquad (4.12)$$

The second method of population management is based on a dispersal mechanism controlled by a parameter called the *dispersal value* (*DV*). Like *DL*, *DV* also serves as a threshold criterion for accepting new population members. A new chromosome *C* is accepted if and only if it has a fitness-value gap larger than the *DV*. In other words, *C* is accepted if and only if (4.13) holds (*C* = newly generated chromosome; p_t = chromosome number *t* in the population; *S* = number of population).

$$|F(C) - F(p_t)| > DV \qquad\qquad t = 1..S \qquad (4.13)$$

In the initialization stage, after good chromosomes are generated by the heuristics, each subsequent chromosome is then generated and checked whether its fitness value is larger or smaller by DV than the fitness value of the other already accepted chromosomes in the population. If (4.13) is not satisfied, the new chromosome is rejected and the next generation process takes place. If, before one new chromosome is produced, the rejection is too excessive and has been repeated more than a certain time, the generation is stopped and the population size is accepted at whatever available at that point. Otherwise, the process is repeated until a targeted population size is reached. At the end of this stage, the population is sorted in an ascending fashion so the best chromosome is p_1. This mechanism remains in effect during the iterations stage, but is overridden if the fitness value of the new chromosome is smaller than that of the best chromosome, i.e. $F(C) < F(p_1)$.

In the main stage (GA iterations), two population members (parents) are selected by binary tournament then undergo order crossover (OX) to produce two children. Figure 4.1 shows an example of this operator with crossover points at the 4th and 6th nodes. One child is then selected randomly to replace one of the chromosomes in the lower-half of population. As in the initialization stage, the child is also required to be *spaced* with respect to the other existing members.

				i = 4 ↓		j = 6 ↓			
P1 :	4	8	7	3	6	5	2	10	9
P2 :	3	5	4	2	7	9	10	8	6
C1 :	2	7	9	3	6	5	10	8	4
C2 :	3	6	5	2	7	9	4	10	8

Figure 4.1 Example of Order Crossover

d. Mutation using local search

A mutation operator is given a probability p_m for occurring after a successful reproduction of a new chromosome. The operator works by scanning the $O(n^2)$ neighborhoods of n (cities) and $O(k^2)$ neighborhoods of k (vehicles) via a number of moves as shown in Figure 4.2. Each time a chromosome is improved by one move, the iteration restarts from the first move. A number of different local search algorithms have been proposed for this GA. In Prins (2009) with heterogeneous vehicles, two versions of local search (LS_1 and LS_2) are employed. LS_1 does not allow change of vehicles but LS_2 does otherwise. The moves in the second part of LS_2 evaluate the swap of vehicles between two trips and each move is carried out inside each move in LS_1, thus LS_1 has $O(n^2)$ complexity whereas LS_2 has $O(n^2k^2)$.

LS_1: u and v are nodes in different trips; x is the successor of u, y is the successor of v

M1. Relocate u to a different trip,
M2. Swap u and v,
M3. Replace (u; x) and (v; y) by (u; y) and (v; x),
M4. Replace (u; x) and (v; y) by (u; v) and (x; y).

LS_2 = LS_1 + the following:
F is the set of free vehicles; T_1 and T_2 are two different trips
M1. The two trips exchange their vehicles,
M2. T_1 gives its vehicle to T_2 and takes one in F,
M3. T_2 gives its vehicle to T_1 and takes one in F,
M4. Both T_1 and T_2 exchange their current vehicle with a free one.

Figure 4.2 Local search mutation LS_1 and LS_2

4.3.3 Model development

The GA mechanism described in the preceding sub-section will be improved in the following aspects. First, time windows constraints are added in the *Split* and mutation procedures as part of trip feasibility tests. Second, two heuristics are developed for generating good chromosomes in the initial population. Third, the mutation operator is enhanced with an additional local search. Since adding time windows formulation is not too difficult (similar to capacity constraints), the following explanation will focus on the heuristics and the additional local search.

a. Heuristics for HVRPTW

Two simple heuristics are proposed as part of the initial population construction. The first heuristic is based on load assignment and the second heuristic employs port sequencing in accordance to the topology of the cities layout. The load assignment heuristic is inspired by a method in assembly line-balancing problem called the largest-candidate rule (Groover, 2007). In this method, work elements are grouped in workstations by putting each element one by one to a workstation until the maximum designated cycle time is reached. The work elements are sorted in descending order, from the longest time to the smallest, and the inclusion to the workstations follows this order. The idea of this method is to arrange the 'chunky' work elements first before working on the easier (smaller) ones. In our problem, the work elements are the port demands, workstations are the trips, and the targeted cycle time is the capacity and time constraints. The load assignment heuristic is as follows:

1. Sort vessels and ports based on capacity and demand, respectively, in descending order.

2. Select the available highest-capacity vessel to serve the remaining port with the highest-demand.
3. Following the order in the port list, continue selecting the other ports to be serviced by the same vessel, maintaining capacity and due date feasibilities.
4. If no more port can be scheduled (the remaining ports violate feasibilities), return to step 2. Repeat until all ports are serviced.

The second heuristic is similar to the sweep algorithm by forming a rotating ray centered at the depot with the zero degree of the ray starts from the West. The resulting sequence is a giant tour, which will then be partitioned using *Split*. This heuristic is very effective in our problem as it takes advantage of the relative position of the depot port to the other ports of call. The port sequencings obtained from applying this heuristic are:

- Small case: Bjm-Bpn-Smr-Tar-Mks-Kdi-Bit-Amb
- Large case: Jk1/2-Mdn-Btm-Ptk-Bjm-Bpn-Smr-Tar-Mks-Kdi-Bit-Amb

b. Additional LS procedure

When used sparingly, LS_2 proves to be sufficiently good in helping the algorithm maintain population diversity. The dispersal mechanism guided by *DL* or *DV* allows aggressive exploration, but excessive use of local search mutation with higher probability rate will deteriorate the GA performance due to its higher tendency of getting trapped in several local-optima solutions. However, as indicated in the experiments, in cases where the GA fails to reach the optimal point, another version of local search can be adopted to improve the solution. This version of local search is called LS_v and it is run *only* at the end of the algorithm. This local search is similar to the second part of LS_2 concerning the swaps of vehicles, but not necessarily involves two trips. The argument of invoking LS_v only at the end of the algorithm rather than treating it as a continuation of the mutation procedure and running it behind LS_2 is because LS_2 is powerful enough for a problem with dozens of cities and having LS_v in the mutation block will only add unnecessary computation time. Putting LS_v in the last step guarantees its one-time execution on a solution that is already near optimal (if the solution is optimal, LS_v has no effect.). Figure 4.3 shows the three moves in LS_v.

M1. T_1 exchanges its vehicle with one in F, M2. T_1 and T_2 exchange their vehicles, M3. T_1 gives its vehicle to T_2 and takes one in F.

Figure 4.3 Local search mutation LS_v

c. The formulated GA

Incorporating the time windows, load and sequencing heuristics, and the added LS_v, the GA for HVRPTW is developed as shown in the pseudo-code in Figure 4.4 (DL-based version). After reading the case data in line 1, the population is initialized in lines 2-14. Lines 2-3 generate the first two population members using the proposed heuristics and line 4 generates the third solution using random permutation. All three initial solutions are enhanced by LS_2 and *Split*. Lines 5-14 generate the rest of population using random permutation. This is similar to the approach in generating the third solution, but the generated chromosomes are not enhanced to ensure diversity. The chromosome is rejected in case of infeasible splitting.

```
read input data;
initialize population #1 with load assignment heuristic; LS_2; Split;
initialize population #2 with sequencing heuristic; LS_2; Split;
initialize population #3 with random permutation; LS_2; Split;
ctrPop = 4;
while ctrPop <= popSize
  spaced = false; noSplit = true;
  while not(spaced) and noSplit
    generate new chromosome C by random permutation;
    if D(P, C) > 0, spaced = true; end
    if F(C) ≠ ∞, noSplit = false; end
  end %while
  accept new chromosome; ctrPop = ctrPop + 1;
end %while
sort the population ascending based on fitness values;
for i = 1:maxIter
  set the value of DL based on iteration number;
  noSplit = true;
  while noSplit
    select two parents by binary tournament;
    apply OX operator and randomly select one child; Split;
    if F(C) ≠ ∞, noSplit = false; end
  end %while
  if rand(1) < probMut
    run mutation procedure with LS_2; Split; M = mutated chromosome;
    if F(M) < F(p_1) or D(P, M) > DL
      C = M;
    end
  end
  if F(C) < F(p_1)
    accept new/mutated chromosome, replace one in the lower half;
    count productive iteration;
  elseif D(P, C) > DL
    accept new/mutated chromosome, replace one in the lower half;
    count productive iteration; count unimproved iteration;
  end
  sort the population ascending based on fitness values;
end %for
run mutation procedure with LS_v;
```

Figure 4.4 Pseudo-code GA for HVRPTW

For a version with dispersal value, changes need to be made in lines 10, 26, and 30 regarding the check of the *spaced* criterion. The generated population is then sorted ascending based on fitness value (line 15), so the best solution is the first member.

After the initial population is constructed, the main GA procedure begins. Iterations run up to *maxIter* times and in each iteration the following steps (lines 17-37) are executed. Two parents are selected by binary tournament followed by a crossover using OX operator. *Split* is then applied to partition the giant-tour chromosome into trips. Infeasible splitting can also occur at this stage that will prompt repeat of the process. After the reproduction and crossover phases are passed, a mutation module is invoked with a probability *probMut*, and LS_2 is applied (lines 24-29). In lines 30-32, the spaced requirement is overridden and the new chromosome is accepted if it has a smaller cost than that of the best chromosome, and one productive iteration is counted. In lines 33-35, spaced criterion is again checked to see if the new chromosome can be accepted. If it is accepted, since in this case this new chromosome is not the best, productive iteration and also unimproved iteration are counted. The new chromosome will replace one of the old chromosomes, randomly selected in the worse lower-half of the population. The rationale of this approach is to preserve good chromosomes in the upper-half of population while advancing the search. Throughout the algorithm, time windows feasibilities are checked within the *Split* and mutation blocks. Finally, the population is resorted (line 37) and after *maxIter* iterations, LS_v is invoked (line 39).

