



THE UNIVERSITY OF QUEENSLAND
AUSTRALIA

Contributions to Behavioural Freight Transport Modelling

Elnaz Irannezhad

B.Eng. (Hons), M.Sc

A thesis submitted for the degree of Doctor of Philosophy at

The University of Queensland in 2018

School of Civil Engineering

Abstract

The empirical applications of behavioural freight transport models accounting for several dimensions of decision-making process strengthen our understanding of the impacts of various freight-related policies. Several developments have been made in recent years to model the choices of freight transport actors. In line with these developments, the goal of this research is to apply a set of models which gain insight into the behavioural underpinnings that affect decision-making in freight sectors. However, it should be noted that the complex and heterogeneous nature of freight decision making is an imperative impediment to developing a behavioural model that can represent all dimensions of decision making.

While this study acknowledges that there are several choice decisions in the freight transportation system, this PhD study focuses on the most important ones including the choices of shipment size, using transshipment points and duration of storage, choosing the mode/vehicle of transport. Accordingly, this research is an effort to apply some empirical tools and approaches including advanced choice models and agent-based simulation in order to yield further gains in understanding of these particular decisions.

Within decision making process of freight transport, there are multiple interrelated constructs that can be tackled from various angles. This research attempts to apply advance choice techniques to model a few of these interrelated decisions in freight transport. To achieve this target, contributions are given to several components of two sets of interrelated decisions by (i) modelling the joint decisions of shipment size and vehicle type using a copula-based continuous-discrete choice model; (ii) modelling the joint decisions of using a container terminal and the resulting dwell-time of staging full containers using a copula-based discrete-discrete choice model.

Considering the differences in decision-making between for-hire carriers and ancillary shippers, separate different models are estimated while the assumption of pure utility maximization is relaxed via a hybrid utility-regret specification. Results of a case study show that differences exist between shippers' and carriers' preferences, and they prove the

importance of considering the two decisions jointly as well as the relevance of using a hybrid utility–regret formulation for the hourly hire cost of for-hire vehicles.

The second set of interrelated decisions are applied in a case study of importers/exporters in the hinterland from the Port of Brisbane (Australia), while the heterogeneity of taste among decision makers (importers/exporters) towards some variables also is taken into account.

Additionally, considering a significant number of observations are missing in this case study and to avoid producing unbiased estimates for the choice model, missing information is treated as a latent variable using a hybrid choice model to compensate for the missing observations. While the main body of literature on the non-response problem or missing data concerns imputation or removing those records prior to the analysis, this study argues that this practice causes the parameter estimates of the models to be biased when the percentage of missing data is significant. Hence, the other contribution of this study is the specification of a hybrid model in the context of freight and logistics with the aim of correcting for missing information. Specifically, variables with missing values are latent by definition and the hybrid model allows circumventing the bias inherent in removing observations or imputing values by expressing the value of the latent variables as a function of explanatory variables. The latent variables considered in this study are the shipment weight and the time of arrival in the import container model, and the shipment weight in the export container model.

Freight transport is a key component of the economy, productivity growth, and sustainable development. Rapid increasing the scale of freight tasks in the port's hinterland demands the new strategies to increase efficiency, profit, and infrastructure utilisation. In the current fragmented freight market, hinterland logistics operators seek to 'do their own thing' in terms of their operations, with little interest or ability to interact with their competitors. As a result of the lack of coordination, the numerous externalities are imposed such as extra trips, higher logistics costs, longer delays, and customer dissatisfaction. As a new practice in several ports over the past few decades, freight agents can be aided by the exchange of information and collaboration across agents of the same type (so-called horizontal integration), and between different logistics providers across the supply chain (so-called vertical integration).

While the main body of the literature on horizontal and vertical integration and cooperation is limited to the qualitative analysis, this research contributes to the literature by formulating and quantifying the effects of cooperation in a real case study. Accordingly, this study considers the joint vehicle routing problem and empty container repositioning problem, using a simulated dynamic capacitated vehicle routing problem with time windows. Two weeks of container transport through the Port of Brisbane (Australia) is used to ensure the capability of the simulation to solve the real-world problem. More specifically, this research simulates an integrated hinterland container repositioning and vehicle routing problem in a time-varying large-scale network. In this study two types of vehicles (semi-trailer and B-Doubles), two types of containers (20- and 40-foot containers), and a two dimensional capacity of trucks (weight and size) are considered, while constraints on some road segments for B-Doubles operation also are taken into account.

Container repositioning is not only costly for freight actors but it is also expensive in terms of negative externalities on the environment, energy consumption, and congestion. Accordingly, this study estimates the emission reduction for the most important pollutants as a result of inland empty container repositioning and truck-sharing. Specifically, average speed is calculated for every segment of the route of every vehicle and ecological footprints are estimated according to the COPERT model calibrated for Australia (EMISIA; Commonwealth of Australia, 2016) that is a function of the average speed of travelled links and the Australian fleet vintage configuration registered in Queensland (Queensland Government, 2013). The findings from this study highlight the benefits of cooperation among actors involved in inland container transportation, through a reduction in the logistics costs and a higher utilisation of larger trucks, as well as a significant reduction (between 40 and 45%) in fuel consumption and pollutant emissions.

Additionally, this research contributes to the state-of-the-art by applying an agent-based simulation by using two different reinforcement learning algorithms namely Q-learning and a quasi-learning algorithm based on the probability matching theory. Agent-based simulations can assist to model the individual heterogeneous agents and determine whether cooperation brings about gains or losses in a dynamic environment. Accordingly, each shipping line is given the opportunity to explore and exploit two options (individual vs. cooperative delivery plans) through a reinforcement learning (RL) process. The shipping lines' beliefs change according to their accumulated knowledge from previous experiences

of gains and losses. The results of individuals' decisions imply day-to-day dynamism in the market and the potential for day-to-day payoff variability because the decision of shipping lines to cooperate is determined based on the probability of saving logistics cost in a previous day with similar shipment characteristics.

Interestingly, the savings in logistics costs in cooperation are generally higher for shipping lines who have fewer shipments to deliver, while cooperation sometimes imposes a higher logistics cost upon the major shipping lines. This is why some shipping lines would prefer individual action over cooperation in the proposed RL algorithm, and leads to a less total improvement compared to the full cooperation approach. As a result of reinforcement learning, some agents would continue cooperating, while others would prefer individual operation over cooperation but still are more likely to use the information sharing platform to get a higher profit as a result of shifting to the off-peak period.

Lastly, this study offers practitioners several managerial insights into the role of horizontal and vertical cooperation in hinterland container transport. In maritime transport industry, the coordination between various freight actors is provided by the concept of 'port community system'. While all the previous studies on this concept are limited to the qualitative approach, this PhD study provides a quantitative proof of concept for an application of this system. The large-scale optimisation at the cooperation scenario also ensures the capability of the algorithm to solve the real-world problem.

To sum up, this research has given contributions to a number of components of freight transport choice modelling techniques in the status quo (i.e. individual action), while the choice of freight actors with regards to the cooperative strategies also is modelled by an agent-based simulation.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly–authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice, financial support and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my higher degree by research candidature and does not include a substantial part of work that has been submitted to qualify for the award of any other degree or diploma in any university or other tertiary institution. I have clearly stated which parts of my thesis, if any, have been submitted to qualify for another award.

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Publications during candidature

Refereed Journal Papers

1. Nassir, Neema, Hickman, Mark, Malekzadeh, Ali, and **Irannezhad, Elnaz** (2015) Modeling transit passenger choices of access stop. *Transportation Research Record*, 2493(2493), pp.70–77. (ERA rank: B).
2. Nassir, Neema, Hickman, Mark, Malekzadeh, Ali, and **Irannezhad, Elnaz** (2016) A utility–based travel impedance measure for public transit network accessibility. *Transportation Research Part A: Policy and Practice*, 88, pp. 26–39. (ERA rank: A*).
3. **Irannezhad, Elnaz**, Prato, Carlo, Hickman, Mark, and Shariat, Afshin (2017) copula–based joint discrete–continuous model of road vehicle type and shipment sizes. *Transportation Research Record: Journal of the Transportation Research Board*, (2610), pp.87-96. (ERA rank: B).
4. **Irannezhad, Elnaz**, Prato, Carlo, and Hickman, Mark (2017); A Joint Hybrid Model of the Choice of Container Terminals and Dwell Time. *Journal of Transportation Research Part E: Logistics and Transportation Review*. (ERA rank: A*). (In Press)
5. **Irannezhad, Elnaz**, Hickman, Mark, and Prato, Carlo (2017); Modeling the Efficiency of a Port Community System as an Agent–based Process. *Procedia of Computer Science*, 109, PP 918–923, Elsevier.
6. **Irannezhad, Elnaz**, Prato, Carlo, and Hickman, Mark (2017) The Choice of Using Distribution Centers in Container Import Chain: A Hybrid Model Correcting for Missing Information, *Procedia of City Logistics*, Wiley–ISTE. (In press)
7. **Irannezhad, Elnaz**, Prato, Carlo, and Hickman, Mark (2018); The effect of cooperation among shipping lines on transport costs and pollutant emissions; *Transportation Research Part D: Transport and Environment*, 65, PP 312-323.

Peer-Reviewed Conference Papers

8. **Irannezhad, Elnaz** , Hickman, Mark and Mousavi, Seyed Hossein (2015). New approach to calculation of a transfer matrix in a transit network. In: *37th*

- Australian Transport Research Forum. Australian Transport Research Forum* , Sydney, Australia. 30 September – 2 October 2015. (ERA conference rank: A).
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 10. **Irannezhad, Elnaz** and Hickman, Mark (2016). Behavioural urban freight modelling: exploring effects of policies on an urban freight distribution system. In: *38th Australian Transport Research Forum (ATRF 2016)*, Melbourne, Australia. 27–29 November 2016. (ERA conference rank: A).
 11. **Irannezhad, Elnaz**, Prato, Carlo, and Hickman, Mark (2018); A Cooperative Model of Inland Container Transportation; *presented in the 97th Annual Meeting Transportation Research Board*, Jan 2018. (ERA conference rank: A).

Publications included in this thesis

The thesis consists of the papers listed below:

1. **Irannezhad, Elnaz**, Prato, Carlo, Hickman, Mark, and Shariat, Afshin (2017) copula-based joint discrete-continuous model of road vehicle type and shipment sizes. *Transportation Research Record: Journal of the Transportation Research Board*, (2610), pp.87-96. (ERA rank: B) - incorporated as Chapter 2.

Contributor	Statement of contribution
Elnaz Irannezhad (Candidate)	Conception and design (65%) Analysis and interpretation (70%) Drafting and production (70%)
Mark Hickman (Main supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)
Carlo G.Prato (Associate supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)
Afshin Shairat	Conception and design (5%) Analysis and interpretation (0%) Drafting and production (0%)

2. **Irannezhad, Elnaz**, Prato, Carlo, and Hickman, Mark (2017) The Choice of Using Distribution Centers in Container Import Chain: A Hybrid Model Correcting for Missing Information, *Procedia of City Logistcis*, Wiley-ISTE (In Press) – incorporated as Chapter 3.

Contributor	Statement of contribution
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Elnaz Irannezhad (Candidate)	Conception and design (70%) Analysis and interpretation (70%) Drafting and production (70%)
Mark Hickman (Main supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)
Carlo G. Prato (Associate supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)

3. **Irannezhad, Elnaz**, Prato, Carlo, and Hickman, Mark (2017); A Joint Hybrid Model of the Choice of Container Terminals and Dwell Time; *Journal of Transportation Research Part E: Logistics and Transportation Review*. (In Press), (ERA rank: A*)– incorporated as Chapter 4.

Contributor	Statement of contribution
Elnaz Irannezhad (Candidate)	Conception and design (70%) Analysis and interpretation (70%) Drafting and production (70%)
Mark Hickman (Main supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)
Carlo G. Prato (Associate supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)

4. **Irannezhad, Elnaz**, Hickman, Mark, and Prato, Carlo (2017); Modeling the Efficiency of a Port Community System as an Agent-based Process. *Procedia of Computer Science*, 109C, PP 918–923, Elsevier – incorporated as Chapter 5.

Contributor	Statement of contribution
Elnaz Irannezhad (Candidate)	Conception and design (70%) Analysis and interpretation (70%) Drafting and production (70%)
Mark Hickman (Main supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)
Carlo G. Prato (Associate supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)

5. **Irannezhad, Elnaz**, Prato, Carlo, and Hickman, Mark (2018); The effect of cooperation among shipping lines on transport costs and pollutant emissions; *Transportation Research Part D: Transport and Environment*, 65, PP 312-323. (ERA rank: B) – incorporated as Chapter 6.

Contributor	Statement of contribution
Elnaz Irannezhad (Candidate)	Conception and design (70%) Analysis and interpretation (70%) Drafting and production (70%)
Mark Hickman (Main supervisor)	Conception and design (15%) Analysis and interpretation (15%)

	Drafting and production (15%)
Carlo G. Prato (Associate supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)

Manuscripts included in this thesis

The thesis consists of two manuscripts listed below:

1. **Irannezhad, Elnaz**, Prato, Carlo, and Hickman, Mark; An agent–based model of hinterland container transport to evaluate cooperation efficiency, *Submitted to the journal of Transportation Research Part E: Logistics and Transportation Review*, in Dec 2017. (ERA rank: A*) – incorporated as Chapter 7.

Contributor	Statement of contribution
Elnaz Irannezhad (Candidate)	Conception and design (70%) Analysis and interpretation (70%) Drafting and production (70%)
Mark Hickman (Main supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)
Carlo G. Prato (Associate supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)

2. **Irannezhad, Elnaz**, Prato, Carlo, and Hickman, Mark; Research Opportunities in Behavioral Freight Transport Modelling, *Submitted to the journal of Transport Review*, in Jan 2018. (ERA rank: A) – incorporated as Chapter 7.

Contributor	Statement of contribution
Elnaz Irannezhad (Candidate)	Conception and design (70%) Analysis and interpretation (70%) Drafting and production (70%)

Mark Hickman (Main supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)
Carlo G. Prato (Associate supervisor)	Conception and design (15%) Analysis and interpretation (15%) Drafting and production (15%)

Contribution by others to the thesis

No contributions

Statement of parts of the thesis submitted to qualify for the award of another degree

None

Research Involving Human or Animal Subjects

No animal or human participants were involved in this research.

Acknowledgments

My utmost respect and unending gratitude go to my advisors, Professor Mark Hickman and Professor Carlo Prato, who gave me the courage and freedom to pursue my ambition. This dissertation would not have been possible without their constant and generous help, intellectual guidance, and financial support throughout the three years of my program at the University of Queensland. Their great patience, support, understanding, and inspirational attitudes are precious lessons for my life. I owe much of my success to their guidance and professionalism.

I am enormously grateful to my panel members Professor Ling Lee, and Professor Philip Charles for all the instructive brainstorming that I received at every milestone. I am also grateful to my previous co–advisor Dr Neema Nassir and Associate Professor Adam Pekol for the useful discussions and invaluable inspirations.

Finally, I want to gratefully and sincerely thank my dear parents Abodlrahman and Alavieh Mirzadeh who seeded the passion for science and learning in my soul, my beloved husband Hossein who sacrificed himself to patiently support me in this journey, and my dear sister Azadeh who has inspired me since my childhood. Without their love, support, and encouragement, this PhD would not have been possible to achieve.

Financial support

This research was supported by UQ International Scholarship (UQI), and Transport Academic Partnership (TAP) agreement between UQ and Department of Transport and Main Roads.

I also acknowledge the support provided by the port partnership program between the Port of Brisbane Pty Ltd (PBPL) and the University of Queensland.

Keywords

Behavioural freight modelling, freight econometric modelling, agent-based modelling, freight transportation, hinterland container transportation, container movement modeling, port community system, vehicle routing problem, joint choice modelling.

Australian and New Zealand Standard Research Classifications (ANZSRC)

This thesis belongs to the following disciplines in the Federal Government's Excellence in Research for Australia (ERA) initiative.

ANZSRC code: 090507, Transport Engineering, 70%

ANZSRC code: 140302, Econometric and Statistical Methods, 15%

ANZSRC code: 150309, Logistics and Supply Chain Management, 15%

Fields of Research (FoR) Classification

This thesis allocates to the following fields of research (FoR) codes.