4.4 Results and Discussion

GA for HVRP has been shown to be as competitive as other metaheuristics when tested on the same benchmark instances. However, to the best of our knowledge, real example of its application has never been published in the literature. Moreover, the benchmark instances used in the literature do not consider time windows and fixed costs, which are important attributes for cases in maritime logistics, particularly in liner shipping. One of the aims of this chapter is therefore to demonstrate a real-life example of this method in a maritime case study of Indonesian archipelago. Fleet data of a domestic liner shipping company are used, however, for confidentiality purpose, demands are assumed as percentage of the company's market share of the national outputs. Since due dates are an important attribute in liner operations, HVRPTW is formulated by adding feasibility tests on time constraints in the routing.

Different scenarios involving a number of parameters are investigated in the case study. In addition to the case size (small and large), the effects of dispersal mechanism, number of iterations, mutation probability, and the population size on the GA performance are also evaluated. Three types of dispersal mechanism are tested based on the following parameters: increasing distance limit, decreasing distance limit, and dispersal value, denoted with DL+, DL-, and DV1, respectively. Given eight ports in the small case and thirteen ports in the large case, the distance limits are 1 to 3 and 1 to 6 in the small case and large case, respectively, whereas the dispersal value is set at 1 for all scenarios. The number of iterations is set at 150 in the small case, but is varied at 300 and 600 in the large case. The last two parameters, mutation probability p_m and population size S, are paired to represent the characteristics of population. One set of parameters, $p_m = 0.2$ and $S = 30$, follows what are used in Prins (2009). However, a more aggressive mutation and dense population with $p_m = 0.3$ and $S = 40$ are also tested. The combination of the above parameters produces multiple scenarios. Since a randomization effect occurs in many stages of the GA run, each scenario is run for ten times and the averages are collected and reported.

The results of branch-and-bound (B&B) optimization using Lingo 11.0 and GA using Matlab R2100b are compared, both on an Intel i5-2430M processor running at 2.4 GHz and 4 MB of RAM on Windows 7 Ultimate. The results are summarized in Table 4.3 for the primary outputs and Table 4.4 for the secondary outputs. The primary outputs concern with the ability of the GA to reach optimality and are measured in optimality gap, frequency in reaching the optimal solution, and computation times. The secondary outputs discuss the quality of iterations, the performance of heuristics in the initial solutions, and the frequency of infeasible splitting.

Table 4.3 indicates that in general the GA cannot outperform B&B. However, as the case gets larger, the relative performance of GA over B&B (the ratio of running times of the two methods) gets more competitive. This suggests that the GA is more suitable to more complex problems, thus the algorithm used here is promising but still needs to be developed further to tackle such problems. Among different GA scenarios, the set of parameters $p_m = 0.3$ and $S = 40$ performs better than $p_m = 0.2$ and $S = 30$ that is used for benchmark test in the other literature. This applies in all case sizes and it implies that the GA favors more aggressive exploration with higher mutation probability in a larger population. On the dispersal mechanism, despite of its well performance in the small case, DV1 worsens in the large case. Since GA will be more likely used for large-scale cases, the method based on distance limit should be preferred. For the large case using this method, DL+ is better than DL- in terms of optimality search but not in computation time. Overall, the ability to find the optimal solution is mainly influenced by the number of iterations, as shown in the results of the large case. Figure 4.5 shows several charts of various typical GA runs. In some of these runs, the jump to the optimal point is made beyond the 300th iteration (Figure 4.5a) or even beyond the 400th iteration (Figure 4.5b). Another observation from these charts is related to the impact of additional local search LS_v at the end of the algorithm. Note the dip in Figure 4.5c (the red circle) where the best solution is improved by LS_v at the end of iterations. As to the algorithm running times, a percentage shift from population initialization time to the iterations time is noticeable when the number of iterations is increased, but the total running times are relatively in par for scenarios within each group of the same number of iterations.

Table 4.3 Experiment results (primary outputs) of Model III

Scenario	Cost	%Gap	Optimal	Time (seconds)				
				Init	%Init	Run	%Run	Total
Small case								
B&B (benchmark)	393,781							7
DL+;it150;p_m0.2;N30	398,854	1.38	6/10	5	19.04	22	80.96	27
DL+;it150;p_m0.3;N40	395,143	0.56	8/10	7	22.70	24	77.30	31
DL-;it150;p_m0.3;N40	393,781	0.25	9/10	7	22.48	24	77.52	31
DV1;it150;p_m0.3;N40	395,143	0.35	9/10	10	28.74	25	71.26	35
Large case								
B&B (benchmark)	528,270							1818
DL+;it300;p_m0.2;N30	573,217	8.51	2/10	367	25.86	1046	74.14	1413
DL+;it300;p_m0.3;N40	560,718	6.14	4/10	472	28.30	1194	71.70	1666
DL-;it300;p_m0.3;N40	561,563	6.30	4/10	456	27.32	1207	72.68	1663
DV1;it300;p_m0.3;N40	566,382	7.21	2/10	465	27.59	1218	72.41	1683
DL+;it600;p_m0.3;N40	539,086	2.05	8/10	438	15.15	2456	84.85	2894
DL-;it600;p_m0.3;N40	550,746	4.25	6/10	416	15.32	2300	84.68	2716
DV1;it600;p_m0.3;N40	555,578	5.17	4/10	446	16.09	2322	83.91	2768

Table 4.4 Experiment results (secondary outputs) of Model III

Scenario	Iterations		Heuristic's rank			Infeasible splitting	
	Prod.	Unimpr.	Heu1	Heu2	Heu3	Init	Run
Small case							
DL+;it150;p_m0.2;N30	46	44	1.3	3.6	3.3	19	16
DL+;it150;p_m0.3;N40	41	40	1.4	3.9	5.0	28	17
DL-;it150;p_m0.3;N40	43	41	1.3	4.0	3.2	31	23
DV1;it150;p_m0.3;N40	95	93	1.2	4.1	4.1	41	16
Large case							
DL+;it300;p_m0.2;N30	177	172	3.1	1.7	2.0	151	20
DL+;it300;p_m0.3;N40	170	163	3.0	1.8	1.6	194	18
DL-;it300;p_m0.3;N40	217	212	3.5	1.8	1.8	184	32
DV1;it300;p_m0.3;N40	267	262	3.1	2.0	1.7	194	19
DL+;it600;p_m0.3;N40	322	316	2.8	1.8	1.5	172	30
DL-;it600;p_m0.3;N40	397	391	3.2	2.0	1.3	176	51
DV1;it600;p_m0.3;N40	533	529	3.2	2.0	1.3	188	25

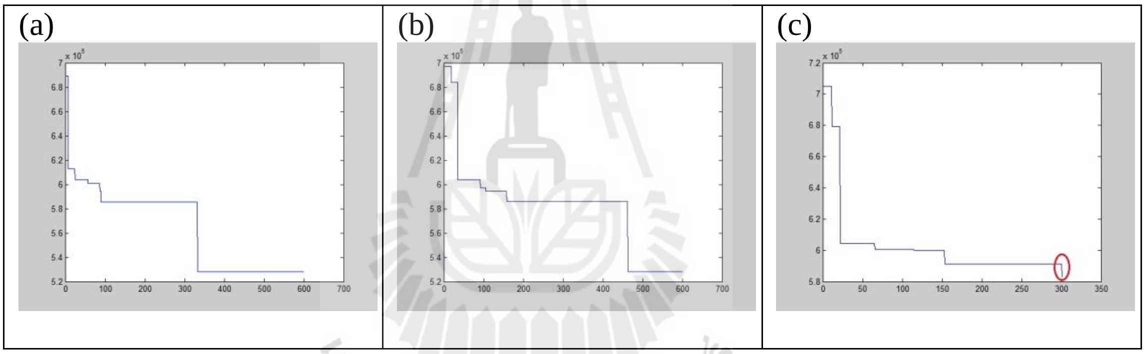

Figure 4.5 Various typical GA runs

The number of productive iterations and its ratio to that of the unimproved iterations exhibit similar patterns among all scenarios, with an exception in the DV1 case where the numbers are significantly higher. However, this only highlights the nature of the mechanism as its running time is proven competitive to the other mechanisms'. For the heuristics in the initial solution, the enhanced load-assignment heuristic works best in the small case, but averages third in the large case. The enhanced sequencing heuristic competes with the third heuristic (enhanced random permutation), but is superior to the other two in the large case. Given this satisfactory performance, it can be concluded that the heuristics serve their purpose in the algorithm. The last part of the secondary outputs is regarding the amount of infeasible splitting. It is clear from Table 4.4 that the *Split* procedure has difficulty to form feasible trip partitions when the number of cities is high and its sequence is purely randomized. The problem is not apparent in the small case (in some of the runs, infeasible splitting is in fact more frequent in the iterations than in population initialization stage). However, in the large case, the frequency of infeasible splitting is fairly high during initialization. This marks an area for improvement as better splitting might be able to reduce computation time.

Finally, the optimized liner route from the large case is shown in Table 4.5. It is interesting to note a long sequence of cities to be visited by two large-capacity vessels of type E since the total demands in each trip is less than one-fourth of the vessel capacity. However, if these trips are to be served by smaller and slower vessels, the number of vessels required would probably increase and given high fixed costs of vessels, this could increase total costs. In other words, long voyages by utilizing fewer vessels is preferable, provided due dates in each port-of-call are manageable and not too much pampered by unpredictable events such as disruptions in port operations. This highlights the importance of fixed costs in maritime logistics cases and it would be unrealistic to ignore this factor. It is also important to reiterate that designing a liner route/network is a medium-term tactical activity for a shipping company and once the route is established, it is published and takes effect for months in order for the customers to adapt with their shipment schedule. Therefore, the demands used as the basis in setting up the route must also be estimated from a similar time horizon.

Table 4.5 Optimized liner route for the large case of Model III

Vessel (capacity)	Route (figures denote port demand)
B (500)	Sby-Ptk (90)-Btm (28)-Mdn (254)-Sby
C (600)	Sby-Bjm (102)-Jk1 (456)-Sby
D (800)	Sby-Jk2 (707)-Sby
E (800)	Sby-Mks (149)-Kdi (9)-Amb (14)-Sby
E (800)	Sby-Bpn (32)-Smr (90)-Tar (10)-Bit (39)-Sby

4.5 Chapter Summary

This chapter demonstrates the application of genetic algorithm (GA) for heterogeneous vehicle routing problem with time windows (HVRPTW) in short-sea shipping, specifically in Indonesian archipelago. Two heuristics are built as part of initial population construction phase for the GA to help accelerate its convergence. The first heuristic is based on load assignment and the second heuristic employs port sequencing based on a rotating ray. Time windows and additional local search mutation procedure are added to the algorithm. Two methods of population management are used as dispersal mechanism to keep the population spaced so the search progresses better. The model is tested on two cases differing in size. The small case consists of eight ports-of-call and six vessels and the large case involves thirteen ports-of-call and nine vessels.

Experiment results indicate that the proposed heuristics and the added local search are beneficial in boosting the GA performance. For dispersal mechanism, the method based on distance limit shows better performance than the method based on dispersal value.

CHAPTER V

MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM FOR SHIP ROUTING PROBLEM IN MARITIME LOGISTICS COLLABORATION[4]

5.1. Introduction

Shipping companies have been embarking on various efforts to respond today's fierce challenges and collaboration is one viable path. In the segment of liner shipping, a common collaboration theme is the formation of alliances to enlarge service coverage by taking advantage of the economies of scale. Collaboration entails certain impacts that should be evaluated. When companies form an alliance, the next strategic decision will be how to assign each company's role and how to fairly divide the works in their operations to serve the aggregate market demands. A number of factors must be determined and investigated in this phase, e.g. how many vessels each company shall contribute to the joint fleet, what is the route of each vessel, what is the resulting total profit/cost and whether or not it is acceptable by the collaborating parties, etc. The answers to these questions are very important and will determine sustainability of partnership. However, as highlighted in chapter two, most studies in maritime logistics collaboration are on the qualitative side and only a few quantitative studies are encountered.

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[4] Materials in this chapter are part of a paper submitted for publication at *The International Journal of Shipping and Transport Logistics*.

This chapter is the heart of the research topic in this dissertation that studies maritime logistics collaboration using a multi-objective evolutionary algorithm for a ship routing problem (MOEA-SRP). The SRP is a variant of the vehicle routing problem (VRP) that considers important attributes in maritime logistics such as heterogeneous vessels, time windows, and fixed cost. These attributes are usually not formulated simultaneously in land-logistics VRP applications. The heterogeneity aspect comes from the fact that shipping companies normally own different types of vessels in terms of speeds and capacities. Time windows in the model are common constraints that dictate a visit to a customer be made within a certain time interval. For liner operations where shipping schedules are published, due dates are critical factor.

The scope of the problem is collaboration of two liner shipping companies in determining the routing of their fleet. The multi-objective approach is used because real-life problems are seldom one-dimensional and single-objective models are usually built by discharging some factors with assumptions and/or other simplification schemes. The first objective is the natural minimization of total cost. The second objective is a novel formulation of fair cost distribution. The rationale behind the second objective is to control the impacts of collaboration so that cost is not minimized in such an unfair proportion, sacrificing the interests of either company.

The algorithm proposed in this chapter is inspired by two different methods, each is oriented towards a different background of the problem. First, NSGA-II (elitist non-dominated sorting genetic algorithm) from Deb *et al* (2000) will be used to tackle the multi-objective part. Second, aggressive but effective genetic algorithm (GA) for VRP/HVRP from Prins (2004, 2009) will be responsible for the routing part. The strengths of these two methods are combined and used to find the set of non-dominated solutions (Pareto points) for the particular problem discussed in this paper. A case study using the Indonesian archipelago for the data background is setup to evaluate the proposed algorithm. The objectives of this chapter are therefore:

1. to introduce the concept of multi-objective optimization in maritime logistics collaboration
2. to propose (and investigate the properties of) a new method by combining the key concepts and strengths of two already established methods that are normally used independently to address a partial dimension of the problem presented in this paper
3. to show an application example of the proposed method in a domestic shipping of the Indonesian archipelago.

5.2. Problem Description

The problem description of Model IV in this chapter is similar to that of Model II in chapter three. Two domestic liner shipping companies operate from the same depot and serve several ports/cities in the Indonesian archipelago. Both carriers plan to collaborate by joining their service routes via capacity sharing to increase the utilization of their vessels. Capacity sharing means Carrier A will allocate a portion of its capacity to be used by Carrier B going to a number of ports-of-call, such that Carrier B does not have to use its own vessels going to the same destination (except if the demand is high and cannot be served by one vessel), and vice versa. The problem on hand is how to design the new joint routing network resulting from the collaboration, optimizing two objectives; namely, total costs and fairness in cost-sharing distribution. The first objective is straightforward and typical in optimization programming. This objective is preferred over profit maximization since all demands are assumed to be satisfied, thus the same amount of profit will be generated. The second objective is part of the novelty of this research, and its formulation is motivated by the collaboration background in the problem. The idea is, while costs are minimized, the distribution of total cost should be in a fair proportion that is acceptable by the collaborating parties.

The carriers are of different sizes: Carrier A is larger than Carrier B in terms of fleet size and demands. Carrier A owns six vessels and Carrier B has three vessels, all in the category of feeder vessels with capacities in the range of 400 to 850 TEUs (twenty-foot equivalent units) and speeds in 13-17.5 knots. The costs of vessels are extrapolated from the larger ships' in Stopford (2009), without inflation adjustment. Two cost components include weekly fixed/overhead costs and variable costs measured as bunker cost per nautical mile at a certain speed. Vessels data are listed in Table 5.1. Note that the fixed costs are relatively high and thus cannot be ignored.

Table 5.1 Data of vessels for Model IV

Carrier A						
Type	Capacity (TEUs)	Speed (knots)	Weekly fixed cost (USD)	Bunker cost per nm (USD)	Units available	Total capacity
A1	400	13.0	81,638.20	3.53	1	400
A2	500	13.5	84,756.00	4.02	2	1,000
A3	650	16.5	89,432.70	7.54	2	1,300
A4	850	14.0	95,668.30	4.77	1	850
				Total	6	3,550
Carrier B						
Type	Capacity (TEUs)	Speed (knots)	Weekly fixed cost (USD)	Bunker cost per nm (USD)	Units available	Total capacity
B1	450	13.5	83,197.10	3.98	1	450
B2	700	16.5	90,991.60	7.61	1	700
B3	850	17.5	95,668.30	9.32	1	850
				Total	3	2,000

Data of ports-of-call are listed in Table 5.2 and the geographical spread of the cities is similar to that in Figure 3.5, except that the case in Model IV is not divided in two sizes as in Model II. For convenience, the figure is reproduced and shown in Figure 5.1 with all cities must be served without any distinction of small or large case. The same URL given in 4.2 contains the details of port distances.

Port demands are estimated from OECD (2012) where domestic throughputs of containers are reported. The figures are converted to weekly demands and 2.5% is assumed for the demand of Carrier A and 1.25% for Carrier B. Demand of Jakarta is very large and cannot be served by any of the vessel in the combined fleet, thus for simplicity it is evenly split and half of it is assigned to a dummy city at the same coordinate, making a total of 13 ports-of-call excluding the depot Surabaya. Service times are incurred in ports by a constant of eight hours plus a fixed 40-container-per-hour unloading times, except for the depot where only eight hours of service time are assumed. Finally, time windows are formulated as due dates of the ports-of-call. Only upper time windows that represent due dates are formulated and none of these due dates exceeds seven days, hence corresponds to a weekly liner service which is equivalent to the period of demands.

5.3. Methodology

This section describes an overview of the basic methods, particularly the LP-formulation of multiple carriers HVRPTW, followed by model development.

Table 5.2 Data of ports for Model IV

No.	City	Abbrev.	Due date (hours)	Carrier A		Carrier B		Total	
				Demand (TEUs)	Port time (hours)	Demand (TEUs)	Port time (hours)	Demand (TEUs)	Port time (hours)
1	Samarinda	Smr	66	46	9.15	23	8.58	69	9.73
2	Balikpapan	Bpn	66	17	8.43	8	8.20	25	8.63
3	Banjarmasin	Bjm	54	57	9.43	28	8.70	85	10.13
4	Kendari	Kdi	90	7	8.18	0	0	7	8.18
5	Makassar	Mks	66	119	10.98	60	9.50	179	12.48
6	Ambon	Amb	108	7	8.18	0	0	7	8.18
7	Tarakan	Tar	108	8	8.20	0	0	8	8.20
8	Bitung	Bit	126	30	8.75	15	8.38	45	9.13
9	Medan	Mdn	126	134	11.35	0	0	134	11.35
10	Pontianak	Ptk	90	48	9.20	0	0	48	9.20
11	Jakarta1	Jk1	78	400	18.00	200	18.00	600	23.00
12	Jakarta2	Jk2	78	400	13.00	200	13.00	600	23.00
13	Batam	Btm	102	13	8.33	0	0	13	8.33
Total				1,286		534			

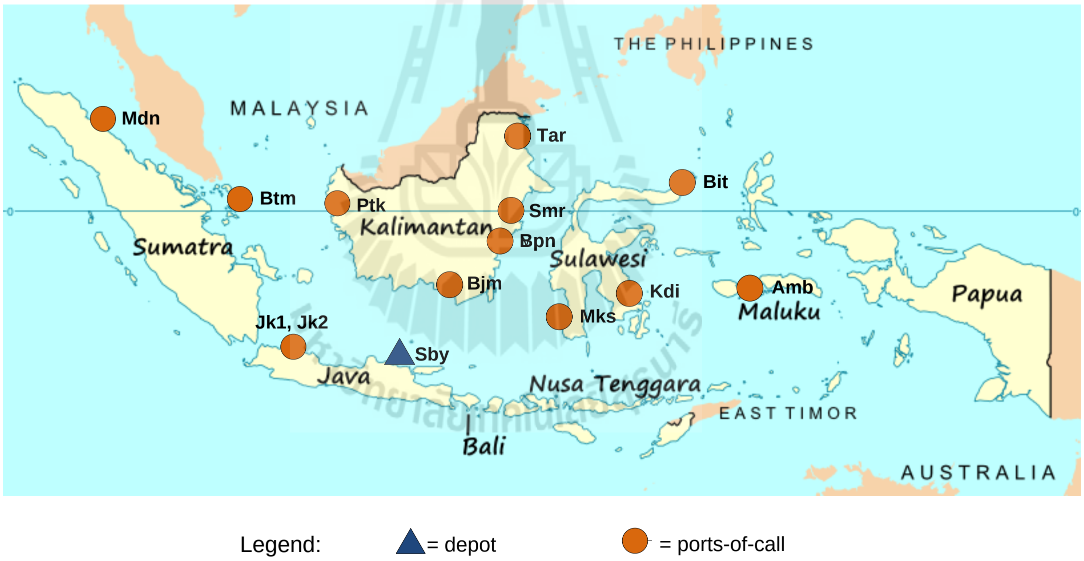

Figure 5.1 Map of Indonesia with cities being studied in Model IV

5.3.1 Overview of the basic methods

Throughout this dissertation, there have been a number of VRP models elaborated. In chapter four (4.3.1), a linear-programming formulation of SRP (HVRPTW-F) is given, emphasizing the fixed-cost element of the vessels. This sub-section will extend that formulation with the inclusion of an additional carrier. In other words, the following model is called multiple carriers SRP.