FoR code: 0905, Civil Engineering, 70%

FoR code: 1403, Econometrics, 15%

FoR code: 1503, Business and Management, 15%

Dedicated to my beloved husband and my dear parents

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List of Abbreviations

Abbreviation	Description
3PL	Third-party Logistics
ABM	Agent-based Model
CDC	Consolidation/ Distribution Centre
CT	Container Terminal
DC	Distribution Centre
DCM	Discrete Choice Model
DCVRPTW	Dynamic Capacitated Vehicle Routing Problem with Time Windows
DO	Delivery Order
DOT	Department of Transport
ECP	Empty container Park
EOQ	Economic Order Quantity
IIA	Independence From Irrelevant Alternatives
IID	Independently and Identically Distributed
I-O	Input-Output
LTL	Less-Than-Truckload
ML	Mixed Logit
MLHS	Modified Latin Hypercube Sampling
MNL	Multinomial Logit
NL	Nested Logit
O-D	Origin-Destination
PCS	Port Community System
RL	Reinforcement Learning
RP	Revealed Preference
PRA	Pre-advised Export Receival Advice
RRM	Random Regret Minimization
RUM	Random Utility Maximization
SP	Stated Preference
SPE	Spatial Price Equilibrium
TEU	Twenty-foot Equivalent Unit
UDC	Urban Distribution Centre
VCY	Virtual Container Yard
VKT	Vehicle Kilometre Travelled
VRPTW	Vehicle Routing Problem with Time Windows

Chapter 1: Introduction

Freight transport is a key component of the economy, productivity growth, and sustainable development. The importance of freight systems in the economy, environment, and modern life, as well as the rapid increase in scale of freight tasks, necessitates further study and research in this field. Inducing behavioral changes in the freight industry and supply chain, as well as changes in infrastructure and policies, could help provide improvements in economic efficiency as well as alleviate or reduce the negative impacts.

However, the proprietary nature of freight systems, the wide range of commodities that are shipped, the confidentiality of disaggregate data on freight movements, and the complex logistics of goods delivery are all obstacles in developing a comprehensive freight model. Lack of information about the underlying mechanisms of decision-making imposes a serious barrier to building a behavioral freight model which encompasses the dynamic evolution and oligopolistic nature of the market (Nagurney, 2010; Lee et al., 2014). Notably, to evaluate several policies in the freight transport market, the challenge of understanding and interpreting detailed logistics decisions and their interactions must be met.

Therefore, it is important to understand which attributes affect the different decisions of freight actors. While the cornerstone of freight transport models is the physical movement in terms of vehicle trip or commodity flow, behavioural freight models represent the factors that determine how freight actors make decisions about these physical movements. Representing the underlying behavioural mechanisms and decision making offers opportunities to link the market attributes with the physical movements.

1.1 Background

Freight refers to the movement of commodities as part of collection, production, or distribution within the transport and logistics chain. Movements in freight transport can be expressed in terms of commodity, container, and/or vehicle.

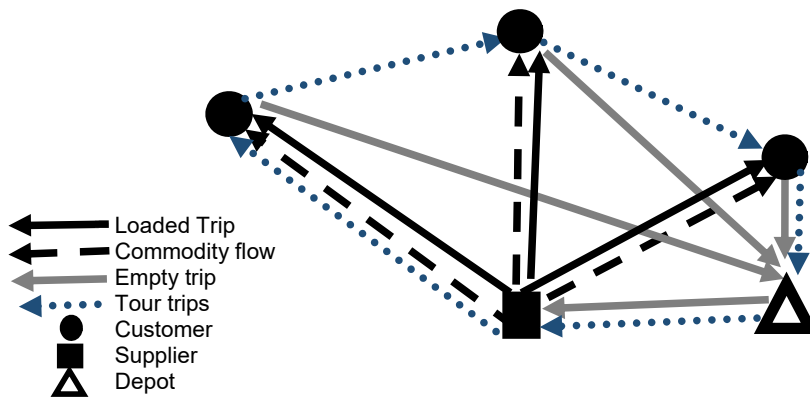


Figure 1 – Trip-based, commodity-based and tour-based flows

As shown in Figure 1, a one-way freight movement connecting either a supplier or depot to a customer is referred to as a trip, while a tour is made of consecutive trips between suppliers and other intermediate stops. A commodity flow represents the quantity and direction of goods flow from the supplier to the customer. A shipment is defined as a certain quantity of the commodity that is ordered from the shipper and delivered to the customer and can consist of several containers, pallets, or other units, transported by one or several vehicles.

Freight transport is a combination of nodal and modal activities, as shown in Figure 2. Modal activity includes the preferred mode of transport for each shipment based on the commodity type, size (weight and dimension), and other specifications such as the time at which a pick-up or delivery is made, often referred to as time windows. Nodal activity identifies the location where key activities occur, including origins (pick-ups), destinations (deliveries), and intermediate locations (transshipment) used for distribution, consolidation, and storage. A transshipment point (also referred to as a transport yard, terminal, distribution centre, or warehouse) is the location where goods are transshipped and possibly stored for a period of time. Transshipment points could be consolidation centres (with small loads coming in and larger loads going out), distribution centres (with large loads coming in and smaller loads going out), or temporary storage to wait for large vehicles with lower frequency.

The interaction between various freight transport actors create these nodal and modal activities, while these interactions are highly complex and heterogeneous. For the purpose of model practicality, several decisions undertaken by actors are simplified in most freight transport studies.

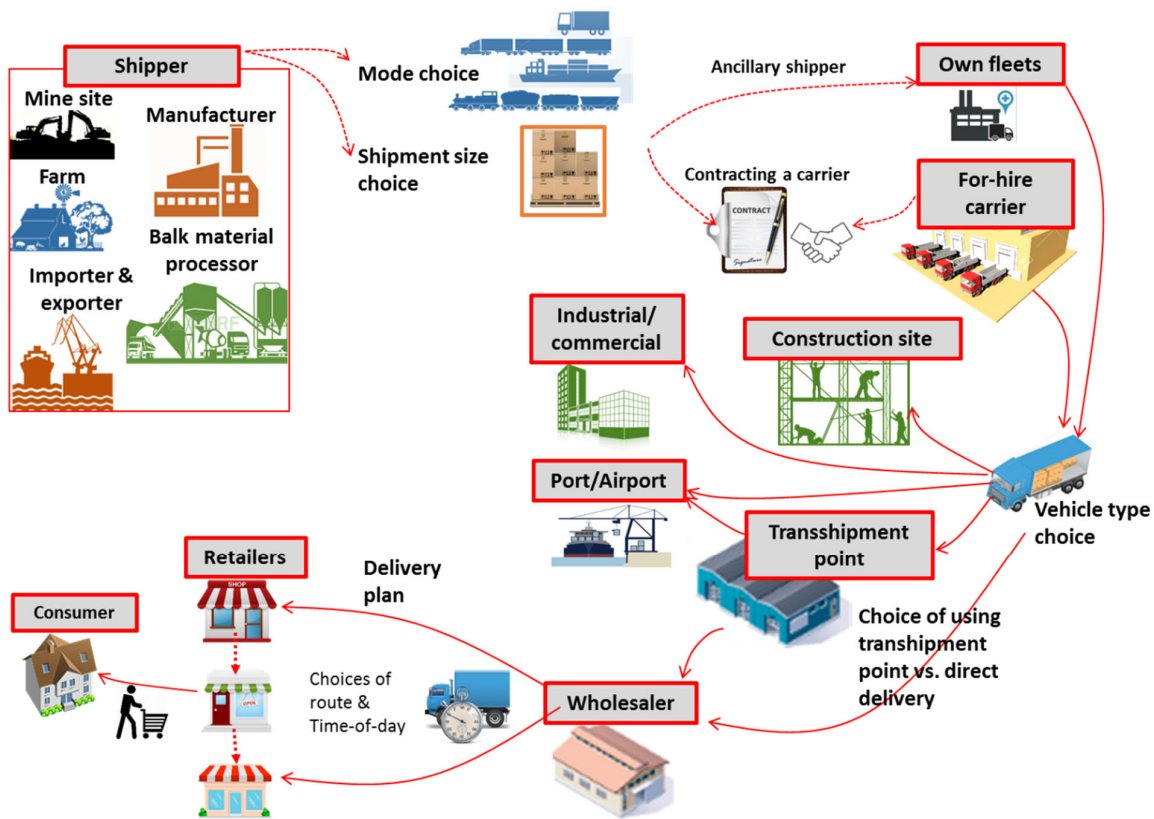


Figure 2 – Freight distribution system

The main freight actors in the literature are shippers and carriers. Shippers are the owners of goods being transported by any mode of transport, while carriers (including air, road, rail, and sea carriers) are responsible for transporting goods from shippers to customers. Shippers may manage their own logistics (e.g. make their own decisions about mode/vehicle type and the use of transshipment points), or they may contract third-party logistics (3PL) providers (also called freight forwarders) for arranging and managing contracts and balancing the risk and cost of transport services. Shippers may have their own fleet of vehicles, in which case they are called ancillary shippers; or, they may contract a transport company or so-called for-hire carrier, which serves the transport task from/to the shipper. Contracts in the freight transport system differ in various forms of interactions from long-term to short-term to spot contracts.

Logistics decisions are categorized into three levels: strategic, tactical and operational (Caris et al., 2008). Strategic decisions represent long-term plans such as designing a new freight transport network or establishing a new intermodal or transshipment facility. Tactical decisions represent mid-term plans such as optimisation of the inventory or

increasing the capacity of existing facilities, while operational decisions represent short-term plans or spot decisions such as fleet management, load acceptance, routing, delivery, and vehicle allocation.

The focus of this research is on the decisions of carriers and shippers at the operational level. More specifically, this study explores the behaviour of agents and their interactions by modelling four main operational-level decisions: the choice of shipment size, the choice of vehicle type, the choice of transshipment point, and the choice of route. To incorporate behavioural elements, these models include but are not constrained to the conventional random utility models. To illustrate these behavioural elements, an agent-based simulation is applied to evaluate the choice of freight actors to cooperate as part of the hinterland container supply chain. The research in this dissertation explores these operational decisions in two different contexts: first, in terms of urban commodity distribution; and second, in terms of import and export supply chains.

To more fully appreciate the details and complexities of freight decision-making, consider the case of import and export supply chains. It should be noted that interactions in the import and export supply chain market are more complex than the urban distribution system. In the import and export market, multiple logistics agents interact in a wide network which involves a few more nodes and activities. To clarify the underlying mechanism of the import and export market, a detailed study was undertaken at the Port of Brisbane, which involved several interviews and meetings with multiple freight actors.

Import/export trade starts with a contract between consignor (seller or exporter) and consignee (buyer or importer) where the terms of sale and payments have been identified. This contract can differ on a case-by-case basis. Hence, international rules or so-called International Commercial Terms (Incoterms) have been standardized since 1936 in order to assist traders in different countries. Incoterms are used for the interpretation of trade terms and determine transactions and procurement processes in every contract. Figure 3 presents the most recent version of Incoterms, released in 2015. It consists of 11 various types of contracts, four of which apply only to sea and waterways transport. According to the Australian Chamber of Commerce and Industry¹, FOB is one of the most popular contract types in Australia. FOB (“Free On Board”) means that the seller is responsible for

¹ <https://www.australianchamber.com.au/publications/>

the shipment until it is on board the ship, while the buyer is responsible for the rest of journey and pays for the transport, insurance, unloading, and shipping to their destination.


 Incoterms® 2015 Rules C H A R T O F R E S P O N S I B I L I T Y											
Charges/Fees	Any Transport Mode		Sea/Inland Waterway Transport				Any Transport Mode				
	EXW	FCA	FAS	FOB	CFR	CIF	CPT	CIP	DAT	DAP	DDP
	Ex Works	Free Carrier	Free Alongside Ship	Free On Board	Cost & Freight	Cost Insurance & Freight	Carriage Paid To	Carriage Insurance Paid To	Delivered at Terminal	Delivered at Place	Delivered Duty Paid
Packaging	Buyer or Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller
Loading Charges	Buyer	Seller*	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller
Delivery to Port/Place	Buyer	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller
Export Duty & Taxes	Buyer	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller
Origin Terminal Charges	Buyer	Buyer	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller
Loading on Carriage	Buyer	Buyer	Buyer	Seller	Seller	Seller	Seller	Seller	Seller	Seller	Seller
Carriage Charges	Buyer	Buyer	Buyer	Buyer	Seller	Seller	Seller	Seller	Seller	Seller	Seller
Insurance						Seller		Seller			
Destination Terminal Charges	Buyer	Buyer	Buyer	Buyer	Buyer	Buyer	Seller	Seller	Seller	Seller	Seller
Delivery to Destination	Buyer	Buyer	Buyer	Buyer	Buyer	Buyer	Buyer	Buyer	Buyer	Seller	Seller
Import Duty & Taxes	Buyer	Buyer	Buyer	Buyer	Buyer	Buyer	Buyer	Buyer	Buyer	Buyer	Seller

Figure 3 – INCOTERM 2015

In the import supply chain, the importer should lodge a delivery order (DO) to Customs (e.g. Australian Customs and Border Protection) in order to receive a customs permit, which may be paper-based or electronic. As discussed in the previous section, the importer may manage their own logistics (e.g. as done by big companies), or they may contract third-party logistics (3PL) providers (or freight forwarders) for arranging and managing contracts. If an importer or freight forwarder has their own customs broker, they proceed themselves through the customs permit procedure, otherwise, they contract with a customs broker who then takes responsibility for obtaining the final quarantine permit. Having this permit along with other documents such as a packing declaration, a manifest (a document showing the physical aspects of cargo such as size and weight), a commercial invoice and payment of port charges and fees, the freight forwarder is able to contract with shipping lines (ocean carriers) for the seaborne transport, and this contract is called the “Bill of Lading”. Sometimes

a long-term contract is signed between an importer and shipping lines which helps shipping lines to manage their container stock and flow.

Sea carriers refer to shipping lines who operate the ships that actually carry the containers (owned or leased) and/or cargo, from the loading port to discharge at the destination port. Shipping lines may sign long-term contracts with inland carriers and offer door-to-door service (i.e. carrier haulage). Shipping lines may operate, own, or share vessels, and may own or rent containers. However, they are responsible for arranging berthing/unberthing and contracting with the stevedores (wharf/store bonds) to discharge the vessel. They also notify the importer about the estimated arrival date and the name of stevedore to which the cargo is discharged.

Stevedores refer to businesses that engage in loading and unloading a ship's cargo. They are responsible for checking the discharged cargo against manifest and notifying the importer that cargo is ready for collection. Depending on the day that cargo arrives, they may offer free storage for a limited number of days (e.g. 3 days free of charge in the Port of Brisbane, and 7 days free in the Port of Townsville, Queensland). However, the stevedores should also be given the date of collection by shippers. In the case of import containers, the daily storage rate increases the longer the container is left on the stevedore's side in order to encourage the importer to collect the container as soon as possible, perhaps due to limited wharf capacity.

A container terminal (CT) is a business that focuses on staging containers between inland transportation modes and container vessels. Several activities may also occur in the CTs, namely cross-docking, transshipment, and storage. Staging is the process of storing containers prior to delivery to importers, exporters, or stevedores. In general, CTs may be state-run (public), operator-leased, operator-built and operated, carrier-built and operated, or run by a joint operator-carrier alliance. For example, a state-run container terminal operator (CT) serves all customers with the same service and on a first-come-first-serve basis, whereas other types of CTs act as hub-and-spoke system and may be used solely by certain customers or give priority to some according to existing contracts. However, in the Port of Brisbane, all CTs are operator-leased, meaning they are leased out to private operators.

Importers sign contracts with CTs to either store cargo or pack/unpack. Storage is one option if the arrival date and time is not consistent with the working hours of the consignee or vessel, or if the shipment needs to be bundled with other cargoes. After cargo discharges from stevedores in the import trade, either the importer or CT should remove the cargo from stevedores which implies cartage, lift, and storage/unpacking costs that would be borne by the importer, as specified in advance in the contract.

If the importer has their own carrier (road truck or railways), then they are called ancillary operators, otherwise they contract a carrier which serves the transport task, carrying the freight from/to their location. Shipping lines, however, may sign long-term contracts with inland carriers and offer door-to-door service or so-called carrier haulage (Frémont, 2009; Chung-Yee and Qiang, 2015; Beškovnik, 2016).

Empty containers cannot be held by the importer for longer than a standard period (e.g. 7-10 days in Brisbane), otherwise the importer has to pay the detention/demurrage empty container (DEC) fee which varies among shipping lines (typically ranging from \$50.00 to \$100.00 per day in the Port of Brisbane). The shipping lines collect the empty containers and transport them either to the Empty container parks (ECP) or to the exporter's location. ECPs are facilities which provide longer-term storage for empty containers.

It should be noted that all import/export containers (full or empty) to and from Australia are subject to Australian Customs control and are not available for general storage applications; i.e. they cannot be used as for-hire containers in domestic use. Strict legislative laws/rules apply to these containers including how long they are allowed to stay in Australia.

Figure 4 represents a simplified version of import chain activities and interactions between seven major actors: importer, freight forwarder, shipping line, stevedores, road carrier, container terminal operator, and empty container park. Some of these actors can be integrated into one single business as described previously.

There are parallel activities done by each agent which have been shown in partitions (Swimlanes). Actions are shown in grey rectangles, some of which are single operations (action states, e.g. "lodge Delivery order D/O"), while others are activity states in which multiple activities take place in the process, such as "Arrangements of transport()".

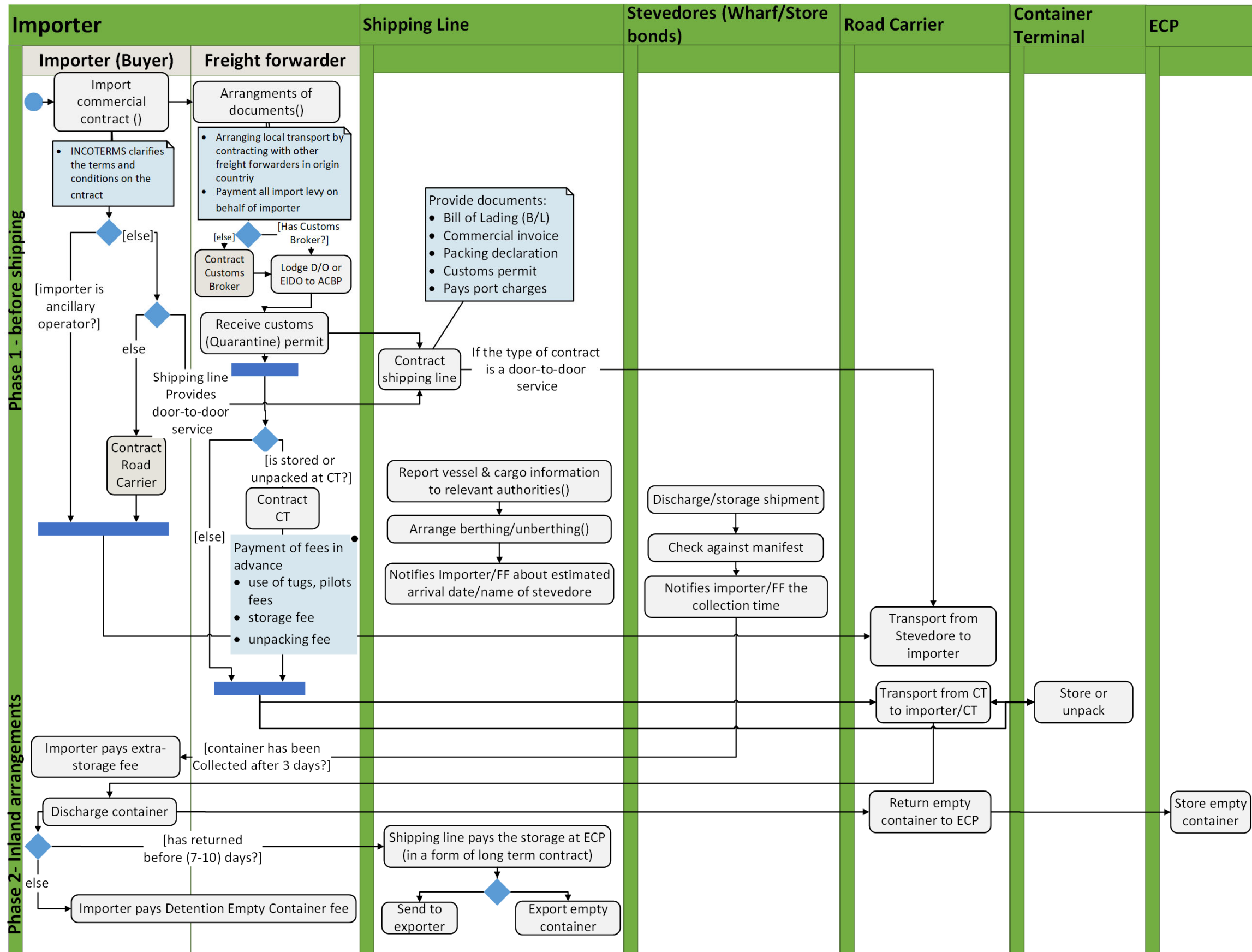


Figure 4 – Simplified import chain activities in Australian ports

In the export chain, however, activities are slightly different. Figure 5 presents a simplified activity chain for a typical exporter before shipping from Queensland, Australia. The exporter submits a cover booking to a shipping line that includes an approximate export volume (e.g. approximate number of containers) and the requested date. Cover-booking allows the shipping line to pre-plan the probable demands with respect to vessel capacities and schedules. Final booking is confirmed by the shipping line when the details of the export amount and dates are finalised by the exporter, and a vessel and an empty container are assigned by the shipping line. Accordingly, the shipping line sends an empty container release number to the ECP and a booking number to the stevedores.

Once a booking is confirmed, the empty container should be collected from the ECP and transported to the exporter's location or to a CT for packing. If the booking type is a door-to-door service, the shipping line arranges a pickup by an owned/contracted inland carrier, otherwise the exporter requests and contracts an inland carrier. The carrier is required to book a timeslot at the stevedore web portal (e.g. Vehicle Booking System (VBS) in the Port of Brisbane). Carriers often book the timeslots in advance in bulk since the system allows them to finalise the booking a couple of days ahead.

After packing and prior to arrival at the stevedores, exporters are required to submit a mandatory electronic document called a "Pre-advise Export Recieveal Advice (PRA)" to the stevedores and receive a confirmation. The PRA includes details of the packed container such as the contents, booking number, container number, and booking timeslot at the stevedore. The valid PRAs are manifested to the truck registration number and are entered in the timeslot booking at the stevedores.

If for any reason there is an inconsistency in the information in the PRA, exporters must submit an amendment and pay an amendment fee (\$125 in the Port of Brisbane). If the carrier misses the booked timeslot, they must pay any of the following penalty fees: a late show fee (\$250 in the Port of Brisbane), a wrong timeslot (\$58 in the Port of Brisbane), and a no show fee (\$110-\$135 in the Port of Brisbane). PRA adjustment not only imposes these amendment fees but also includes an unpacking and repacking as well as an extra transport fee. There may be several reasons for an invalid PRA, but this event typically occurs when the wrong container is packed.

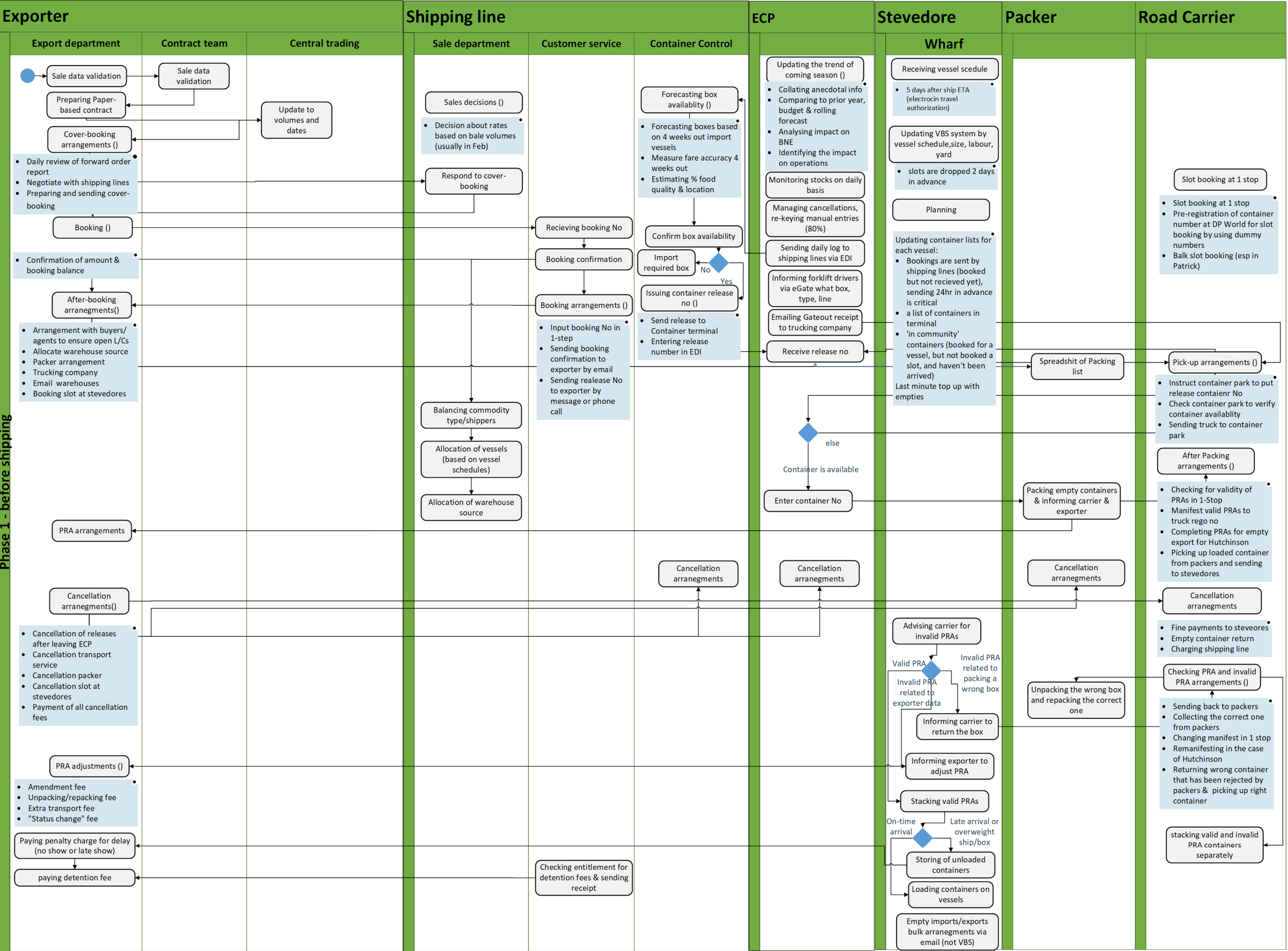


Figure 5 – Simplified export chain activiteis in Australian ports

Exporters are given a longer duration for holding a container (full or empty) compared to importers (21 days for export vs. 10 days for import in the Port of Brisbane). However, a detention fee applies for both importers and exporters after free days. The unexpected costs such as a detention fee or storage fee at the stevedore (more than the free days) are usually a source of many disputes over which party is ultimately liable since culpability for delay is often unclear.

Whilst the import and export supply chains are a key driver of sustainable development, the mismatch between modal and nodal activities imposes staggering negative externalities and inefficiencies. The invisibility of the decision making within the supply chain generates delay, congestion, double work, and higher logistics costs, all of which directly affects the economy.

Forecasts of import/export growth indicate that the total container movements (full and empty) through the Port of Brisbane are expected to increase 2.3 times by 2040 (Port of Brisbane Pty Ltd, 2013). While the road transport sector accounted for 24.7% of the total CO₂ emissions in Australia in 2014 (The World Bank, 2014a), articulated and rigid trucks contributed to about 23.3% of the annual road transport emissions (Pekol Traffic and Transport, 2015), where the truck emissions within the precinct of Port of Brisbane alone were estimated to be more than 24. 4 million kilograms of CO₂ per year (Smit et al., 2010).

While billions of dollars are spent on infrastructure to facilitate this growth, the lack of collaboration between various agents in this market often leads to sub-optimal use of that infrastructure. Freight agents mostly aim for profitable and safe operations, and they share or interact with the same infrastructure. Yet, due to data confidentiality and to competition among freight actors at the horizontal level (e.g. among shipping lines), there is poor information sharing, which contributes to the sub-optimal decisions and resulting sub-optimal use of infrastructure. Incompatible interfaces between different freight agents, reliance on manual transactions, and lack of interoperability among them results in invisibility and increased cost. Individual freight agents optimize their own logistics process while failing to coordinate with other agents, which may result in more freight movements than necessary and therefore incur higher transport costs.

The inefficiency of decisions and the lack of integration among agents happens on a larger scale in the import/export container supply chain because of the number of agents

involved (e.g. imports, exporters, stevedores, CTs, shipping lines, carriers). For example, empty container management consumes an equal amount of transport resources as the movement of full containers. All associated handling and storage costs of empty containers and operations are borne by shipping lines (Chung-Yee and Qiang, 2015). Due to an imbalance of trade in Australia, a significant volume of empty containers are exported, which imposes high logistics costs on shipping lines. In the financial year 2016/17, 312,149 full TEUs were exported, compared to 249,897 empty TEUs, and 505,342 full TEUs were imported, compared to 70,669 empty TEUs (Port of Brisbane Pty Ltd, 2017). Partially due to a good infrastructure for high-performance vehicles in Queensland, importers prefer 40-foot containers, while this type of container is less preferred by exporters since their international customers cannot easily deal with the larger box due to infrastructure constraints. Accordingly, this leads to exporting empty 40-foot containers and importing 20-foot containers through the Port of Brisbane. Another reason for inefficiency lies in the mismatch of demand and supply of different types of containers (e.g. food certificate, general, or refrigerated containers).

Most of these movements occur on the hinterland road network, because this is where container origins and destinations are located. Whilst there are three large ECPs located at the Port of Brisbane precinct, reducing the cost of transport from/to ECPs and stevedores, the task of transporting empty containers to exporters' premises (mostly within South East Queensland and the rest at adjacent regions), and from importers to ECPs (mostly within South East Queensland), is costly. Furthermore, this task is not only costly for shipping lines but it is also expensive in terms of negative externalities on the environment, energy consumption, and congestion.

The aforementioned inefficiencies can be overcome by the exchange of information, and hence better agent decision making, concerning opportunities for shipment bundling, vehicle sharing, vehicle routing, and direct delivery of empty containers (without storage at ECPs). Accordingly, information sharing and value-added services delivered by ports can help integrate logistics operations, positively affect end-users, influence the wider economy, and as a secondary result, assist in reducing externalities such as pollution, congestion, and poor land use.

To this aim, the goal of this research is to uncover the main operational decisions in the status quo as well as studying the impact of information sharing and cooperative strategies for decisions made in hinterland container transport.

1.2 Operational logistics decisions

With the previous section as the critical background to freight decision making, we may look more specifically at the primary focus of this research, in terms of the decisions of carriers and shippers at the operational level. We explore four main operational-level decisions: the choice of shipment size, the choice of vehicle type, the choice of transshipment point, and the choice of route. Each of these decisions is discussed in some detail here, with specific analyses later in this dissertation.

1.2.1 Shipment size and vehicle type

One of the more well-studied logistics decisions is the choice of shipment size. At the tactical level, shipment size is often classified as a part of inventory models (e.g. the Economic Order Quantity (EOQ) model), where the optimum shipment size is determined by minimizing the inventory, handling, and transport costs (Baumol and Vinod, 1970; Wisetjindawat et al., 2006; De Jong and Johnson, 2009); (Piendl et al., 2017). At the operational level, shipment size is modelled either by discrete choice models (Pourabdollahi et al., 2013; Abate and de Jong, 2014), or regression models (Holguin-Veras, 2002) as a function of shipment characteristics (e.g. the type of commodity) and the attributes of the associated transport mode (transport cost). Since this relationship introduces endogenous factors, a shipment size model is usually integrated into shippers' mode/vehicle choice models.