$\mathcal{C}$	Set of carriers, indexed by a
$\mathcal{V}_a$	Set of vehicles of carrier a, indexed by v
$\mathcal{A}$	Set of arcs (i, j) denoting a flow from city i to city j
$\mathcal{N}$	Set of all cities $\mathcal{N}$={0, 1, …, N}; {0} is the depot
$\mathcal{P}$	Set of customers, or $\mathcal{N} \setminus \{0\}$
$f^{a,v}$	Weekly fixed cost of vehicle v of carrier a
$c_{i,j}^{a,v}$	Travel cost of vehicle v of carrier a if it goes from city i to city j
$t_{i,j}^{a,v}$	Travel time of vehicle v of carrier a if it goes from city i to city j
$C^{a,v}$	Capacity of vehicle v of carrier a
D_i	Total demand of all carriers at city i
T_i	Due date at city i
p_i	Service time at city i
M	Big M
$x_{i,j}^{a,v}$	Binary variables for vehicle v of carrier a in arc (i, j); $x_{i,j}^{a,v} = 1$ if the vehicle traverses arc (i, j) and equals 0 otherwise
$s_i^{a,v}$	Time window for vehicle v of carrier a at city i

The multiple carriers SRP can now be formulated as follows:

$$\text{Minimize} \sum_{a \in \mathcal{C}} \sum_{v \in \mathcal{V}_a} \left(\sum_{j \in \mathcal{A}} f^{a,v} . x_{0,j}^{a,v} + \sum_{i,j \in \mathcal{A}} x_{i,j}^{a,v} . c_{i,j}^{a,v} \right) \tag{5.1}$$

Subject to:

$$\sum_{a \in \mathcal{C}} \sum_{v \in \mathcal{V}_a} \sum_{i,j \in \mathcal{A}} x_{i,j}^{a,v} . C^{a,v} \geq D_i \qquad \forall\, i \in \mathcal{P} \tag{5.2}$$

$$\sum_{i \in \mathcal{P}} D_i \sum_{j \in \mathcal{N}} x_{i,j}^{a,v} \leq C^{a,v} \qquad \forall\, a \in \mathcal{C};\ v \in \mathcal{V}_a \tag{5.3}$$

$$\sum_{i \in \mathcal{N}} x_{i,k}^{a,v} - \sum_{j \in \mathcal{N}} x_{k,j}^{a,v} = 0 \qquad \forall\, k \in \mathcal{P};\ a \in \mathcal{C};\ v \in \mathcal{V}_a \tag{5.4}$$

$$x_{i,i}^{a,v} = 0 \qquad \forall\, i \in \mathcal{N};\ a \in \mathcal{C};\ v \in \mathcal{V}_a \tag{5.5}$$

$$\sum_{j \in \mathcal{P}} x_{0,j}^{a,v} \leq 1 \qquad \forall\, a \in \mathcal{C};\ v \in \mathcal{V}_a \tag{5.6}$$

$$s_i^{a,v} \leq T_i \qquad \forall\, i \in \mathcal{P};\ a \in \mathcal{C};\ v \in \mathcal{V}_a \tag{5.7}$$

$$s_i^{a,v} + t_{i,j}^{a,v} + p_i - M(1 - x_{i,j}^{a,v}) \leq s_j^{a,v} \qquad \forall\, i \in \mathcal{N}; j \in \mathcal{P};\ a \in \mathcal{C};\ v \in \mathcal{V}_a \tag{5.8}$$

$$x_{i,j}^{a,v} \in \{0, 1\} \qquad \forall\, i,j \in \mathcal{A};\ a \in \mathcal{C};\ v \in \mathcal{V}_a \tag{5.9}$$

$$s_0^{a,v} = 0 \qquad \forall\, a \in \mathcal{C};\ v \in \mathcal{V}_a \tag{5.10}$$

$$s_i^{a,v} \geq 0 \qquad \forall\, i \in \mathcal{N};\ a \in \mathcal{C};\ v \in \mathcal{V}_a \tag{5.11}$$

The objective function (5.1) minimizes total cost that is composed of the fixed cost if a vehicle is used, and the variable cost derived from the travel cost. Constraints (5.2) and (5.3) warrant demand fulfilment in each city without violating capacity of the vehicle used. Constraints (5.4) balance the incoming and outgoing trips in each city. The next two sets of constraints regulate the trips by preventing looping in the same node (5.5) and assigning not more than one tour to one vehicle (5.6).

Time windows are formulated by introducing variables $s_i^{a,v}$ that represent the time vehicle v of carrier a starts to service customer i. Constraints (5.7) are the upper-bound of $s_i^{a,v}$ and constraints (5.8) indicate that a vehicle cannot arrive at city j before $s_i^{a,v} + \text{travel time from city } i \text{ to city } j + \text{service time at city } i$. If arc (i,j) is not traversed by vehicle v of carrier a ($x_{i,j}^{a,v} = 0$), the constraints become redundant due to the presence of Big M. The rest of the equations describe the nature of decision variables. Variables $x_{i,j}^{a,v}$ are binary integer while variables $s_i^{a,v}$ are continuous, thus the model is a mixed integer programming.

One approach in multi-objective optimization (MOO) is finding a set of non-dominated solutions, also called the Pareto set. The Pareto approach returns several alternative solutions to the decision makers who can exercise other higher-level considerations that probably have not been embedded in the model. This approach is more practical especially when a trade-off relation of objective functions is not a priori known.

NSGA-II is an MOO technique based on evolutionary search algorithm proposed by Deb *et al* (2000) as a refinement from the earlier version (NSGA) from Srinivas and Deb (1994). A significant difference between the two methods is that NSGA-II uses an elite-preserving mechanism to prevent good solutions from being discarded by the genetic operators during iterations. After an initial parent population is generated, crossovers are performed to produce child population. Both populations are then combined and a number of best solutions, dictated by population size, from the combined population are carried out to the subsequent iterations. NSGA-II classifies population members based on ranks and distance measures which set the criteria to determine best solutions. The basic principles of how NSGA-II works have been outlined in 2.5.3 and a more detailed description can be traced in Deb *et al* (2000) or Deb (2008) that provides examples with hand calculations.

The last part of the basic methods is the genetic algorithms for VRP (Prins, 2004) and for HVRP (Prins, 2009). The strengths of the GAs come from the formulation of tour-splitting procedure called *Split*, dispersal mechanisms to prevent identical solutions (clones) in the population, and mutation operator using local search. The first component helps partition the chromosomes into feasible trips while the latter two components, often referred as memetic algorithm, are the key for faster convergence of the GAs to the best solution. The idea of *Split* has been discussed in 2.4.3, and its application, together with the memetic algorithm, has been demonstrated in 4.3.1 for a single-carrier/single-objective optimization problem. To be more specific, *Split*, the ray heuristic, population management using two dispersal mechanisms, i.e. *distance limit* and *dispersal value*, order crossover (OX) operator, and LS_2 local search mutation are the elements of the GA that will be extended by combining it with NSGA-II to form an algorithm for a multi-objective HVRPTW that will be applied in a case of maritime logistics collaboration.

5.3.2 Model development

There have been a number of studies on multi-objective VRPTW as discussed in 2.5.2, but none considers the use of heterogeneous vehicles because they are not oriented toward the applications in maritime logistics. Furthermore, in some of the studies, in addition to the natural total cost/time/distance minimization as the first objective, the second objective is formulated as minimization of the number of vehicles. If the fixed cost of vehicles is very significant as in the case in shipping, these two objectives will be very likely correlated and the problem can be treated as a single-objective problem.

In this chapter, a second objective that reflects a fair distribution of the total cost is proposed. Such distribution is considered fair if its proportion is in line with the proportion of the capital contributed to the joint operations. The deviation between the targeted and actual total costs of each carrier is calculated, summed for all carriers, and subject to minimization. Wibisono and Jittamai (*in press*) proposed the idea of this sharing policy and named it *proportionate-sharing policy*. The authors also showed that the policy leads to a smaller variance compared to the other sharing policies, thus is more reliable to be used in planning (see Model II in chapter three). Before moving forward with the formulation of objectives, the parameters q_A as the cost proportion of Carrier A and $q_B = 1 - q_A$ as the cost proportion of Carrier B need to be introduced. Recall in the data in Table 5.1, Carrier A contributes six vessels and Carrier B contributes three vessels to the joint fleet, thus $q_A = \frac{2}{3}$ and $q_B = \frac{1}{3}$. The total cost in (5.1) needs to be broken down for each carrier to ease readability and (5.12) and (5.13) are obtained for the total cost of Carrier A and Carrier B, respectively.

$$\sum_{v \in \mathcal{V}_A} \left(\sum_{j \in \mathcal{A}} f^{a,v} . x_{0,j}^{a,v} + \sum_{i,j \in \mathcal{A}} x_{i,j}^{a,v} . c_{i,j}^{a,v} \right) = TC_A \tag{5.12}$$

$$\sum_{v \in \mathcal{V}_B} \left(\sum_{j \in \mathcal{A}} f^{a,v} . x_{0,j}^{a,v} + \sum_{i,j \in \mathcal{A}} x_{i,j}^{a,v} . c_{i,j}^{a,v} \right) = TC_B \tag{5.13}$$

$$TC_A - q_A(TC_A + TC_B) = \delta_A \tag{5.14}$$

$$TC_B - q_B(TC_A + TC_B) = \delta_B \tag{5.15}$$

Define δ_A as the total cost of Carrier A minus its targeted proportionate cost, and, likewise, δ_B for the total cost minus the targeted proportionate cost of Carrier B. Now, the dual objectives of the problem can be formulated as follows, subject to the same set of constraints (5.2) to (5.11):

1. $$\text{Minimize } TC_A + TC_B \tag{5.16}$$
2. $$\text{Minimize } |\delta_A| + |\delta_B| \tag{5.17}$$

The second objective function (5.17) minimizes total absolute deviation of discrepancies between carrier's fair cost proportion and carrier's total cost. This equation is non-linear but can easily be transformed to a linear form by a technique described in (5.18)-(5.20).

$$\text{Minimize } |a - b| = \text{Minimize max.}\{a - b, b - a\} = \text{Minimize } y \tag{5.18}$$

$$y \geq a - b \tag{5.19}$$

$$y \geq b - a \tag{5.20}$$

The multi-carrier/single-objective SRP in 5.3.1 is run to find the optimal route of each carrier separately using each carrier's data of vessels and demands. The resulting total costs of all carriers are summed and compared to the joint-routing total cost to validate the financial impact of collaboration. Next, the multi-carrier/dual-objective SRP is minimized and maximized on each objective. The obtained minimum values on each objective are none other the extreme points of the true Pareto front. These two solutions alone may not suffice as decision alternatives given their extreme nature where one best solution is achieved at the expense of the other. However, these are true Pareto points, therefore cannot be ignored. As part of the elitism principle of NSGA-II, these solutions will be included and always kept as population members. As to the maximum values, these are needed as required parameters in the *crowding distance* procedure of the algorithm. Lingo 11.0 on an Intel i5-2430M processor running at 2.4 GHz and 4 MB of RAM on Windows 7 Ultimate is used for the above optimization.

After the key parameters are found by means of optimization, the search algorithm is performed using Matlab R2100b on the same computer. The algorithm is developed by combining the principles of NSGA-II for the multi-objective part and Prins' GA for the evolutionary search process. The main algorithm is detailed in Figure 5.2. After input data and parameters are read, the parent population is initialized. The population is halved and each group weighs on each objective. This approach is necessary because on every solution (chromosome) that is generated by random permutation, *Split* is called to form the trip partition and the procedure needs to know on what ground a good partition should be constructed. Population number one uses the minimum-cost solution already found by the linear programming optimization. Population number two is built with the ray heuristic that works by forming a rotating ray centered at the depot with the zero degree starts at West. This heuristic is very suited to the problem given the centralized position of the depot relative to the other cities. A cost-based *Split* (*splitcost*) is then performed on this second chromosome. The inclusion of good solutions in the initial population can help jump-start the search exploration. Population number three up to half of the population size are generated randomly, each is evaluated by *Split* and *spaced* criteria according to the dispersal mechanism. The other half of parent population are generated in a similar fashion: population number (*halfpop*+1) uses the minimum-deviation solution; population number (*halfpop*+2) uses ray heuristic evaluated by deviation-based *Split* (*splitdevn*); and the rest of the population use random generation, evaluated by *splitdevn* and *spaced* criteria.

01. **read** input data and parameters; *halfpop* = *popsize* / 2;
02. initialize parent population:
    a) parent #1: *mincost*;
    b) parent #2: *ray* heuristic, *splitcost*;
    c) parent #3-parent #*halfpop*: *random*, *splitcost*(*feasible*, *spaced*);
    d) parent #(*halfpop*+1): *mindevn*;
    e) parent #(*halfpop*+2): *ray* heuristic, *splitdevn*;
    f) parent #(*halfpop*+3)-parent #*popsize*: *random*, *splitdevn*(*feasible*, *spaced*);
03. initialize child population by *binary tournament* and *order crossover*:
    a) child #1-child #*halfpop*: *bintourn*, *OX*, *splitcost*(*feasible*, *spaced*);
    b) child #(*halfpop*+1)-child #*popsize*: *bintourn*, *OX*, *splitdevn*(*feasible*, *spaced*);
04. **for** *iter* = 1:*maxiter*
05. combine parent population and child population;
06. select members from the combined population to create new parent population;
07. create new child population using *modified crowded tournament*;
08. **end**

Figure 5.2 MOEA-SRP main algorithm

```
ctrchld = 1;
while ctrchld <= halfpop
    nosplit = true; spaced = false;
    while nosplit and not(spaced)
        select two parents by crowded tournament;
        apply OX to produce new child C;
        splitcost(C, feasible);
        if feasible
            nosplit = false;
        end
        if not(nosplit) and rand(1) < probmut
            M = mutation(C);
            if M belongs to Pareto rank 1
                mutoverride = true; else mutoverride = false;
            end
            if not(mutoverride)
                check spaced against both parent population and child population;
                if spacedprnt and spacedchld
                    mutspaced = true; else mutspaced = false;
                end
            end
            if mutoverride or mutspaced
                C = M;
            end
        end
        if not(nosplit)
            if C belongs to Pareto rank 1
                override = true; else override = false;
            end
        end
        if not(nosplit) and not(override)
            check spaced against both parent population and child population;
            if spacedprnt and spacedchld
                spaced = true; else spaced = false;
            end
        end
    end %while
    if (not(nosplit) and override) or (not(nosplit) and spaced)
        accept C in new child population;
        ctrchld = ctrchld + 1;
    end
end %while
```

Figure 5.3 Modified *crowded tournament* procedure (for half population)

Afterward, a population of child is initialized. The regular binary tournament is applied to select two parents to produce offspring using order crossover operator. As in the parent initialization, *splitcost*, *splitdevn*, and *spaced* criteria are the backbone of the process. With one parent population and one child population, the iterations can start. These are executed through lines 04-08, which are standard NSGA-II iterations except for line 07 where some principles of Prins' GA are inserted in the algorithm to form the modified *crowded tournament*. The pseudo-code of this procedure is listed in Figure 5.3, which is more detailed than the main algorithm in Figure 5.2 for better clarification of this important procedure. The code is listed for the creation of only half of the new child population. The creation of the other half is a replication and the only change needed is to replace *splitcost* with *splitdevn* so each half of the new child favors each of the two objectives.

The parent population becomes an input to this procedure. Two parents are selected randomly, then compete via the *crowded tournament*. The working principle of *crowded tournament* is basically as explained in Figure 2.9 in 2.5.3: two chromosomes are compared based on their ranks; if the ranks are equal, then their distance measures become the deciding criteria. Two random parents again compete and the two winners perform crossover to produce child chromosome *C* (lines 5-6). *Splitcost* then detects whether *C* can be feasibly partitioned into trips (lines 7-10) and if successful, the rest of the lines are executed. If mutation is triggered, *C* is improved by a local search on trip and vehicle exchanges, and temporarily copied to *M* (lines 11-12). Next, *M* is compared to all members of the first-rank Pareto set on its non-domination status. If *M* is not dominated by all first-rank Pareto members, then it is marked for acceptance (lines 13-15). This test is called *overriding* rule since if it is passed, *spaced* requirement is no longer checked.

If the new mutated chromosome *M* does not belong to the first-rank Pareto, it is tested for *spaced* criteria against both parent and child populations (lines 16-21). If either of the *overriding* or *spaced* tests passes, *M* is copied back to *C* (lines 22-24). The temporary copy of *C* to *M* is necessary since if mutation is not triggered, *C* is subject to the same tests for *overriding* rule (lines 26-30) and *spaced* criteria (lines 31-36). Finally, if either of the tests on *C* passes (and *Split* is feasible from the beginning), lines 38-41 perform acceptance of the new chromosome to the new child population, and a counter is increased for the next generation process.

The source codes of the above algorithm are uploaded in a website and the website URL and the list of the source codes are given in Appendix B.

5.4. Results and Discussion

The results of linear programming optimization are reported in Table 5.3. Table 5.3 shows that the collaborative joint-routing results in lower total cost compared to the total cost if the carriers work independently. Another observable point is the comparison of the minimization results of each objective separately under collaboration, or the comparison of the two most extreme Pareto points. When only the total cost is minimized, the deviation is not concurrently minimized, and the routing suggests that Carrier B is forced to use two of its most expensive vessels (those with the highest capacity). On the other hand, when only the deviation is minimized, even near to non-existent, the total cost shoots up as both carriers are scheduled to route all their vessels. This suggests a conflicting nature between the two objectives, and other non-dominated alternative solutions are worth exploring using the algorithm developed in the previous section.

Table 5.3 Results of linear programming optimization

Per-carrier optimization	
Carrier A: Minimize cost Cost: $589,605.50	Carrier B: Minimize cost Cost: $304,554.90
Total Cost: **$894,160.40**	
Routing: A1: Sby-Btm-Mdn-Sby A2: Sby-Bpn-Bit-Sby A2: Sby-Smr-Tar-Sby A3: Sby-Bjm-Ptk-Sby A3: Sby-Mks-Kdi-Amb-Sby A4: Sby-Jk2/Jk1-Sby	Routing: B1: Sby-Jk2/Jk1-Sby B2: Sby-Bpn-Smr-Bit-Sby B3: Sby-Bjm-Mks-Sby
Both-carriers optimization	
Minimize cost Cost: **$548,692.44** Deviation: $83,568.52	Minimize deviation Cost: $891,170.59 Deviation: **$0.04**
Routing: A1: - A2: - A2: - A3: Sby-Bjm-Mks-Bit-Sby A3: Sby-Bpn-Smr-Tar-Sby A4: Sby-Kdi-Amb-Sby B1: - B2: Sby-Jk1-Ptk-Sby B3: Sby-Jk2-Btm-Mdn-Sby	Routing: A1: Sby-Tar-Sby A2: Sby-Ptk-Mdn-Sby A2: Sby-Btm-Sby A3: Sby-Amb-Sby A3: Sby-Bjm-Bpn-Bit-Sby A4: Sby-Jk2-Sby B1: Sby-Smr-Sby B2: Sby-Mks-Kdi-Sby B3: Sby-Jk1-Sby
$TC_A = 324{,}010.70$ $\delta_A = -41{,}784.26$ $TC_B = 224{,}681.74$ $\delta_B = 41{,}784.26$	$TC_A = 594{,}113.75$ $\delta_A = 0.02$ $TC_B = 297{,}056.84$ $\delta_B = -0.02$

Various scenarios involving different dispersal mechanisms and controlled parameters are tested. Four types of dispersal mechanism are used and named DV(1)/50, DV(1)/100, DL(+), and DL(-). The DV-based mechanisms use a dispersal value of 1 and run on 50 and 100 iterations. The DL-based mechanisms use increasing (or decreasing) distance limits from 1 to 5 (or 5 to 1), equally spread on 50 iterations. Note that according to (4.12), the maximum distance limit is 6 on a case with 13 ports, but in this case the actual number of ports is 12 with an additional dummy port, therefore the maximum distance limit is set at 5.