With respect to the decision of shipment size and vehicle/mode type, it is likely that these decisions are either a result of several interactions among various freight transport actors (e.g. between buyer and seller) or of interrelated decisions by the same actor. For example, a freight shipper might decide the quantity and frequency of shipments on the basis of inventory costs and customer demand, and then choose a transport mode and vehicle type suitable for that quantity. However, the order of these decisions may be reversed or, for instance, be based on the available vehicle types and their operating costs that might affect the shipment size. Accordingly, when observing choices of vehicle type and

shipment size, it is uncertain whether the question is, “What shipment size does the freight actor choose if vehicle type X is available?”, or instead, “What vehicle type does the freight actor choose if shipment size Y has to be moved?”.

Moreover, the choice of shipment size is often assumed to be a long-established business relationship between shipper and receiver. Albeit this long-term relationship may be true for large shippers, but not every shipment in the context of urban freight transport has this same property. A significant proportion of urban freight belongs to the household and general cargoes which are owned by smaller shippers (buyers or sellers) who use the for-hire carriers to transport their shipments. For-hire carriers including intra-urban, intercity carriers, and for-hire pickup vans may break down or bundle shipments with the objective of minimizing the operational costs of their fleet. On the other hand, customers may decide on the optimum vehicle with respect to their shipment size considering the hourly hire cost of various for-hire carriers. Hence, the joint choices of shipment size and vehicle type may differ between ancillary shippers and for-hire carriers.

1.2.2 Use of transshipment

Another important choice in the freight transport context is the choice of using a transshipment point. Factors influencing the choice of using transshipment points as intermediate stops or packing/unpacking stations (versus direct delivery) could include: (1) the characteristics of the shipment (e.g., size, commodity type, arrival time, departure time); (2) the characteristics of the shipper (e.g., in terms of resource availability, working hours); and, (3) the attributes of these points (e.g., cost, capacity, geographic location). These factors may also influence the dwell time, or how long shipments stay in these intermediate points before being delivered to the next point in the chain. It should be noted that the dwell time relates to the choice of using a transshipment point, as the imposed rehandling and storage costs are an impedance for shippers using these facilities in the first place.

Again it is debatable whether we should ask, “How long is the optimum dwell time that the shipper considers, if a shipment is to be stored at a distribution centre?” or instead, “Does the shipper consider storage at the distribution centre, if the shipment needs to be stored for a certain time?”. Arguably, there is no clear causality and/or sequence between these decisions, and there is no clear-cut explanation about which of the interrelated

decisions is conditional on or a result of the other. Accordingly, there is a need to study how these interwoven decisions should be modelled.

The interrelation between logistics choices can be seen as a learning process that freight agents undertake to optimize their logistics process, with the aim of minimising their cost and/or maximising their level of service. A major issue in conventional four-step demand modelling is that it is often assumed that a shipper decides the quantity and frequency of shipments on the basis of inventory costs and customer demand, and then chooses a transport mode and vehicle type suitable for that quantity.

The freight transport literature is not entirely devoid of studies that recognize the interplay between decisions. McFadden and Winston (1981) introduced the notion of joint decisions in freight transport by proposing a simultaneous model of mode choice and shipment size. Later on, some studies modeled the interrelation between mode choice and supplier choice or transport chain (Chiang et al., 1981; Windisch et al., 2010; Samimi et al., 2014).

When looking at interrelated freight transport decisions, a major dichotomy exists between sequential and simultaneous models. For example, the instrumental variable approach is a sequential method in which the shipment size (continuous variable) is regressed on the exogenous variables in the first step, and the estimated value is used to calculate the probability of a certain vehicle choice in the second step; this would mean that vehicle type is assumed to be dependent on the shipment size (Holguin-Veras, 2002). Also, the expected value method is a sequential method in which the endogenous variable is replaced by its expected value, derived from probabilities estimated by the vehicle choice model (Abate and de Jong, 2014). On the other hand, simultaneous models increase the precision of the estimates by estimating models jointly using a full information method. Several studies have modelled joint freight decisions by jointly estimating multinomial logit (MNL) models for mode and shipment size categories (Chiang et al., 1981; De Jong and Ben-Akiva, 2007; De Jong and Johnson, 2009), where the shipment size was transformed from a continuous to a discrete variable.

There are only a few examples of simultaneous discrete-continuous models in the freight modelling literature. McFadden et al. (1986), Abdelwahab and Sargious (1992), and Abdelwahab (1998) developed systems of simultaneous equations that model the choice of

vehicle type via a binary Probit and shipment size via a linear regression, and solved these systems by the switching regression technique. These models are however computationally difficult to estimate for more than two alternatives, and a discrete–continuous copula–based approach appears as a viable solution to this problem.

A copula–based approach was first proposed by Bhat and Eluru (2009) in the transportation literature to model a joint discrete–continuous choice (residential self–selection effects on the chosen travel mileage) without any restriction on the number of parameters. A copula is a parametrically–specified joint distribution of random variables derived purely from their marginal distributions on the basis of Sklar’s theorem (Sklar, 1973). The advantages of copula models consist include lower computational burden related to the use of the familiar maximum likelihood framework, flexibility in the marginal distributions of discrete and continuous variables taking any parametric distribution, and the possibility of considering nonlinear dependence structures that facilitate modelling the dependence in the tails of the joint distributions (Trivedi and Zimmer, 2007). In the freight transportation literature, only one study proposed a copula–based model (Pourabdollahi et al., 2013), with joint MNL models of shipment size and mode choice using data from an establishment survey in Chicago. Arguably, the discretization of the shipment size is a limitation of the model in that it is often superimposed arbitrarily, it ignores the nature of the size variable, and most relevantly it leads to different behavioural responses (De Jong and Johnson, 2009).

Furthermore, the choice of using transshipment points was studied in the German Federal Transport Investment Plan (2003), where a logit model was estimated to determine this choice as a function of the location of the available container terminals, transportation costs, travel time, and the surrounding area of the terminals. Goodchild et al. (2008) minimised logistics costs to capture the underlying economic forces explaining the preference of direct versus indirect (i.e., through trans-shipment points) distribution. Relevant parameters were transportation costs, distribution costs, inventory costs, goods’ value, interest rates, transit times, and safety factors. Kim et al. (2010) estimated a logit model of the distribution channel choice, where the alternatives were a direct channel, the channel through a wholesale store, the channel through a distribution center, and the channel through outsourcing logistics. Relevant parameters were the market characteristics

(i.e., population and firm density), commodity type, average order frequency, company size, and annual sales.

The remaining body of literature concerning transshipment points is concerned with the design of efficient logistics and infrastructure networks, where the focus is on optimising the location of these facilities and/or its allocation to freight consumption points, either for a specific commodity (Maurer, 2008; Friedrich, 2009), or a container chain (Limbourg and Jourquin, 2009; Davydenko and Tavasszy, 2013; Gu and Lam, 2013; Zhang, 2013; Halim et al., 2016). Agent-based models are also used to analyse policy impacts on the use of these facilities (van Duin et al., 2012; Teo et al., 2015), but none of these researches investigated the factors underlying the preferences for transshipment point usage.

According to the aforementioned review, the first research gap is identified as the explanation of the aforementioned logistics choices where the nature and interrelation of the choices are also taken into account.

1.2.3 Shipment bundling and routing

Shipment bundling and routing are the other main choices in freight transport. Since economies of scale/scope exist in the freight markets, carriers are likely to combine diverse less-than-truckload shipments to reduce transport costs. Then, the question is "What is the optimal set of routes for a fleet of vehicles to traverse in order to deliver a bundle of shipments to a given set of customers?". In the literature, this question is answered by the vehicle routing problem (VRP), which is a combinatorial optimization and integer programming problem. Accordingly, a set of shipments needs to be assigned to a set of routes or vehicles such that the overall path cost is minimized and the bundled shipments do not violate the vehicle capacity. Although the VRP is a very well-studied domain, there are only a few VRP studies that evaluate the impacts of truck sharing and container allocation jointly in the import and export supply chain. Furthermore, in these models, the optimum solution is obtained regardless of the heterogeneous choice of agents in truck sharing, assuming all customers participate in this cooperative strategy.

In addition to uncovering the logistics choices in the current situation, agent-based models can be applied to examine various policies by changing the environment and observing how heterogeneous agents would make decisions in the new environment. For example, Taniguchi et al. (2007) developed a multi-agent-based model (including shippers,

carriers, and administrators) on a small test network to study the effects of road pricing on shippers' and carriers' strategies. Abdul-Mageed (2012) examined a coordinated truck assignment system for five trucking companies, comparing direct competition with cooperation by sharing vehicles. Agent-based models have been adopted in several domains, such as the interactions of economic agents in financial markets (Bonabeau, 2002; Xu and Chi, 2007; Taghawi-Nejad, 2013), fleet management including scheduling (Bouazid, 2003) and dispatching (Burckert et al., 2000), terminal management (Henesey, 2006), and intermodal transportation (Dong and Li, 2003; Baidur and Viegas, 2011). For freight transport systems, this approach seems very suitable to illustrate interaction among various agents. INTERLOG (Liedtke, 2009), FREMIS (Roorda et al., 2010), and TAPAS-Z (Holmgren et al., 2013) are examples of agent-based freight transport models at the regional level.

1.2.4 Cooperation and information sharing

As discussed in the previous section, freight agents can be aided by the exchange of information concerning opportunities for shipment bundling, vehicle sharing, routing decisions, and a direct delivery of empty container without storing at the ECP.

The literature on the cooperation of maritime transport is gaining momentum, mainly because of emerging strategic alliances and acquisitions in the shipping industry (Heaver et al., 2000; Sheppard and Seidman, 2001; Crujssen et al., 2007; Lun et al., 2010). Notably, quantitative studies on hinterland cooperation are scarce (van de Voorde and Vanelander, 2010). Given that hinterland transport costs are generally higher than maritime costs, and most bottlenecks and delays occur on the landside, the limited attention paid to cooperation and coordination in hinterland container transport is surprising (Van Der Horst and De Langen, 2008).

A few existing studies have mathematically formulated the benefits of cooperation in hinterland transport and the repositioning of empty containers as an optimisation problem. For example, Sterzik et al. (2015) examined the possible benefits of exchanging empty containers, simultaneously with solving a vehicle routing problem on a hypothetical static network, while assuming only one type of vehicle and one type of container (40-foot container). The literature on vehicle routing and allocation problems often make simplifying assumptions such as assuming homogenous vehicles (i.e. only one type of fleet), a static

supply chain network, or considering only one criterion for capacity (i.e. either weight, or size). Notably, the existing literature is often a prototype of a hypothetical or a toy network with the limited number of supply and demands.

Accordingly, there is a research gap with regard to empirically demonstrating the capability of an optimisation model which is able to solve a real-size problem with more realistic assumptions. Furthermore, there is no agent-based study to evaluate the impacts of cooperation in truck sharing and container allocation where the heterogeneous choice of freight actors to cooperate is taken into account.

1.3 Research questions

In summary, two main research gaps are outlined as:

- Uncovering logistics choices where the nature and interrelation of the decisions are taken into account.
- Modelling the heterogeneous choices of freight actors with regards to cooperative strategies in hinterland container transport in a real-size case study with more realistic assumptions.

The above research gaps led to the specific research questions and the general data needs, whilst the research question and modelling methods also were refined based on data availability. For example, during the course of this research, the issue of missing data led to the second research question (RQ2, below). In order to gain a better understanding the aforementioned gaps in the previous section, the following research questions were identified:

RQ1: How should interrelated freight decisions be modelled to avoid bias in estimation?

RQ2: Considering the issue of missing data is quite common in freight surveys, what robust approach can be undertaken as an alternative to removing records with missing data or to imputing missing values?

RQ3: What might be the likely decisions of freight actors with regard to the opportunity to cooperate in hinterland container transport, as a result of information sharing and

integration? How can the optimum cooperative strategy be formulated to meet the dynamic demand and supply of freight agents on a real-size scale?

1.4 Research Approach

Notably, the complexity and heterogeneity of contract types and the lack of data are major hurdles in formulating a fully behavioural freight transport model covering the full range of decisions and contexts. Understanding a holistic freight transport market requires an appropriate degree of aggregation and abstraction. In order to mathematically model the logistics choices and empirically test them, generalization and simplification are required, while the traceability of causes and effects and the variability in the behaviours are also maintained.

This research is an effort to propose some empirical tools and approaches at the operational level, including advanced choice models and agent-based simulation, to answer the research questions. The work is broken down into the following subsections which state how and in which papers the abovementioned areas are addressed.

1.4.1 The choices of shipment size and vehicle type

Chapter 2 presents an attempt to model the joint decisions of shipment size and vehicle type in an urban area using a copula-based continuous-discrete choice model, as summarised in Figure 6. Models are estimated from a sample of 550 ancillary shippers' observations and 1,484 for-hire carriers' observations in Mashhad, Iran. This research contributes to the state-of-the-art by considering the continuous nature of the choice of shipment size in a copula-based model.

Considering the differences in decision-making between carriers and shippers, two different models are estimated, while the assumption of pure utility maximization is relaxed via a hybrid utility-regret specification. Results show that differences existed between shippers' and carriers' preferences. The results also prove the importance of considering the two decisions jointly as well as the relevance of using a hybrid utility-regret formulation for the cost of transport.

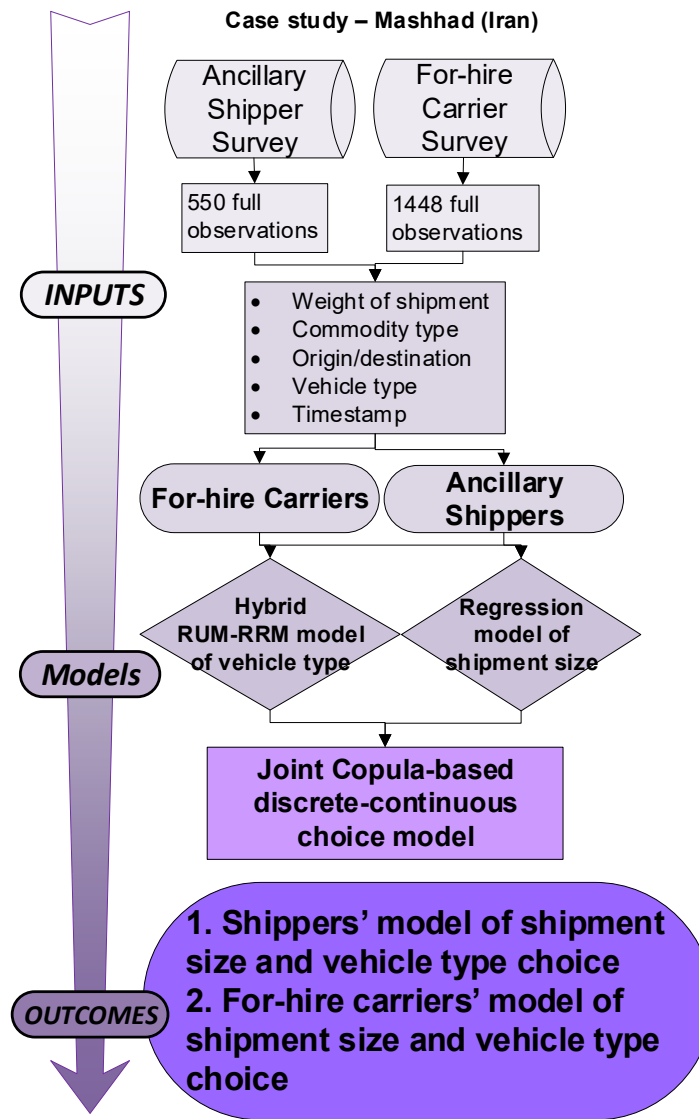


Figure 6 – Modeling of shipment size and vehicle type

1.4.2 The choices of using container terminal and dwell time

Considering the growth in maritime containerised trade, limited availability of land around ports, and the increase in vessel size, it is important to understand the circumstances under which freight operators use CTs in order to allocate their resources effectively. The analysis of preferences for the use of CTs by importers in the hinterland of the Port of Brisbane (Australia), is studied in Chapter 3. However, a considerable number of observations in this case study have missing information regarding the weight and timestamp(s) for the shipment. In most choice models, records with missing data are removed prior to analysis, a practice that causes the parameter estimates of the models to be biased when the

percentage of missing data is significant. The main body of literature on the non-response problem concerns imputation (Ramalho and Smith, 2002), but latent variable models to address non-response to attitudinal items have been applied in some social science studies (Knott et al., 1991; Albanese and Knott, 1992; Muirheartaigh and Moustaki, 1999). Notably, these studies were unable to handle more than two latent variables due to computational difficulties. Ramalho and Smith (2002) proposed a likelihood-based approach to deal with missing data in discrete choice models when there is either “unit non-response” or “item non-response”. Sanko et al. (2014) addressed missing responses for household income in travel surveys with hybrid choice models. To avoid producing unbiased estimates for the choice model in this study, missing information is treated as a latent variable using a hybrid choice model to compensate for the missing observations. That is how the second research question is answered in this case study.

According to the previous discussion on the interrelation between decisions of using transshipment points and the dwell time at these facilities (i.e. the staging duration), Chapter 3 is extended to cover the endogeneity and simultaneity of these decisions for both import and export container movements, as shown in Figure 7. Accordingly, Chapter 4 investigates the relationship between shipment characteristics and the decision to use CTs as well as the duration of the dwell time at CTs, either as an intermediate stop or as a location for unpacking and separate distribution by presenting a joint hybrid discrete–discrete choice model.

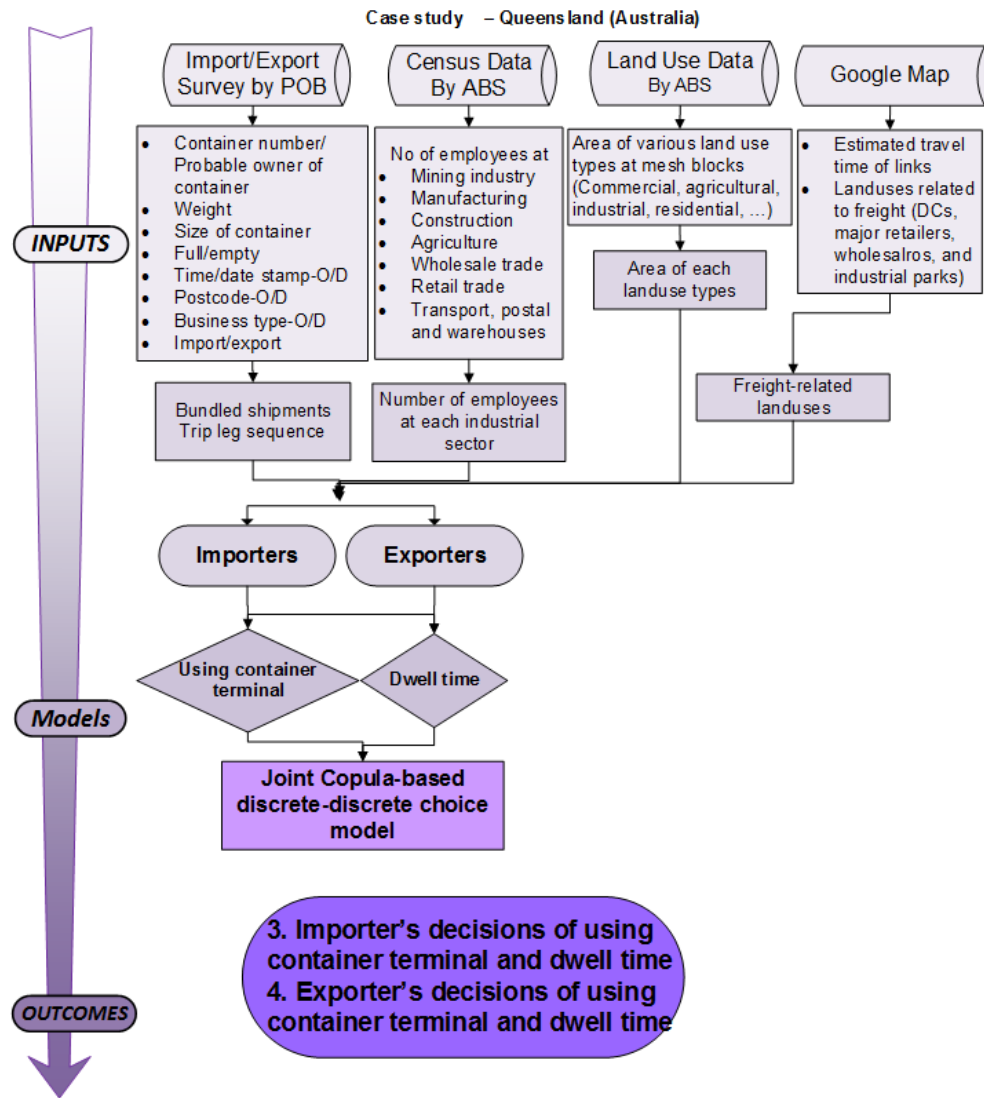


Figure 7 – Modeling of using container terminal and dwell time

1.4.3 Impact analysis of cooperation in hinterland container delivery

Chapters 5, 6 and 7 consider the effects of cooperation between freight agents to answer the last research question, as shown in Figure 8. Chapter 5 presents an agent-based simulation in order to analyse the heterogeneous choice of freight actors to implement truck-sharing strategies in the import container movements, using a Q-learning algorithm.

Chapter 6 presents an optimisation problem (a dynamic capacitated vehicle routing problem with time windows) for both import and export movements integrated with empty container repositioning (street-turn strategy). Given that only full container movements are paid, empty container repositioning is directly linked to profits. Accordingly, the demand of

an exporter for empty containers can be connected to the presence of nearby empty containers stored by an importer. This concept is termed “street-turn” and is an important objective from the shipping lines’ perspective to the point that coordination between shipping lines would not only reduce the number of empty container movements but also increase profits. This coordination can be provided through an online market supported by a port authority, where information about the containers becomes available to all involved actors. This web-based information exchange platform allows shipping lines to match empty container needs without storing them in the ECP. This concept is also sometimes referred to as a “virtual container yard (VCY)” or “triangulation” and has been successfully applied as either a module of a Port Community System (e.g., Virtuele Haven in the Port of Rotterdam), or a standalone market (e.g., Ports of Oakland, Los Angeles, Long Beach, and Montreal) (Maguire et al., 2010).

This research contributes to the state-of-the-art of vehicle routing and allocation problems by considering a two-dimensional capacity, including the weight and size of the container, and of dynamic travel times of links. Considering a multi-dimensional capacity is imperative for container movement because it is important to consider that a 40-foot container does not violate the weight constraint imposed by either the vehicle itself or road authorities. Moreover, real-time network dynamics assure the optimum strategy is considered in the vehicle routing problem, where the total transport cost considers both time-based and distance-based operational costs.

Furthermore, emissions reduction for the most important pollutants as a result of inland empty container repositioning and truck-sharing is presented. Specifically, average speed is calculated for every route segment of every vehicle, and ecological footprints are estimated according to the COPERT model calibrated for Australia (EMISIA; Commonwealth of Australia, 2016). The model is a function of the average speed of travelled links and the Australian fleet vintage configuration registered in Queensland (Queensland Government, 2013).

Chapter 7 presents an extension of the previous chapters by relaxing the time-windows constraint and using a probability matching reinforcement algorithm in order to evaluate the effects of cooperation in import and export container delivery. In this study we consider two main reinforcement learning strategies: (i) freight agents diversify in their first few choices and gradually converge to a single preferred option; (ii) freight agents learn the

probabilities of different outcomes, and ultimately the actions that were successful in the past are more likely to be adopted in the future. In the latter approach, agents predict their future reward in a multi-step task while learning from their previous experiences.

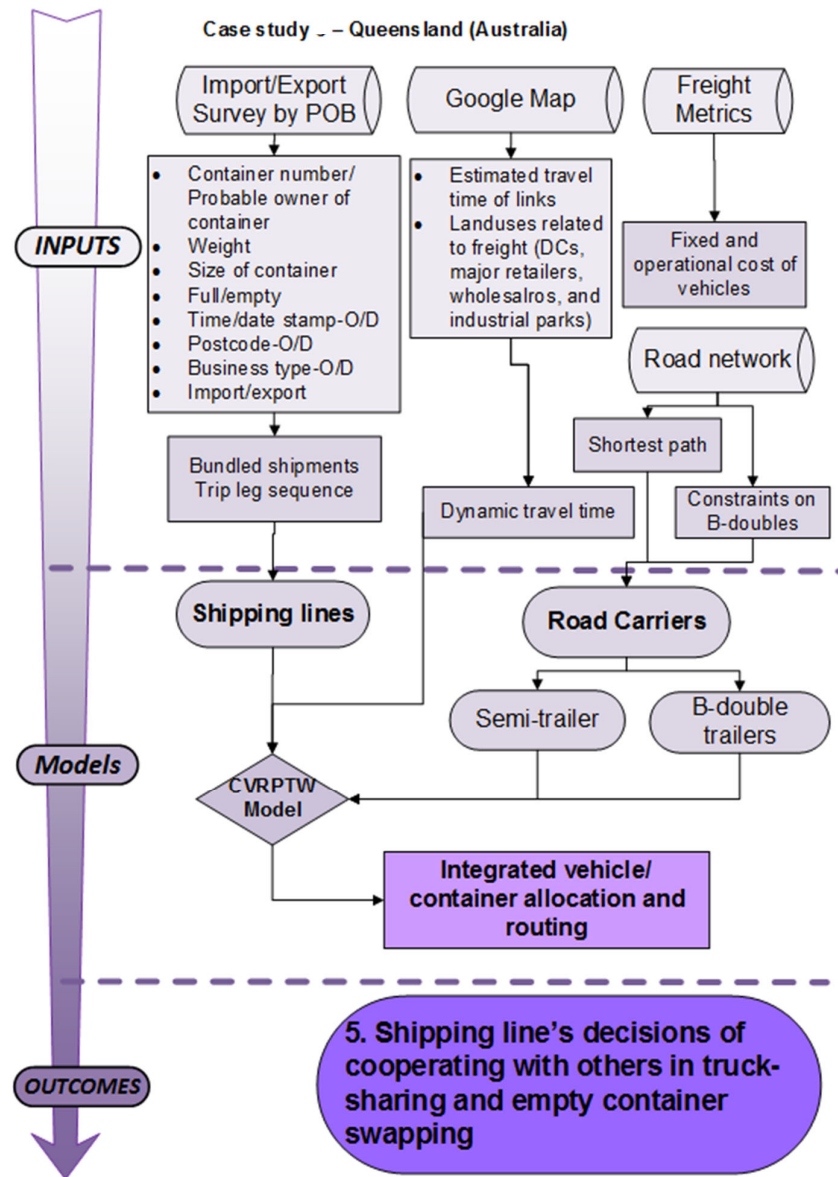


Figure 8 – Modelling the cooperation in hinterland container delivery

1.5 Outline

This dissertation consists of nine chapters. Chapter 1 introduces the problem, the more specific context of freight shipments in import and export supply chains, the specific decisions to be modelled in the research, and the major research questions. Chapters 2

through 7 constitute the specific contributions of this PhD study to answer these research questions.

Chapter 2, under the title “Copula-based joint discrete–continuous model of road vehicle type and shipment size”, presents a copula-based model designed to capture the interdependency of vehicle type choice and shipment size in urban freight transportation, while considering the differences in decision-making between shippers and carriers. This paper was published in the *Journal of the Transportation Research Board: Transportation Research Record* and presented by Prof. Mark Hickman at the 96th Annual Meeting of the Transportation Research Board, Washington DC in January 2017.

Chapter 3, under the title “The choice of using distribution centres in the container import chain: a hybrid model correcting for missing information”, presents the interrelationship between import container shipments and the choice of using distribution centres as either an intermediate stop or as a site to transship goods. This paper was published in *City Logistics 2018* by Wiley–ISTE, and presented in the 10th International Conference on City Logistics, 14–16 June 2017 in Phuket, Thailand.

Chapter 4, under the title “A joint hybrid model of the choice of container terminals and of dwell time”, presents an extension of Chapter 3, specifying a joint discrete–discrete choice model of the use of container terminals and the resulting number of storage days at these terminals, for both import and export containers. This paper has been accepted for publication in the journal *Transportation Research Part E: Logistics and Transportation Review*.

Chapter 5, under the title “Modelling the efficiency of a port community system as an agent-based process,” presents an agent-based method using reinforcement learning in order to estimate the efficiency of a Port Community System for inland movement of the import container chain. This paper was presented at the 6th International Workshop on Agent-based Mobility, Traffic and Transportation Models, Methodologies and Applications (ABMTrans 2017) and was published in the *Procedia of Computer Science*, Vol 109C, pp 918–923, Elsevier, 2017.

Chapter 6, under the title “The effect of cooperation among shipping lines on transport costs and pollutant emissions”, presents the effects of truck-sharing and inland empty container repositioning through cooperation among shipping lines. Accordingly, a

simulation-based model is presented to identify the quantitative benefits of cooperation, where inland empty container reuse is optimized through a dynamic vehicle allocation and routing problem with time window constraints and the environmental impact is assessed as a result of cooperation. This paper was published in the *Journal of Transportation Research Part D: Transport and Environment*, and also was presented at the 97th Annual Meeting of Transportation Research Board, Washington DC, in January 2018.

Chapter 7, under the title “An agent-based model of hinterland container transport to evaluate cooperation efficiency”, presents an extension of Chapter 5. In this work, an agent-based model for hinterland container chains explores the savings in hinterland transport costs stemming from cooperation among shipping lines, as a value-added service of a Port Community System (PCS). This value-added service is realised via a dynamic vehicle allocation and routing solution, where real-world constraints and dynamics are taken into account. Moreover, a reinforcement learning-based model based on probability matching theory was applied, in order to realistically simulate the adaptive behaviour of agents. This paper was submitted to the journal *Transportation Research Part E: Logistics and Transportation Review* in December 2017.

Chapter 8, under the title “Research opportunities in behavioural freight transport modelling”, presents a critical literature review and research opportunities in this field. This paper was submitted to the journal *Transport Reviews* in February 2018. However, it should be noted that this dissertation does not intend to address all the identified research gaps in this chapter, but instead leaves a great deal of ground for researchers in future freight behavioural studies to cover.

Chapter 9 summarizes the conclusions and contributions of this dissertation, and future research opportunities with regards to the limitations of this PhD thesis.

Chapter 2: Copula-based joint discrete-continuous model of road vehicle type and shipment size

Elnaz Irannezhad, Carlo G. Prato, Mark Hickman, Afshin Shariat Mohaymany

<https://doi.org/10.3141/2610-10>

Published paper in the Transportation Research Record: Journal of the Transportation Research Board and presented in the 96th Transportation Research Board 2017.

2.1 Abstract

A major issue in freight modelling is the interrelation between logistics choices that can be seen as a learning process that shippers or carriers undertake to optimize their logistics process, with the aim of minimising their cost and/or maximising their level of service. This study looks at the interrelated decisions of vehicle type choice and shipment size in urban freight transportation by formulating a model that considers (i) the different nature of these two dependent variables via a discrete-continuous joint model, (ii) the correlation between the two decisions via a copula-based approach, (iii) the differences in decision-making between carriers and shippers via the estimation of two different models, and (iv) the relaxation of the assumption of pure utility maximization via a hybrid utility-regret specification. Results show that differences exist between shippers' and carriers' preferences, which appear logical as many urban shippers own an efficient fleet of commercial vehicles, while carriers evaluate alternatives to maximize their aggregated utility as well as to minimize their direct costs. Results also show the importance of considering jointly the two decisions as well as the relevance of using a hybrid utility-regret formulation for the cost. Practical findings emerge from the model: (i) when faced with night delivery and intercity trips, carriers are more likely to use heavier vehicles and more voluminous shipments, while smaller shipments are preferred during the afternoon peak hour; (ii) urban shippers tend to deliver larger shipments during night by light trucks, but prefer trailers for longer distances; (iii) commodity types play a role in these joint decisions,

as some commodities are more likely to be transported by for-hire carriers whereas others are more likely to be transported by shippers.