In Prins (2004) and Prins (2009), the author proposed an aggressive set of parameters, i.e. higher mutation rate (10%-50%) and small population size (30-50), leading to fast convergence. In this study, a mutation probability of 20% is used, which can also be considered aggressive. A mutation rate beyond this figure is also tested, but a higher rate leads to a poor convergence whereas a lower rate dampen the search speed and can only be compensated by increasing the number of iterations but at the expense of algorithm running time. The running times are already quite expensive: DV(1)/50 spends roughly five hours to complete the iterations, and the other scenarios require approximately twice longer. Given the strategic level of the activity where the results can be used for a period of several months, such a long computation time is still acceptable. However, going for further iterations is highly inefficient. In fact, combining the results from different scenarios is a better approach than forcing one particular scenario to run longer, since there are unique Pareto points in each scenario that cannot be found in others, proving that no scenario is most superior, except for DV(1)/100 that is naturally better than DV(1)/50.

The population size is set at 100. Smaller population size does not work in this case since instead of finding one best solution, we are interested in finding a set of non-dominated solutions. The randomization effects in the chromosome construction are controlled with the ‘rng’ function in Matlab so the results from different scenarios are comparable. The ray heuristic results in the following order of ports: Sby-Jk1-Jk2-

Mdn-Btm-Ptk-Bjm-Bpn-Smr-Tar-Mks-Kdi-Bit-Amb. Table 5.4 details the final solutions found in different scenarios.

Table 5.4 Final solutions from various scenarios

DV(1)/50			DV(1)/100		
No.	Cost	Devn.	No.	Cost	Devn.
1	548,692.44	83,568.52	1	548,692.44	83,568.52
2	600,788.37	10,128.61	2	600,788.37	10,128.61
3	607,837.82	729.35	3	607,837.82	729.35
4	622,997.69	393.77	4	622,997.69	393.77
5	695,639.25	16.44	5	695,639.25	16.44
6	873,342.11	6.38	6	873,342.11	6.38
7	*877,835.85*	*3.85*	7	**874,042.13**	**1.66**
8	*877,953.29*	*1.53*	8	**877,508.05**	**0.79**
9	*884,889.29*	*1.25*	9	*890,655.38*	*0.68*
10	891,170.59	0.04	10	891,170.59	0.04
	Unique: 0			Unique: 2	
	Untrue: 3			Untrue: 1	
	KNF: 7			KNF: 5	
	Inf. Split.: 1541			Inf. Split.: 2458	
	Runtime: 5.05 hrs.			Runtime: 9.58 hrs.	
DL(-)			DL(+)		
No.	Cost	Devn.	No.	Cost	Devn.
1	548,692.44	83,568.52	1	548,692.44	83,568.52
2	600,788.37	10,128.61	2	600,788.37	10,128.61
3	**629,684.60**	**358.44**	3	607,837.82	729.35
4	695,639.25	16.44	4	695,639.25	16.44
5	*876,624.05*	*4.22*	5	**873,730.58**	**1.82**
6	**877,848.66**	**0.61**	6	*877,953.29*	*1.53*
7	**881,074.66**	**0.45**	7	*881,879.48*	*1.02*
8	891,170.59	0.04	8	**885,682.20**	**0.10**
			9	891,170.59	0.04
	Unique: 3			Unique: 2	
	Untrue: 1			Untrue: 2	
	KNF: 7			KNF: 7	
	Inf. Split.: 3850			Inf. Split.: 2294	
	Runtime: 10.38 hrs.			Runtime: 11.99 hrs.	

Note:
1. Bold: unique solutions;
2. Italic: solutions non-dominated within scenario;
3. KNF = Known not found.

Table 5.4 listed the Pareto members found in four scenarios and it is shown that the DV mechanisms are able to obtain 10 solutions, whereas the DL(-) and DL(+) mechanisms found 8 and 9 solutions, respectively. The bolded solutions are unique solutions within a scenario that are not found in the other scenarios. The italicized solutions are untrue Pareto, i.e. they are non-dominated only within a scenario where they reside, but if all solutions are combined, they become dominated. For example, solution 890,655/0.68 is non-dominated in DV(1)/100, but dominated in DL(-) or DL(+). Known-not-found solutions are the Pareto points not found in one scenario. For example, for DV(1)/100, these are solutions in DL(-) and DL(+) with deviation 0.10, 0.45, 0.61, 1.82, and 358.44. Overall, the results in Table 5.4 suggest that each scenario, geared by different dispersal mechanism, has its own unique solutions that cannot be found in the other scenarios. DV(1)/100 is slightly better than the DL-based mechanisms in terms of the number of Pareto points unable to be discovered (KNF) and computation time. The population members of DV(1)/100 at final iteration are also spread in the bottom-left section of the feasible space where solutions for a min-min problem are supposed to be (Figure 5.4). In contrast, a large portion of solutions of the DV-based mechanisms at final iteration are still "inside" the feasible region.

Part of the long running times are suspected due to the amount of infeasible splitting during the chromosome construction. The construction process works by randomly generating the sequence of ports in the chromosome, and if an infeasible splitting occurs, the next random generation is called for, without any marking on the generated infeasible chromosome. Such markings are the notion of a tabu-search procedure and incorporating it is a potential area for future algorithm improvement.

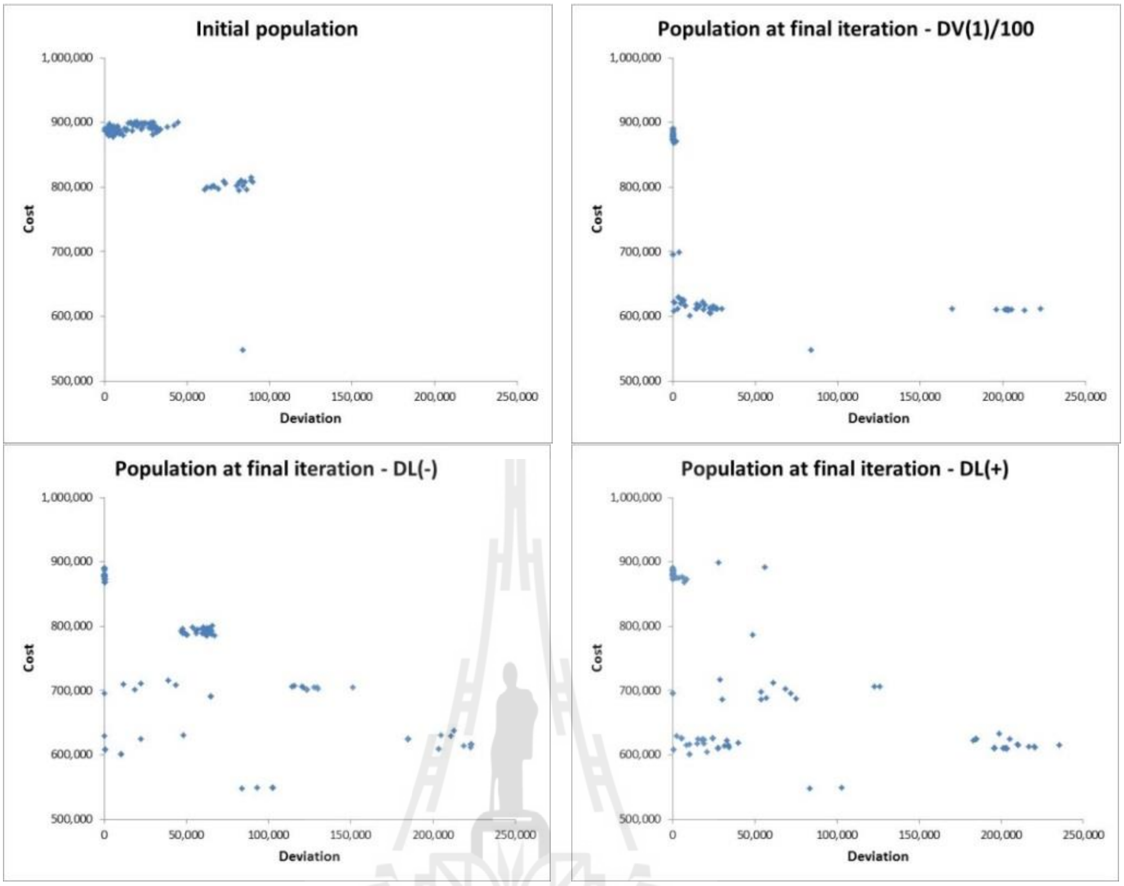

Figure 5.4 Scatter plots of population from Model IV

Finally, two non-dominated routing solutions are provided in Table 5.5 and visualized in Figure 5.5. Interestingly, these two solutions are found in the scenario with the least computation time DV(1)/50. It is clear that the number of routes in the obtained solutions is much less than that in the per-carrier optimization listed in Table 5.3. Moreover, with total costs not too far away from the minimum-cost solution in Table 5.3, these can be considered acceptable for both carriers. Carrier B can now use its smallest vessel B1 instead of being forced to use both of its two expensive vessels, B2 and B3. Initially, in the minimum-cost solution, Carrier B is the “losing” side because its total cost is $41,784 above its targeted proportionate cost, whereas Carrier

A benefits from the partnership by a saving of that amount (see Table 5.3). In the two solutions in Table 5.5, Carrier B now gets the benefit at the expense of Carrier A, however, the discrepancy of $5,064 or $365 is much lower than $41,784.