2.2 Introduction

Recent literature reflects the interest in advanced models able to represent decisions by actors responsible for freight movement within urban transportation systems (Tavasszy et al., 1998; Chow et al., 2010; De Jong et al., 2013). A major issue in freight modelling is the interrelation between logistics choices that can be seen as a learning process that shippers or carriers undertake to optimize their logistics process, with the aim of minimising their cost and/or maximising their level of service. For example, a freight shipper might decide the quantity and frequency of shipments on the basis of inventory costs and customer demand, and then choose a transport mode and vehicle type suitable for that quantity. However, the order of these decisions may be reversed and, for instance, be based on the available vehicle types and their operating costs that might affect the shipment size. The problem is not trivial, as there is no clear causality and/or sequence between these decisions, and there is no clear-cut explanation about which one is conditional on or a result of the other (McFadden et al., 1986; Inaba and Wallace, 1989; Abdelwahab and Sargious, 1991; Holguín-Veras, 2002; De Jong and Johnson, 2009; Holguín-Veras et al., 2011).

Accordingly, when observing choices of vehicle type and shipment size, it is uncertain whether the question is, “What shipment size does the freight actor consider to be optimum if vehicle type X is available?” or instead, “What vehicle type does the freight actor choose if shipment quantity Y has to be moved?”. From a broader perspective, interrelated choices are one of the most common and also challenging econometric problems, and associated econometric techniques are used for example to correct for self-selection bias (Heckman, 1977), to represent jointly activity participation and episode duration (Born et al., 2014), or to analyse jointly commuting mode choice and non-work related stops (Portoghese et al., 2011).

The freight transport literature is not devoid of studies that recognize the interplay between decisions, as summarized in Table 1. McFadden and Winston (1981) introduced the notion of joint decisions in freight transport by proposing a simultaneous model of mode choice and shipment size. Later on, some studies modelled the interrelation between mode

choice and supplier choice or transport chain (Chiang et al., 1981; Windisch et al., 2010; Samimi et al., 2014).

When looking at interrelated freight transport decisions, a major dichotomy exists between sequential and simultaneous models. For example, the instrumental variable approach is a sequential method in which the shipment size (continuous variable) is regressed on the exogenous variables in the first step, and the estimated value is used to calculate the probability of a certain vehicle choice in the second step; this would mean that vehicle type is assumed to be dependent on the shipment size (Holguin-Veras, 2002). Also, the expected value method is a sequential method in which the endogenous variable is replaced by its expected value, derived from probabilities estimated by the vehicle choice model (Abate and de Jong, 2014). On the other hand, simultaneous models increase the precision of the estimates by estimating models jointly using a full information method. Several studies have modelled joint freight decisions by estimating jointly multinomial logit (MNL) models for mode and shipment size categories (Chiang et al., 1981; De Jong and Ben-Akiva, 2007; De Jong and Johnson, 2009), where the shipment size was transformed from a continuous to a discrete variable.

Although simultaneous discrete–continuous models have been applied in the transportation literature, only a few examples are found in the freight modelling literature. McFadden et al. (1986), Abdelwahab and Sargious (1992), and Abdelwahab (1998) developed systems of simultaneous equations that model the choice of vehicle type via a binary Probit and shipment size via a linear regression, and solved these systems via the switching regression technique. These models are however computationally difficult to estimate for more than two alternatives, and a discrete–continuous copula–based approach appears as a viable solution to this problem.

A copula–based approach was first proposed by Bhat and Eluru (2009) in the transportation literature to model a joint discrete–continuous choice (residential self–selection effects on the chosen travel mileage) without any restriction on the number of parameters. A copula is a parametrically–specified joint distribution of random variables derived purely from their marginal distributions on the basis of the Sklar's theorem (Sklar, 1973). The advantages of copula models consist in the lower computational burden related to the use of the familiar maximum likelihood framework, the flexibility in the marginal distributions of discrete and continuous variables taking any parametric distribution, and the

possibility of considering nonlinear dependence structures that facilitate modeling the dependence in the tails of the joint distributions (Trivedi and Zimmer, 2007). In the freight transportation literature, only one study proposed a copula-based model (Pourabdollahi et al., 2013), with joint MNL models of shipment size and mode choice using data from an establishment survey in Chicago. Arguably, the discretization of the shipment size is a limitation of the model in that it is often superimposed arbitrarily, it ignores the nature of the size variable, and most relevantly it leads to different behavioural responses (De Jong and Johnson, 2009).

Given the previous modelling efforts, this study contributes to the literature from three perspectives. Firstly, this study proposes a copula-based discrete-continuous model of vehicle type and shipment size that recognizes the need for modelling these two decisions jointly while considering the nature of the two choices and, in particular, the continuous nature of shipment size. Secondly, this study argues that different freight actors (i.e., carriers and shippers) have different preference structures because the fleet ownership and the operating frequency are different (Fridstrom and Madslien, 1994), and the study accommodates these differences by estimating two different models, when instead they are usually considered as a single homogeneous decision-making process in the literature.

In this research, two sets of surveys were employed to model the aforementioned decisions separately for shippers and for-hire carriers. The first dataset includes shippers that own fleets compatible with their frequent shipments. These are considered as ancillary operators that optimise fleet type with respects to their inventory costs or vice versa. The second dataset include intra-urban and intercity carriers and for-hire pickup vans. They themselves may break down or bundle shipments with respects to the operational costs of fleets. On the other hand, customers may decide about the optimum vehicle with regards to their shipment size considering hourly hire cost of various fleets. In this case-study customers may refer to smaller shippers, buyers or sellers who do not own fleet and use these for-hire carriers to transport their shipments.

Lastly, this study looks at the model formulation where different attributes might have either a utility maximization or a regret minimization expression that suggests how freight actors might process attributes differently. Accordingly, we postulated that the comparison among different vehicle types is not only based on the decision maker (shipper or carrier), but also on the processing of some attributes using regret rather than utility terms.

The remainder of the paper details initially the model formulation and estimation procedure. Then, the case study and the dataset are presented, and the results of the model are illustrated. Last, we summarize our main findings, as well as discuss limitations and possible future extensions.

Table 1 – Summary of joint modeling in freight transportation studies

Study	Joint decisions	Model structure	Predictor variables	Dataset (No. of observations, type of survey)
McFadden and Winston (1981), McFadden et al. (1986)	Mode choice, shipment size	Simultaneous binary discrete–continuous model by switching simultaneous system	Freight rate, mean and reliability of transit time, loss and damage, TL and LTL(truck load, less than truck load),	16,000 manufacturing establishments, RP, National level
Chiang et al. (1981)	Mode choice, supplier choice, and shipment size	Sequential discrete–continuous model	Variables for discrete supplier choice model: store's location, its size, no. of employees per unit floor space, and a revenue function which was modelled as a continuous variable for road and rail carriers	181 retail clothing stores and two industries
Inaba and Wallace (1989)	Market, mode, and destination choice	Simultaneous optimization problem by using a switching regression technique	Waiting, loading, and time in transit, cost, market boundary, mode/destination pairs, facility capacity	183 firms in grain industry, RP, State level
Abdelwahab and Sargious (1992), Abdelwahab (1998)	Mode choice, shipment size	Simultaneous binary discrete–continuous model by switching simultaneous system	Commodity type, density, value, and characteristics, transit time, mode cost, loss and damage rate, transit time reliability, total tonnage of a given commodity moved over a given O–D link	1586 firms, RP, National level
Holguin-Veras (2002)	Vehicle type, shipment size	Sequential discrete–continuous model (instrumental variables)	Variables for vehicle type model: Cost per ton, distance Variables for shipment size model: commodity type, intersectional flow (among retailers, wholesalers, and others)	5276 firms, RP, National level
Hunt and Stefan (2007)	Tour purpose and vehicle type, tour start time, next stop purpose and location, stop duration	Sequential models: Monte Carlo model for tour purpose, next stop location, and several combinations of tour purpose–vehicle type Discrete choice model for time allocation for each establishment type	Variables for tour purpose–vehicle type model: establishment type, zonal accessibility, employment, and land use Variables for next stop purpose: natural logarithm of number of previous businesses and number of previous other stops, elapsed total time, travel utility to return to establishment Variables for next stop location: enclosed angle, average income, density, employment/population attractor point Variables for discrete stop duration model: accessibility to employment, land use type, the percentage of zonal employment in each industry	64,000 firms, RP, State level
De Jong and Ben-Akiva (2007), De Jong and Johnson (2009)	Mode choice, shipment size	Several combinations of discrete choice models	Commodity type, cost, transport time, value of a commodity per weight, company in biggest size class, access to the quay at the origin, access to industrial rail track at the origin	749,000 firms, RP, National level

Table 2 – Summary of joint modelling in freight transportation studies (continued)

Study	Joint decisions	Model structure	Predictor variables	Dataset (No. of observations, type of survey)
Samimi (2010), Samimi et al. (2014)	Supplier choice, shipment size, mode choice	Sequential models: Fuzzy rule-based model for categorical supplier selection, decision tree model for categorical shipment size model, and Probit model for mode choice (shipment size was an explanatory variable)	Variables for supplier selection model: distance between buyer and potential supplier, no. of employees Variables for categorical shipment size model: establishment size of supplier/buyer, shipping distance, commodity type Variables for Probit mode choice: shipment size, rail/road impedance, great circle distance, a dummy variable for containerized commodities and a group of commodity types	Simulated data, 45,206 firms, National level
Habibi (2010)	Mode choice, transport chain, shipment size	Several combinations of discrete choice models	Transport cost, commodity type, season, firm size, transit inventory cost, value of commodity per ton	749,000 firms, RP, National level
Windisch et al. (2010)	Mode choice, supplier choice	Several combinations of discrete choice models	Cost, time of year, commodity characteristics	2,678,527 firms, RP, National level
Combes (2012)	Shipment size, mode choice	Continuous EOQ shipment size model (regression) in which mode type was an explanatory variable	Variable for shipment size model: total commodity flow, commodity value of time, a dummy variable for mode type, origin/destination distance variable, no. of agents intervening in the operation, no. of legs and organization of the transportation operation	10,462 firms, RP, National level
Outwater et al. (2013a)	Transport chain, shipment size, vehicle type, and tour pattern	Several combinations of discrete choice models	No. of manufacturing industries, no. of transport/warehousing firms, great circle distance between buyer and supplier zones, size of firms, trip length, distribution channel, service industry type (SIC1), transport/construction industry type (SIC2), type of cargo (food, manufacture), weight at drop-off, weight at pickup, destination industry (manufacture, office, retail), total employment	5314 firms, RP, State level
Abate and de Jong (2014)	Vehicle type, shipment size	Sequential discrete-continuous model (expected value approach)	Cost per ton, age, fleet size, demand volumes, for-hire, fuel cost, trip distance	38,989 firms, RP, National level
Pourabdollahi et al. (2013)	Mode choice, shipment size	Copula-based discrete-discrete choice models	Commodity type, characteristics and value, international shipment, cost and distance, no. of employees	1302 firms, RP, National level

2.3 Methods

2.3.1 Model formulation

The joint decision of vehicle type and shipment size is a multidimensional problem for which a copula-based approach offers several advantages over the currently used methods. Firstly, copulas determine the dependency by joining marginal distributions to form a new joint distribution, without the need for using any specific distribution family or transforming the marginal distributions when they are not normal. Copulas have proved useful for discrete or joint discrete-continuous models when non-normality and non-linearity frequently arise (Trivedi and Zimmer, 2007). Secondly, multivariate correlation methods (e.g., Pearson, Kendall's tau, Spearman's rho) measure the central dependence and fail to properly estimate near the boundaries. Copulas allow estimating the tail dependence in both symmetric and asymmetric forms (Frey et al., 2001). Thirdly, copulas can handle complex joint distributions in any form of univariate marginal distributions, particularly as the number of dimensions (i.e., the number of joint distributions) increases.

In this study, we express the choice of vehicle type via an MNL model where U_{in} represents the random utility of vehicle type i for shipper (carrier) n , V_{in} is the deterministic part of the utility of vehicle type i for shipper (carrier) n , X_{in} is a K -dimensional vector of attributes x_{kin} of vehicle type i for shipper (carrier) n , and ε_{in} is an error term that is assumed identically and independently Gumbel distributed:

$$U_{in} = V_{in} + \varepsilon_{in} = \sum_{k=1}^K \beta_{ki} x_{kin} + \varepsilon_{in} \quad (2.1)$$

The probability that vehicle type i is selected by shipper (carrier) n among the alternatives j (where $j = 1, \dots, J$) is equal to:

$$P_{in} = Pr \left[(V_{in} + \varepsilon_{in}) \geq \max_{\substack{j \in J \\ j \neq i}} (V_{jn} + \varepsilon_{jn}) \right] \quad (2.2)$$

The maximum utility U'_{jn} of the unchosen alternatives j for individual n is decomposed into a known part V_{jn} and an unknown part ε_{jn} which according to (Ben-Akiva and Lerman, 1985) is Gumbel distributed with parameters $(\mu, \ln(\sum_{j \neq i} \exp(\mu V_{jn})/\mu))$, so we can write:

$$U'_{jn} = \max_{j \in J, j \neq i} (V_{jn} + \varepsilon_{jn}) = \left(\frac{1}{\mu} \ln \sum_{j \neq i} \exp(\mu V_{jn}) \right) + \varepsilon_{jn} \quad (2.3)$$

Since the difference of two random terms with the same mean μ has itself a mean of zero, we can write:

$$P_{in} = Pr \left[(\varepsilon_{jn} - \varepsilon_{in}) \leq \left(V_{in} - \ln \left(\sum_{j \neq i} \exp(V_{jn}) \right) \right) \right] \quad (2.4)$$

The error terms resulting from discrete choice models follow the generalized extreme value type I distribution; thus the difference of two Gumbel-distributed random variables, $\varepsilon^* = (\varepsilon_{jn} - \varepsilon_{in})$ has a logistic distribution with the following cumulative distribution function which equals (Pourabdollahi et al., 2013):

$$F(X) = F \left[V_{in} - \ln \left(\sum_{j \neq i} \exp(V_{jn}) \right) \right] = \frac{1}{1 + \exp \left(V_{in} - \ln \left(\sum_{j \neq i} \exp(V_{jn}) \right) \right)} \quad (2.5)$$

Although the initial assumption is that all variables are utility terms, in this study we test the possibility that some variables are regret terms. Namely, we test the possibility that a hybrid utility-regret formulation is more suitable to represent the choice behaviour of shippers and carriers. Generally, this hybrid specification of V_{in} is (Chorus et al., 2013):

$$V_{in} = \sum_{k=1}^q \beta_{ki} x_{kin} - \sum_{j \neq i} \sum_{k=q+1}^K \ln \left(1 + \exp \left[\beta_{ki} (x_{kjin} - x_{kin}) \right] \right) \quad (2.6)$$

The shipment size model takes the form of a log-linear regression that guarantees non-negative shipment sizes, where y_n represents the logarithm of the shipment size chosen by shipper (carrier) n as a function of a vector Z_{kn} of shipment attributes and a vector of unobserved factors τ_n that are assumed to be normally distributed.

$$y_n = \sum_{l=1}^L \gamma_l z_{ln} + \tau_n \quad (2.7)$$

Let $G(y)$ represent the probability that shipper (carrier) n chooses a shipment size smaller than y . The probability that the random variable y lies approximately around the observed shipment size y is calculated by $\phi(y+\delta) - \phi(y-\delta)$ as follows:

$$G(y) = \phi(y + \delta) - \phi(y - \delta) = \frac{1}{2} \left[\operatorname{erf} \left(\frac{y + \delta - \mu_y}{\sigma \sqrt{2}} \right) - \operatorname{erf} \left(\frac{y - \delta - \mu_y}{\sigma \sqrt{2}} \right) \right] \quad (2.8)$$

where ϕ is the probability density function of the mean value μ_y , σ is the variance, and δ is a very small value. Accordingly, the joint probability that vehicle type i and shipment size y are chosen by shipper (carrier) n is expressed in (2.9), where $\tau^* = \tau' - \tau$, and τ' is the disturbance term of unchosen shipment sizes:

$$P(\varepsilon^*, \tau^*)_n = \Pr \left[\varepsilon_{jn} - \varepsilon_{in} \leq \left(\sum_{k=1}^K \beta_{ki} x_{kin} - \ln \left(\sum_{j \neq i} \exp \left(\sum_{k=1}^K \beta_{kj} x_{kjin} \right) \right) \right), \tau'_n - \tau_n \leq (\phi(y + \delta) - \phi(y - \delta)) \right] \quad (2.9)$$

The use of the copula allows us to join the separate one-dimensional distribution functions to form a multivariate distribution. Copula-based models capture the dependency between the unobserved terms ε^* and τ^* in the vehicle type and shipment size models. Based on Sklar's theorem, there exists an unique copula that connects these two variables (Sklar, 1973). For a review on copula models, see (Trivedi and Zimmer, 2007).

In this study, we aimed for comprehensive copulas not restricted to specific multivariate distributions, allowing for both positive and negative dependence, and defining a symmetric dependence structure, since we assumed that the unobserved factors have the same effect on increasing as well as decreasing the probability of choosing a certain vehicle type and shipment size. Accordingly, we excluded from consideration copulas that are constructed from normal multivariate distributions (e.g., Gaussian), copulas that cannot handle negative dependence (e.g., Joe, Clayton), and copulas that model strong correlation in either higher or lower values with one-tail dependence (e.g., Gumbel). Accordingly, we investigated Archimedean copulas that satisfy our needs and are easier to derive (Trivedi and Zimmer, 2007). From these, we used the Frank copula (Frank, 1978; Charpentier et al., 2007), with the cumulative density function (CDF) in (2.10), and probability density function (PDF) in (2.11).

$$P(x, y)_n = C_\theta(F(x)_n, G(y)_n) = -\frac{1}{\theta} \log \left(1 + \frac{(e^{-\theta F(x)_n} - 1)(e^{-\theta G(y)_n} - 1)}{(e^{-\theta} - 1)} \right) \quad (2.10)$$

$$p(x, y)_n = \frac{\partial^2 C_\theta(F(x)_n, G(y)_n)}{\partial F(x)_n \partial G(y)_n} F(x)_n G(y)_n = \frac{-\theta(e^{-\theta} - 1)e^{-\theta(F(x)_n + G(y)_n)} F(x)_n G(y)_n}{\left((e^{-\theta} - 1) + (e^{-\theta F(x)_n} - 1)(e^{-\theta G(y)_n} - 1)\right)^2} \quad (2.11)$$

Assuming the independence of the joint choice observations over the decision makers (shippers/carriers), the log-likelihood function LL is expressed in (2.12). Alternately, if we assume the independence of vehicle type and shipment size choices, the log-likelihood function follows (2.13).

$$LL = \sum_{n=1}^N \log \left(\frac{-\theta(e^{-\theta} - 1)e^{-\theta(F(x)_n + G(y)_n)} F(x)_n G(y)_n}{\left((e^{-\theta} - 1) + (e^{-\theta F(x)_n} - 1)(e^{-\theta G(y)_n} - 1)\right)^2} \right) \quad (2.12)$$

$$LL = \sum_{n=1}^N \log(F(x)_n \cdot G(y)_n) \quad (2.13)$$

2.3.2 Model estimation

The estimation of the joint copula-based discrete-continuous model involves estimating the marginal CDFs $F(x)_n$ and $G(y)_n$ and the joint CDF $C_\theta(F(x)_n, G(y)_n)$.

Depending on the available information on the marginal distributions, the copula parameter is usually estimated in three ways: (i) a fully parametric maximum likelihood (ML) method, (ii) a stepwise parametric or inference functions for margins (IFM) (Joe and Xu, 1996), or (iii) a semiparametric pseudo-maximum likelihood approach. The first estimation method requires assumptions about the type of distribution for the copula parameter (θ). The second approach decomposes the problem into a multistep estimation procedure where, in the first step, the parameters of the margins are estimated under an independence assumption using individual likelihood functions. Then, the dependency parameter of the copula (θ) is estimated by maximizing the copula log likelihood function with the marginals replaced by their estimated values. However, when empirical marginals are available, the third approach is preferred.

Having an initial assumption about the type of marginal distributions, we used the fully parametric ML method that enables us to estimate the dependency parameter as well as coefficients of the two choices simultaneously. To solve the likelihood maximisation problem, we applied the L-BFGS-B (Limited memory Broyden-Fletcher-Goldfarb-Shanno algorithm with boundary) algorithm, as it is one of the commonly used algorithms for

maximum likelihood (Byrd et al., 1995). This algorithm is an iterative local search algorithm (hill climbing optimization family) that approximates the analytical Newton–Raphson method and has been proven to be efficient when the function is not necessarily concave (Lewis and Overton, 2009). Considering that the surface of the log–likelihood function of the copula is not globally concave (as shown empirically later in Figure 10) finding the maximum is not straightforward.

Accordingly, the following considerations were applied for model estimation:

- We ensured that the predictor variables did not differ vastly in scale, as differences by at least an order of magnitude created scaling problems.
- After solving the scaling problem, we reflected on the expected sign of parameters in order to have reasonable initial values for the optimization algorithm.
- After testing for different initial values, we searched for possible misspecification that might manifest itself, as the Hessian tends to zero for some parameters. As this result is most likely because of the correlation between two parameters that leads to having a flat surface of the likelihood function, we removed those parameters from the model.
- As the second partial derivatives of the copula function are too complex and cumbersome to code, we used the BHHH algorithm as a good approximation (Berndt et al., 1974), (Hensher et al., 2015).
- As the analytical computation of the gradient and the Hessian matrix is very complex, we used numerical methods (A Brodtkorb and D'Errico, 2015). Numerical gradients can be approximated via an iterative algorithm which starts by calculating the log–likelihood for initial values, and then recalculating the difference of the function by subtracting or adding a small value (δ) to each parameter, one at a time (D'Errico, 2013).

We considered that the inverse Hessian matrix is also obtainable through the BFGS algorithm; however, precise validations by Greene (2012) revealed that it is not sufficiently accurate for calculating the standard errors and, after optimization, the second partial

derivative should be computed separately (Hensher et al., 2015). Thus, initially we used the BFGS algorithm to find the set of significant variables and then we used numerical methods to calculate the standard errors in the final models.

2.3.3 Data

The data for this study were obtained from a freight vehicle survey done in 2008 in Mashhad, the second most populous city in Iran. In order to obtain a complete profile of truck movements, a sample was chosen from every category of freight actors, using a stratified random sampling method in which 20% of the actors were interviewed personally and were asked to report about their daily trips. The categories of freight actors for the sample included intra-urban and intercity carriers and for-hire pickup vans, interviewed across the city. Figure 9 shows a summary of the survey data for for-hire carriers and ancillary shippers.

The questionnaire included information on time-of-day, commodity type, type of vehicle, shipment size (tonnage), origin and destination. Given the focus of our study, we excluded empty movements from which the relationship between shipment sizes and vehicle type could not be determined. We also excluded drivers, as they could not be clearly categorized as shippers or carriers. Accordingly, the final data set included 550 observed trips for shippers and 1484 observed trips for carriers.

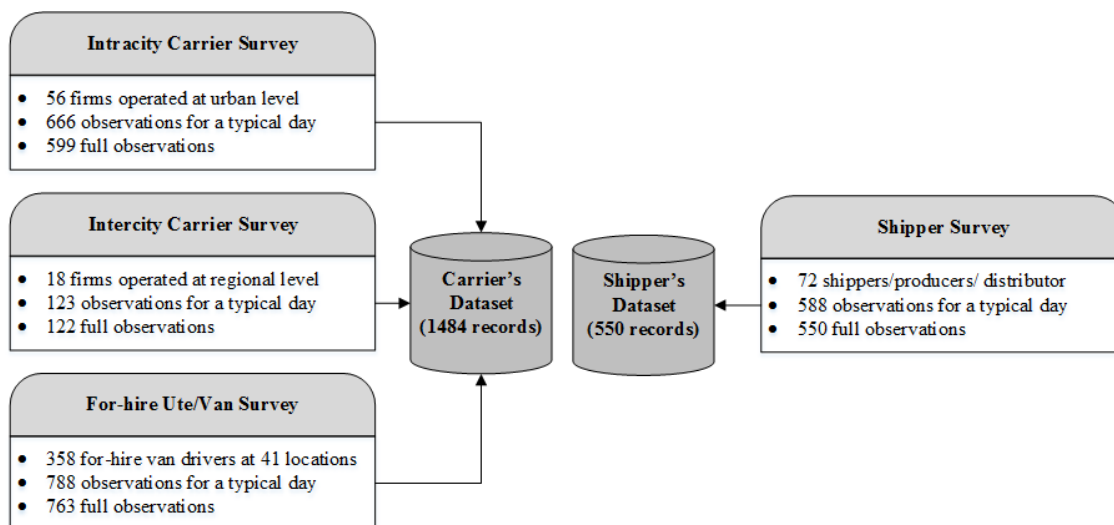


Figure 9 – Dataset

2.4 Results

Initially, the two models were estimated separately in order to have plausible initial values for the estimation of the joint model. The vehicle type discrete choice model was estimated with Biogeme (Bierlaire, 2003) and the log–linear regression of shipment size was estimated with SPSS (IBM Corp, 2016). Normality and partial correlation between the predictor variables were checked, and iteratively all potential explanatory variables were examined individually in various forms to test whether they were statistically significant at least at the 10% level in either utility or regret form. If they were significant, the variables were retained in the model. Finally, the joint model was estimated as discussed in the estimation section in a Python environment using the fmin–BFGS algorithm and SciPy package (Jones et al., 2015) on an Intel(R) Core™i7–4770 CPU @ 3.40 GHz and 16.0 GB RAM.

As mentioned in the introduction, we specified two separate copula models for shippers and carriers. We also postulated that the comparison among different vehicle types is not only based on the decision maker (shipper or carrier), but also on the processing of some attributes using regret rather than utility terms. The best model specification revealed that the hourly hire cost of a vehicle is statistically significant as a regret term in the carrier copula model [likelihood ratio test with respect to the utility based model: 5.5, p–value: 0.019]. This implies that carriers try to maximize their total utility while trading off various vehicle types based on the hire price of the vehicle; whereas, this is not the case for shippers, likely because they might already own the vehicle and do not have to pay any hire costs.

The best model specifications of the two models for shippers and carriers are presented in Table 3, where the van was chosen as the base alternative. When looking at the estimates, it appears that for longer distances, carriers have a preference for larger vehicles over vans as well as larger shipment sizes, while from the shippers' perspective only trailers are preferable over vans for longer trips.

The dummy variable of transporting goods at night is statistically significant with a positive sign for carriers using large trucks and trailers, which indicates the preference of larger vehicles for night deliveries. Trucks and then vans appear to be preferred by shippers for night deliveries, possibly because some shippers have limited working hours from 9am

to 5pm. Interestingly, it seems that shippers tend to increase shipment sizes when the delivery time is at night. When looking at the dummy variable for the afternoon peak, smaller shipment sizes are transported by carriers, probably due to congestion on the urban network. Based on the sign of the coefficient for the dummy variable for external trips, trailers are preferred for intercity shipments rather than vans, from the carriers' perspective.

When looking at the estimates by commodity, it appears that certain commodity types are related to the shipment size and vehicle type choices. This is likely because some commodity types are specifically carried by for-hire carriers, for example furniture and general household commodities, whereas some others such as services and agricultural products are mostly transported by shippers. However, the different sign for fuel products on shipment sizes in shipper and carrier models highlights the fact that, although the shipments are grouped based on their type, they might not be necessarily homogeneous. For example, products of oil consumed for general purposes in small quantities might have been grouped with fuel shipments consumed at gas stations or big factories.

The results imply that heavy trucks and trailers are preferred to carry construction, industrial and manufacturing commodities from the carriers' perspective. Shippers tend to increase the size of industrial shipments, but are less likely to use light trucks for transporting these commodities. The results also indicate that shippers are more likely to distribute food products in larger volumes with light trucks, while carriers are less likely to transport food products by trailer. Moreover, the carriers prefer vans for carrying perishable foods. This is likely because most refrigerated vehicles used for the distribution system are categorized as vans. The results also reflect the preference of shippers for light trucks over vans, since most local farms around the city are small rather than large-scale farms.

Both joint copula models improved the goodness of fit in comparison with the independent copula model, as the likelihood ratio test shows the rejection of the null hypothesis that these decisions are independent. Also, the estimated dependency parameters have a significant *t*-statistic, which suggests that the unobserved factors simultaneously affect both vehicle type and shipment size choices. However, the magnitude of the dependency is slightly higher for shippers.

Table 3 – Models estimates

Variables	Shippers					Carriers				
	Vehicle Type (MNL)				Log-linear regression (Shipment Size)	Vehicle Type (hybrid RRM)				Log-linear regression (Shipment Size)
	Van	Truck	Heavy truck	Trailer		Van	Truck	Heavy truck	Trailer	
constant	–	0.86 (1.13)	–2.07 (–0.85)	7.59 (9.52)***	–0.034 (–1.84)*	–	0.09 (1.41)	0.175 (1.52)	0.438 (2.25)***	–0.57 (–37.27)***
Distance	–	–	–	4.86 (5.67)***	–	–	0.34 (3.01)**	0.23 (2.59)***	4.87 (5.83)***	0.008 (2.16)**
Night a		9.81 (11.82)***	–2.57 (–1.68)*	–5.62 (–4.5)***	0.44 (2.02)**	–	–	0.0008 (1.99)**	0.05 (1.97)**	–
External trips b	–	–	–	–	–0.16 (1.67)*	–	–	–	0.0076 (7.58)***	–
PM peak hour	–	–	–	–	–	–	–	–	–	–0.006 (1.88)**
Commodity type	fuel and products	–	–	–	0.007 (1.63)*	–	–	–	–	–0.076 (–1.66)*
	construction	–	–	–	–	–	–	0.046 (2.01)**	0.063 (2.09)**	–
	non-fresh food and beverage	–	4.17 (2.06)**	–	0.007 (1.71)*	–	–	–	–0.042 (–1.97)**	–
	perishable foods	–	–	–	–	–	–0.069 (–2.0)**	–0.074 (–1.99)**	–0.072 (–1.98)**	–0.039 (–1.86)**
	agricultural products	–	5.86 (2.20)**	–	–	–	–	–	–	–
	industrial and machinery	–	–3.7 (–3.24)***	–	0.05 (1.86)*	–	–	0.083 (2.02)**	0.22 (2.32)**	–
	household, furniture	–	–	–	–	–	–0.045 (–1.94)*	–0.057 (–1.98)**	–0.02 (–2.11)**	0.037 (2.29)**
	service	–	–	–	0.13 (1.92)*	–	–	–	–	–
Hire rate of vehicles per hour (regret attribute)	–					–0.156 (–6.01)***				
Dependency parameter of Copula	16.94 (15.45)***					14.67 (25.22)***				
Kendall's tau	0.27					0.24				
Number of observations	550					1484				
Likelihood ratio test (df = 1)	1099					2265				
a If time of shipment is after 8:00 PM					b If either one leg or both legs of the trip are located outside of the city					
***, **, * significance at 1%, 5%, and 10% level, respectively.					Values in the parenthesis are t-statistics values, (–) Indicates being not significant					

The dependency parameter of the copula can be converted into a Kendall correlation coefficient by using the copula R package (Kojadinovic and Yan, 2010) as shown in Table 3. The Kendall correlation coefficient is a measure of rank correlation for discrete variables (e.g. as marginal values for each shipper/carrier), which is calculated as the probability of concordance minus the probability of discordance (Kendall, 1938). The positive correlation (as shown in Figure 10) implies that the unobserved factors that increase the propensity of choosing vehicle type i also increase the shipment size. As Figure 10 shows, this correlation for carriers is more mild than for shippers as the dependency parameter also is lower.