Table 5.5 Two non-dominated routing solutions

Cost: $600,788.37 Deviation: $10,128.61	Cost: $607,837.82 Deviation: $729.35
Routing: A1: Sby-Btm-Mdn-Sby A2: - A2: - A3: Sby-Bpn-Smr-Tar-Sby A3: Sby-Jk2-Ptk-Sby A4: Sby-Kdi-Amb-Sby B1: Sby-Mks-Bit-Sby B2: Sby-Bjm-Jk1-Sby B3: -	Routing: A1: Sby-Btm-Mdn-Sby A2: - A2: - A3: Sby-Jk1-Ptk-Sby A3: Sby-Bpn-Smr-Tar-Sby A4: Sby-Kdi-Amb-Sby B1: Sby-Mks-Bit-Sby B2: - B3: Sby-Bjm-Jk1-Sby
$TC_A = 405{,}589.88$ $\delta_A = 5{,}064.30$ $TC_B = 195{,}198.49$ $\delta_B = -5{,}064.30$	$TC_A = 405{,}589.88$ $\delta_A = 364.67$ $TC_B = 202{,}247.93$ $\delta_B = -364.68$

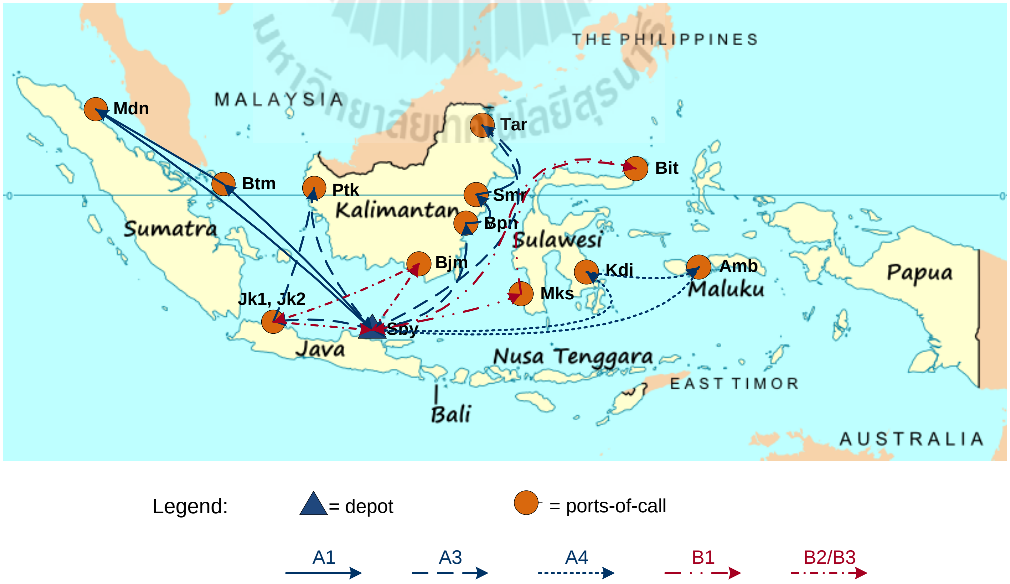

Figure 5.5 Routing visualization of solutions

5.5. Chapter Summary

This chapter discusses the final model of this dissertation, i.e. a multi-objective evolutionary algorithm ship routing problem for a maritime logistics collaboration of two liner companies in the scope of joint-routing network design. Two objectives in the model are minimization of total cost and minimization of deviation in fair cost proportion. The algorithm combines NSGA-II and the principles of aggressive but effective genetic algorithms from the published literature and an example of application with data background from the Indonesian archipelago is demonstrated. Two types of search mechanism are tested on four scenarios and the experiment results suggest that the mechanism based on dispersal value has a slightly better performance than the mechanism based on distance limit. Non-dominated solutions are found and translated to joint routings for both carriers.

CHAPTER VI

SUMMARY AND CONCLUSIONS

6.1. Summary

This dissertation explores a new topic in logistics that, to the best of our knowledge, has never been encountered in any earlier academic publication. The topic discussed is on maritime logistics collaboration with a more specific attention given on the segment of liner shipping that deals with the transportation of containers. A more detailed scope of the research is the construction of joint-routing network of two liner companies. Liner service is characterized by an important factor, i.e. adherence to the companies' published schedule, and therefore the routing model chosen for the foundation is the vehicle routing problem with time windows (VRPTW). Because ships involve high capital costs and since shipping companies are very likely to own and operate heterogeneous vessels, the heterogeneous VRPTW that considers fixed costs is used in the final model and named as the ship routing problem (SRP). Although the formulation of SRP can be found in the literature, due to its immense complexity, it has never been compared on benchmark instances nor has its real application ever been showcased. In the section of method, multi-objective optimization is selected as the approach to accommodate different and conflicting preferences of the collaborating parties. A novel multi-objective evolutionary algorithm (MOEA) combining the strengths from a particular genetic algorithm and an elitist MOEA is proposed. Four models and case studies using the Indonesian archipelago are developed as numerical instances for the purpose of model experimentation and analysis. Each model has its own scope and offers a different approach. The first two models introduce the idea of liner shipping collaboration, whereas the last two delve deeper into the area of methods.

Model I in 3.3.1 introduces the idea of slot-exchange collaboration between two liner companies. The model is formulated as an assignment instead of a routing problem and two objectives are called for minimization: cost and sailing time. Limited scenarios are tested and no search mechanism is developed to explore the Pareto front, hence the model lacks ability to search for non-dominated solutions.

Model II in 3.3.2 investigates different policies on fuel-consumption sharing and their impacts on the collaboration agenda. Two case studies of different sizes are set up but both are larger than the case study in Model I. The collaboration activity is still on capacity sharing, but the model is formulated as a single-objective problem. The model borrows VRPTW formulation but is extended with two distinct measures. The first measure is catered as slow-steaming decision variables and the second measure concerns the sharing policies in fuel consumption and is reflected in one of the sets of constraints. Experimenting with these measures is an attempt to find a better second objective. Three sharing policies are investigated: (1) open policy, where no restriction is applied, (2) proportionate-sharing policy, where the sharing of operational burdens (fuel consumption) is proportionate to the vessels contributed in the joint fleet, and (3) equal-sharing policy, where the fuel-consumption sharing is equal at 50-50 regardless of vessels contribution.

In the next two models, the research stage shifts its focus towards method development. Model III in chapter four develops a population-based algorithm and demonstrates its application in single-objective liner shipping routing problems. The problem is still formulated with single objective, but a search mechanism is developed using a meta-heuristic approach. Genetic algorithms for VRP (Prins, 2004) and HVRP (Prins, 2009) form the foundation of an extended version of this research's own genetic algorithm. The extension includes: (1) two simple yet effective heuristics in the initial population construction stage: load-assignment and shooting ray; (2) time windows in trips' feasibility tests, turning HVRP to HVRPTW, and (3) added local search. Two types of dispersal mechanism are tested based on: (1) distance limit, and (2) dispersal value. The distance-limit mechanism has two variants: increasing and decreasing distances. As in Model II, two case studies differing in sizes are developed to test the algorithm sensitivity against the scale of the problems.

Finally, Model IV in chapter five culminates the research with the development of a MOEA for SRP in maritime logistics collaboration, more specifically in the scope of joint-routing network design of two liner companies. Two objectives are formulated; namely, minimization of total cost and minimization of deviation in fair cost proportion. The model takes into account the important findings from the preceding models. The idea of proportionate-sharing policy from Model II is formulated as the second objective (minimization of deviation in fair cost proportion) and the tenets of effective genetic algorithm developed in Model III is adopted and combined with the strengths of one particular elitist MOEA called the non-dominated sorting genetic algorithm (NSGA-II) from Deb *et al* (2000). The same dispersal mechanisms as in Model III are tested. The model properties, involving the quality of outputs and the computation times, are discussed based on the experiment results.

6.2. Conclusions

Model I, being a preliminary model with the least degree of complexity than Models II-IV, does not provide significant results, but it highlights the need of a search mechanism to explore the Pareto front. The second objective of minimization of sailing time is also proven not critical thus the quest for a more practical objective remained.

The optimization results in Model II show that the slow-steaming decision variables offer no significant value both in model enhancement and practical aspects. On the other hand, the sharing policies are promising to be investigated further. The minimum consumption is found in the open policy but due to its erratic behavior depending on the demands, it unfortunately cannot be used for establishing a liner schedule. This indicates a conflicting nature between the cost and policies, which is a prerequisite for a multi-objective problem. The large case study suggests that the proportionate sharing results in the least variance, thus is more predictable and better suited for planning. Given that the model has only one objective, Model II is still not improved from Model I in terms of the need for a search mechanism to find non-dominated solutions.

Extensive runs are carried out on Model III and the results show that the proposed two heuristics perform well and rank not worse than among the top-four spots in the population after its members are constructed. This conclusion is general for all scenarios, thus it can be concluded that the heuristics serve their purpose by helping the GA jump-start its search towards a better solution space. Three types of dispersal mechanism based on two different methods are also tested and in general the method using distance limit is better than that using dispersal value. Efforts to reach the optimal point are mainly influenced by the number of iterations and to some extent the population size and the mutation rate. As indicated in our experiment results, larger number of iterations and population size, and a higher mutation rate, seem to be the best combination for the GA parameters. Lastly, the added local search procedure also helps the algorithm improve its final solution. By comparing the results of the small case and those of the large case, the proposed GA shows a tendency to become more competitive as the problem size becomes larger. This is indeed the advantage of any metaheuristic approach over a classical optimization approach where the former is more suitable for more complex problems.

In Model IV, two types of search mechanism similar to the ones exercised in Model III are tested on four scenarios. Unlike in Model III, the mechanism based on dispersal value has a slightly better performance than the mechanism based on distance limit in terms of computation time and the ability to reach the true Pareto front. The argument behind this finding is that the mechanism based on distance limit generates more diverse solutions to enlarge the search space and it is advantageous in a single-objective problem, but not necessarily true in a multi-objective problem since the interest of decision makers are the non-dominated solutions in the Pareto front. Examples of non-dominated solutions found by the algorithm are translated as joint-routing of both carriers and it is shown that while the solutions are not minimized in total cost, the inherent fairness that does not sacrifice either of the carrier serves as a balancing factor in the collaboration efforts. Such solutions highlight the practical benefit from this research that an “acceptable” network is not necessarily the least-cost option, especially in a collaboration endeavor involving more than one company.

The nature of real-life problems that has many facets, which are often conflicting, is thus emphasized by this research.

6.3. Research Contribution

The research in this dissertation offers valuable contribution in the following areas. Firstly, this research enriches a growing number of studies in the field of maritime logistics collaboration, with emphasis given on network design and routing of liner shipping, using a quantitative approach. The vehicle routing problem (VRP) is an established concept in this field and it has been extensively studied but its applications are mostly concerned with land-based logistics. The extension of VRP to the ship routing problem (SRP) in this dissertation enriches the scope of VRP applications. To be more specific, the SRP considers heterogeneous vessels, time windows, and fixed cost, and these attributes are highlighted in this research.

Secondly, collaborative activities will entail different and most likely conflicting preferences from the stakeholders. Multi-objective optimization is therefore a key concept in this research. Real-life problems are inherently multi-objective and this approach raises the applicability of the obtained solutions. As suggested by the experiment outcomes, when two or more objectives are being considered, it is possible that optimizing one objective could sacrifice the other(s). Compromise, satisfactory solutions are therefore required and an effective method to obtain these solutions needs to be developed. This research accomplishes that front end from the formulation of a novel multi-objective evolutionary algorithm (MOEA) for SRP. Application of the algorithm is demonstrated on a maritime logistics collaboration problem. Neither the algorithm nor an example of its application has ever been documented in the literature, therefore this research bears high practical values and significant contribution in this domain.

6.4. Future Research Directions

Several notes for future improvement of this research are in order. Firstly, although long computation times (as indicated in the results of Model IV) are still acceptable for an intermediate planning phase such as liner network establishment, efforts to reduce them should be attempted whenever possible. The algorithm is coded and run on Matlab and a switch to a more efficient programming language such as Java could remedy the situation.

Secondly, still related to computation times, the algorithm suffers a drawback from excessive creation of infeasible splitting. This gets worse when the problem scale gets larger. A possible way to cut the amount is by enforcing a tabu list that records chromosomes that have been constructed but failed to be split, and compare each new chromosome with this list before calling the *Split* procedure. This comparison, with much less complexity than *Split*, should take less time than the time required to execute *Split*.

Thirdly, there are other paths from the richness of GA/MOEA that can also be explored fur further study, e.g. exploring the most suitable crossover operator for a possibility of a more efficient algorithm.

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APPENDIX A

DATA FOR MODEL I

Carrier 1

Fuel costs (US$)

	Oil price	100	US$/barrel

No fast steaming

No.	Vessel	Samarinda	Kendari	Makassar	Ambon	Kupang
		Port				
1	SS	10.348	13.173	8.964	20.342	14.265
2	RW-39	10.067	12.815	8.720	19.789	13.877
3	F	10.348	13.173	8.964	20.342	14.265
4	Xpress	11.020	14.029	9.546	21.664	15.191
5	G	9.817	12.498	8.504	19.300	13.534

Fuel costs (US$)

Fast steaming

No.	Vessel	Samarinda	Kendari	Makassar	Ambon	Kupang
		Port				
1	SS	10.782	13.726	9.340	21.196	14.864
2	RW-39	11.454	14.582	9.922	22.518	15.790
3	F	10.782	13.726	9.340	21.196	14.864
4	Xpress	21.095	26.855	18.274	41.469	29.080
5	G	13.327	16.966	11.545	26.200	18.372

Sailing times (hours)

No fast steaming

No.	Vessel	Samarinda	Kendari	Makassar	Ambon	Kupang
		Port				
1	SS	46,36	59,02	40,16	91,14	63,91
2	RW-39	44,58	56,75	38,62	87,64	61,45
3	F	46,36	59,02	40,16	91,14	63,91
4	Xpress	35,12	44,71	30,43	69,05	48,42
5	G	41,40	52,70	35,86	81,38	57,07

Sailing times (hours)

Fast steaming

No.	Vessel	Samarinda	Kendari	Makassar	Ambon	Kupang
		Port				
1	SS	35,66	45,40	30,89	70,11	49,16
2	RW-39	34,29	43,66	29,71	67,41	47,27
3	F	35,66	45,40	30,89	70,11	49,16
4	Xpress	27,02	34,40	23,40	53,11	37,25
5	G	31,84	40,54	27,58	62,60	43,90

Vessels' particulars

No.	Vessel	Number	Cap. (TEUs)	DWT	Speed (n)	Speed (f)
1	SS	1	380	7215	12,5	16,25
2	RW-39	2	526	7855	13	16,9
3	F	1	224	4705	12,5	16,25
4	Xpress	2	662	8652	16,5	21,45
5	G	1	876	10652	14	18,2
		7	2668			

1) Fast steaming speed is 30% faster than the normal speed

Port data

No.	Port	Distance	Demand	Total	Due-min	Due-max
1	Samarinda	579,54	106	221	36	48
2	Kendari	737,79	392	873	48	60
3	Makassar	502,03	170	578	36	48
4	Ambon	1139,29	347	837	72	84
5	Kupang	798,91	328	745	48	60
					1343	3254

1) Distances in nautical miles
2) Demand sizes in number of containers
3) Ambon via Makassar
4) Demand generated with U[100; 500]
5) Due dates in hours

Carrier 2

Fuel costs (US$)

Oil price 100 US$/barrel

No fast steaming

No.	Vessel	Port: Samarinda	Kendari	Makassar	Ambon	Kupang
1	Ultima	9.948	12.664	8.618	19.556	13.714
2	Tangguh	9.824	12.506	8.510	19.313	13.543
3	Spirit	11.122	14.159	9.635	21.865	15.332
4	Marina	12.091	15.393	10.474	23.770	16.668
5	Mamiri	15.248	19.411	13.209	29.975	21.020

Fuel costs (US$)

Fast steaming

No.	Vessel	Port: Samarinda	Kendari	Makassar	Ambon	Kupang
1	Ultima	11.942	15.203	10.345	23.477	16.463
2	Tangguh	14.027	17.857	12.151	27.574	19.336
3	Spirit	21.497	27.367	18.622	42.260	29.635
4	Marina	24.970	31.788	21.631	49.088	34.422
5	Mamiri	34.434	43.837	29.829	67.693	47.468

Sailing times (hours)

No fast steaming

No.	Vessel	Port: Samarinda	Kendari	Makassar	Ambon	Kupang
1	Ultima	43,57	55,47	37,75	85,66	60,07
2	Tangguh	40,53	51,59	35,11	79,67	55,87
3	Spirit	34,91	44,44	30,24	68,63	48,13
4	Marina	33,31	42,40	28,85	65,48	45,91
5	Mamiri	30,18	38,43	26,15	59,34	41,61

Sailing times (hours)

Fast steaming

No.	Vessel	Port: Samarinda	Kendari	Makassar	Ambon	Kupang
1	Ultima	33,52	42,67	29,04	65,89	46,21
2	Tangguh	31,17	39,69	27,01	61,29	42,98
3	Spirit	26,86	34,19	23,26	52,79	37,02
4	Marina	25,62	32,62	22,19	50,37	35,32
5	Mamiri	23,22	29,56	20,11	45,64	32,01

Vessels' particulars

No.	Vessel	Number	Cap. (TEUs)	DWT	Speed (n)	Speed (f)	
1	Ultima	1	455	6013	13,3	17,29	13,32138
2	Tangguh	1	508	8618	14,3	18,59	14,29548
3	Spirit	1	712	13207	16,6	21,58	16,63102
4	Marina	3	846	13193	17,4	22,62	17,37778
5	Mamiri	1	1104	14464	19,2	24,96	19,15304
		7	3625				

1) Fast steaming speed is 30% faster than the normal speed
2) Normal speed is estimated with multiple regression equation 9,21 + 0,0056 Cap. + 0,00026 DWT

Port data

No.	Port	Avg. dist.	Demand	Total	Due-min	Due-max
1	Samarinda	579,54	115	221	36	48
2	Kendari	737,79	481	873	48	60
3	Makassar	502,03	408	578	36	48
4	Ambon	1139,29	490	837	72	84
5	Kupang	798,91	417	745	48	60
					1911	3254

1) Distances in nautical miles
2) Demand sizes in number of containers
3) Ambon via Makassar
4) Demand generated with U[100; 500]
5) Due dates in hours

APPENDIX B

LIST OF SOURCE CODES

Due to the amount of lines of the source codes (Lingo and Matlab), they are not provided in the hardcopy of this dissertation, but they have been uploaded and can be accessed in the following URL (only for Model IV):

http://ti.ubaya.ac.id/index.php/component/content/article/24-dosen/183-list-of-dissertation-source-codes.html

Below is the screenshot of the above URL.

List of Dissertation Source Codes

Eric Wibisono - PhD Dissertation
Multi-Objective Vehicle Routing Problem (MO-VRP) in Maritime Logistics Collaboration

Data

MOEAHVRPTW.xlsx	Excel data for Lingo and Matlab

Lingo

MOEAHVRPTW-L2.lg4	Lingo file for objectives minimization
MOEAHVRPTW-L2-CarrA.lg4	Lingo file for Carrier A cost minimization
MOEAHVRPTW-L2-CarrB.lg4	Lingo file for Carrier B cost minimization

Matlab

crddist1.m	Crowding distance procedure
crdtourn.m	Crowded tournament operator for *dispersal value* mechanism
crdtournpm.m	Crowded tournament operator for *distance limit* mechanism
creacomb.m	Create combined population
creaprnt.m	Create parent population
distance.m	Calculate distance (input to distancemin.m)
distancemin.m	Calculate minimum distance
moeahvrptwl2.m	Main program for *dispersal value* mechanism
moeahvrptwpm.m	Main program for *distance limit* mechanism
mutatels2moea.m	Mutation operator using local search ver. 2 (allowing vehicle swaps)
prtp.m	Find Pareto from two sets of objective outputs
splitcost.m	Split oriented towards minimization of cost
splitdevn.m	Split oriented towards minimization of deviation
trip2pop2.m	Convert trip matrix to population structure
xo.m	Order Crossover operator

Note:
Links (inside all Lingo files and Matlab main programs) to access the Excel data file must be adjusted according to where the file is located.

BIOGRAPHY

Mr. Eric Wibisono was born on February 25, 1972, in Surabaya, Indonesia. He received his B.Eng. in Industrial Engineering from University of Surabaya, Surabaya, Indonesia, in 1995, and M.Eng. in Manufacturing Management from University of South Australia, Adelaide, Australia in 1998. Mr. Wibisono is a teaching and research staff at the School of Industrial Engineering, University of Surabaya. He was admitted to the Ph.D. program in Industrial Engineering at Suranaree University of Technology under the SUT-Ph.D. Scholarship Program for ASEAN in 2012 and completed the program in 2015. His research interest is in the fields of transport management and maritime logistics.