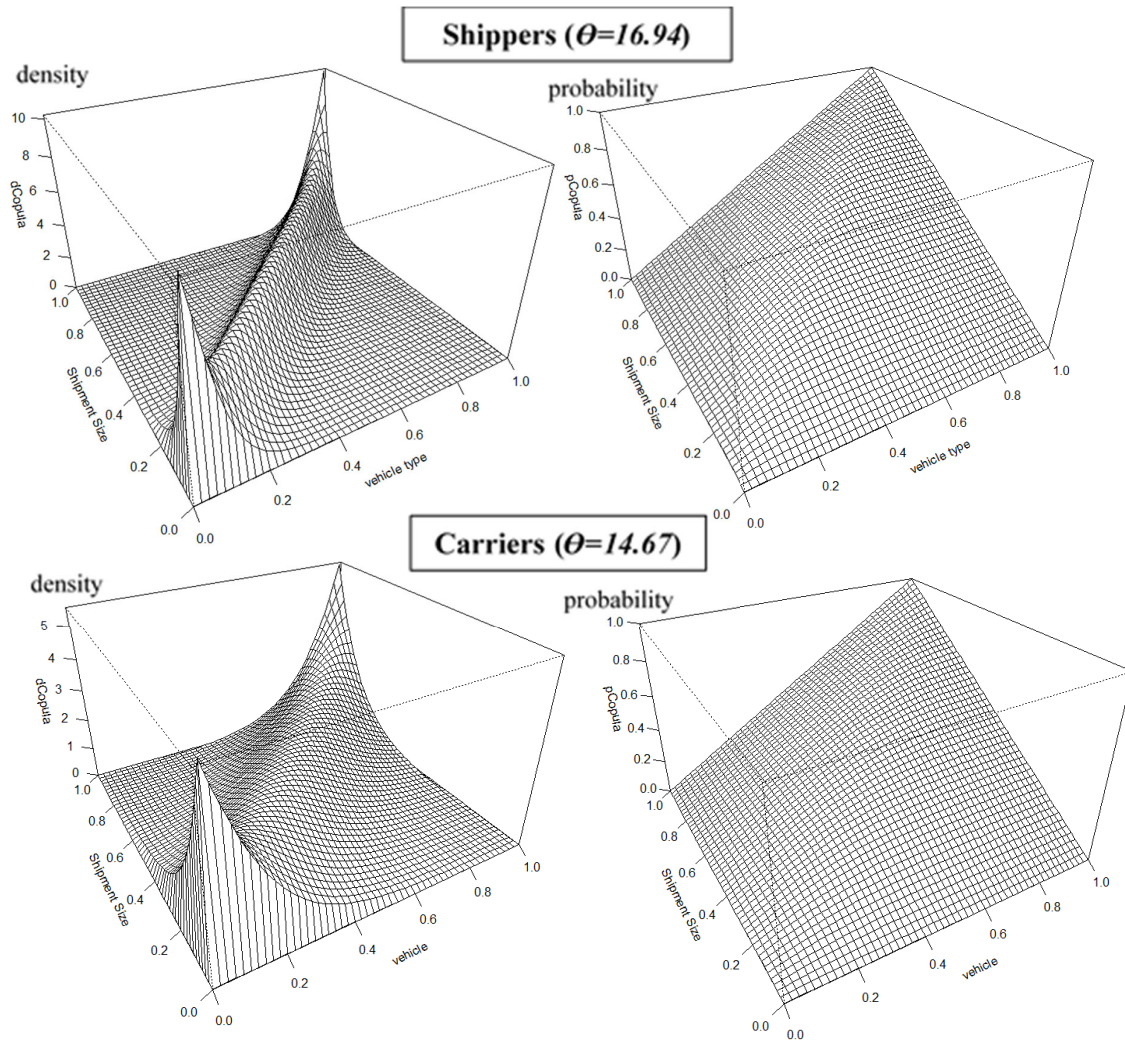


Figure 10 – Density and probability function of fitted copula

It should be noted that a critical assumption in the derivation of the MNL model is that the alternatives do not share any unobserved effects, and the error terms are independently and identically distributed. The consequent independence from irrelevant alternatives (IIA) property was tested in Biogeme for the initial independent model by using the McFadden omitted variable test (McFadden, 1987). The test showed that the null hypothesis cannot be rejected, which means that the IIA property holds. In turn, this implies that the unobserved characteristics over different vehicle types are not correlated.

Furthermore, MNL models assume taste homogeneity across observations. Hence, we tested for the existence of unobserved heterogeneity across the samples since our dataset consists of various shippers and carriers with different firm size and scale of operations. We estimated a Mixed Logit model that revealed that there was no taste heterogeneity in the parameters, possibly because of the smaller sample size. Accordingly, the MNL models are suitable given that the shippers' and carriers' preferences towards different vehicle types in our case study are homogeneous across the respective populations.

2.5 Discussion and conclusions

Model estimation was undertaken on a dataset of 550 shippers' observations and 1484 carriers' observations in Mashhad, Iran. The findings from this study reveal that using heavier vehicles in longer trips by both operators (shippers/carriers) as well as increasing the shipment size proves the economies of scale and distance, in line with previous studies (Abate and de Jong, 2014). Furthermore, carriers' preferences for heavier vehicles over vans for intercity movements and night deliveries, as well as decreasing the shipment size during afternoon peak hours, appear as the result of passage restrictions of heavy vehicles in the congested urban network, particularly during the day hours.

Regarding the estimates of the effects of commodity type, the results show that carriers tend to ship construction and industrial commodities with heavier vehicles, while perishable foods and household commodities are mainly transported by vans. However, the positive sign in the shipment size model reveals that household items and furniture are among the most voluminous commodities, whereas perishable foods and fuel products are transported in smaller sizes by for-hire carriers.

Considering the estimates of the shippers' model, commodities such as fuel, food and beverages, industrial and manufacturing commodities, as well as services, are shipped in larger sizes, particularly when the time of delivery is not during the day hours. Also, light trucks seem to be an efficient alternative over vans for carrying food and agricultural products, as well as for those shippers who have extended working hour at night. Conversely, the light trucks are less likely to be used for industrial and manufacturing commodities.

There are several conclusions that can be drawn from the empirical results. The important research hypothesis is the interrelationship between vehicle type and shipment size, which was validated in the empirical results by obtaining a significant dependency parameter of the copula. The second research hypothesis was the difference between preferences of shippers and carriers. Looking at the variables and the estimated level of significance proved the validity of different decision-making behaviours. The other major hypothesis that was verified includes the finding that carriers compare the hourly hire price of various vehicle types explicitly, as well as the total utility they get from each vehicle type, based on the shipment characteristics.

While the results prove that the proposed model is capable to estimate the joint choices very well, further avenues for research are foreseen. First, while we can make inference about the dependency and significance of the variables of two decisions by applying the Frank copula model, this depends on the context, and other models might be more applicable such as conditional probability hierarchical copulas or other types of copulas. Further research can be done on formulating other copula models and studying the tail dependence of these two choices, as well as developing a nested copula to model more than two joint decisions, such as tour and stop, route or shipment bundling choices. Secondly, fleet ownership might be relevant, although we had no data in this study about whether all shippers own their own trucks or some contract out to carriers.

Chapter 3: The choice of using distribution centers in the container import chain: a hybrid model correcting for missing information

Presented at the 10th International conference on City Logistics, 14th–16th June 2017, Phuket, Thailand, published in the City logistics: Towards sustainable and liveable cities. Vol 3. 2018. ISTE ; John Wiley & Sons.

Elnaz Irannezhad, Carlo G. Prato, Mark Hickman

3.1 Abstract

Distribution centres are considered a sustainable way to decrease the impacts of heavy vehicle movements in urban areas. These transshipment points, which are used either for consolidation, deconsolidation, or cross–docking between different modes or vehicles, help to achieve an effective logistics operation. Therefore, the choice of freight actors to use these facilities is of great interest to logistics managers. This paper examines the choice of using distribution centres in the container import chain, either as an intermediate stop or a location for unpacking, versus direct haul delivery. The data used in this research is drawn from the Import/Export study for the Port of Brisbane, Australia in 2013. As some of the relevant attributes for the choice model may be missing (as is typical in freight studies), the key contribution of this research is in specifying a hybrid choice model where missing information has been treated as a latent variable. Another key contribution is that the results reveal how both the land use at destinations and the number of employees in various sectors play an important role in the choice, in addition to the effects of commodity type on the choice process. Practical findings of this study are: (i) the shipments that are stored in distribution centres have smaller sizes with longer distances, whereas shipments with heavier weight or those that arrive on weekends are delivered directly; (ii) distribution centres are used more when the arrival time is earlier during the day; (iii) the weight of shipments is heavier when the shipments are destined to suburbs with higher commercial land use area, and also when

they are destined to suburbs with a high number of employees in wholesale trade; (iv) the probability of using a distribution center as an intermediate stop increases with an increase in the number of major retailers and the smaller number of employees in the wholesale sector in the destination zone; (v) agricultural commodities are most likely to be transported directly, whereas direct delivery is less preferred when the number of major industrial parks at the destination suburb increases.

3.2 Introduction

With the global growth of containerization, distribution centres (DCs) play an important role to counteract the negative effects of city freight logistics. The primary goal of city logistics managers is to develop strategies that improve customer (importer/exporter) satisfaction through a faster, more economic, and efficient way of moving freight. Secondary objectives include reducing externalities such as pollution, congestion, and land use impacts, and driving economic growth through logistics operations. However, because urban DCs impose an extra cost on carriers, they are unlikely to be successful without the financial support from the city authorities, as their usage has been estimated to be higher in theory than it later turned out to be in practice (Kawamura and Lu, 2006; Kant et al., 2016). Therefore, it is important to understand what attributes affect the choice of direct delivery (without using DCs) versus DCs as either an intermediate stop or a terminal stop for storage or packing/unpacking.

Although the logistics literature is not devoid of studies that embed the use of DCs in the modelling process, modelling the decision to use DCs has not received considerable attention. Goodchild et al. (2008) addressed a gap in the literature by capturing underlying economic forces that make it beneficial for shippers to use multimodal DCs at ports. Carriers' decisions to use DCs and the policy implications of these decisions were modelled with an agent-based approach in other recent works (van Duin et al. (2012); Teo et al. (2015). Davydenko and Tavasszy (2013) presented an extension of a four-step freight model with a logistic chain model. They applied a two-step model that estimates the volume of regional DC throughput by applying gravity model (Davydenko et al., 2014; Davydenko, 2015; Davydenko, 2016). Kim et al. (2010) estimated a logit model of the distribution channel choice, where the alternatives were a direct channel, the channel through a wholesale store, the channel through a DC, and the channel through outsourcing logistics. Relevant parameters were the market characteristics (i.e., population and firm density),

commodity type, average order frequency, company size, and annual sales. The remaining body of literature concerning DCs is concerned with the design of efficient logistics and infrastructure networks, where the focus is on the optimisation of the location of the DC and/or its allocation to freight consumption points, either for a specific commodity (e.g. (Maurer, 2008; Friedrich, 2009), or a container chain (e.g. (Limbourg and Jourquin, 2009; Davydenko and Tavasszy, 2013; Gu and Lam, 2013; Zhang, 2013; Halim et al., 2016). Agent-based models are also used to analyse policy impacts on the use of CTs (e.g. (van Duin et al., 2012; Teo et al., 2015), but none of these researches investigated the factors underlying the preferences for DC usage.

Thus, the objective of this study is to investigate the relationship between shipment characteristics and the decision to use DCs in the container import chain, either as an intermediate stop or as a location for unpacking. DCs in container chain is a facility built to provide a trans-shipment point between sea and hinterland transportation for containers in import and export chains. In DCs, containers can be deconsolidated (in import chains), consolidated (in export chains), or stored for subsequent delivery with more cost-effective and higher-utilisation vehicles with more flexible time-windows.

More specifically, we explore this relationship through a discrete choice model on the use of DCs. As some of the relevant attributes for modelling this choice may be missing among the survey data (e.g., commodity type, weight, or shipment arrival time), this study proposes the use of a hybrid choice model to compensate for the missing observations while producing unbiased estimates for the choice model. Thus, this study focuses on the choices that importers make as to whether to ship containers directly from stevedores to the final destinations or to use DCs as an intermediate stop to transship (unpacking and delivering in smaller quantities). Critically, this study answers this question while it also solves the issue of the missing data that may be typical in freight survey data.

It should be noted that, in most choice models, records with missing data are often removed prior to the analysis. However, when the percentage of missing data is significant, removing the invalid records or missing responses causes the estimates of coefficients in the choice model to be biased. The main body of literature on the non-response problem belongs to imputation (Ramalho and Smith, 2002), but latent variable models have also been applied in some social science studies. In the latter category, early attempts focused on response and non-response to attitudinal items. Knott et al. (1991) used a latent variable

model to recover information from the pattern of non-response when studying attitudes towards abortion; Albanese and Knott (1992) defined a two-dimension latent variable model for handling missing values of binary attitudinal responses in which both variables were assumed to be normally distributed and independent. Muirheartaigh and Moustaki (1999) included metric latent variables. Notably, all of these studies were unable to handle more than two latent variables due to computational difficulties. Ramalho and Smith (2002) proposed a likelihood-based approach to deal with missing data in discrete choice models when there is either “unit non-response” or “item non-response.” Sanko et al. (2014) addressed a missing response for household income with hybrid choice models using both SP and RP data.

Accordingly, this study presents a hybrid choice model for treating missing data in full container movements in the import chain and providing unbiased estimates of the determinants for the choice of using DCs. The case study considers that nothing is known about the contents of containers, but yet there is considerable missing data for the arrival time at the destination and for the weight of the shipment. Therefore, two latent variables were specified, one for missing values of arrival time, and other for commodity type in interaction with the weight of the shipment.

3.3 Methods

3.3.1 Data

Container shipments entering the Port of Brisbane (Australia) were chosen for the case study. The dataset was provided by the Port of Brisbane Import/Export Logistics Chain Study (PBPL, 2013) and includes the details of individual container movements: identification number, timestamps of arrival and departure, postcodes of origin and destination, weight of shipment, and size of container. This study focuses on the movements of full containers in import chains (8167 records) which are destined into different suburbs, mainly in Brisbane and some across the state, as shown in Figure 11. However, the spatial movement by tonnage is different as shown in Figure 12.

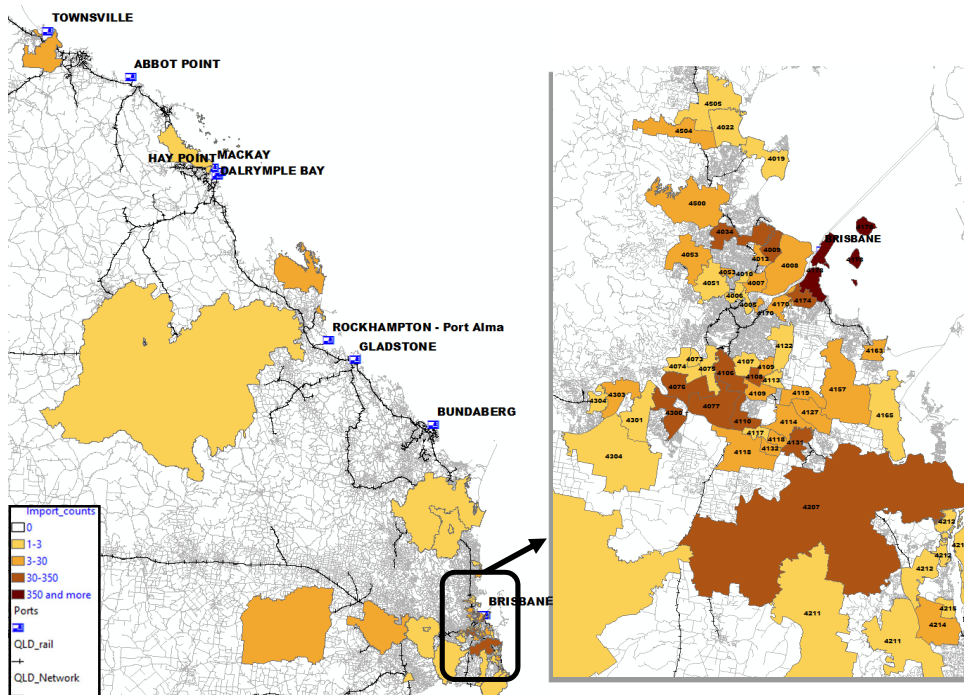


Figure 11 – The number of containers destined for importers (categorized by quantile)

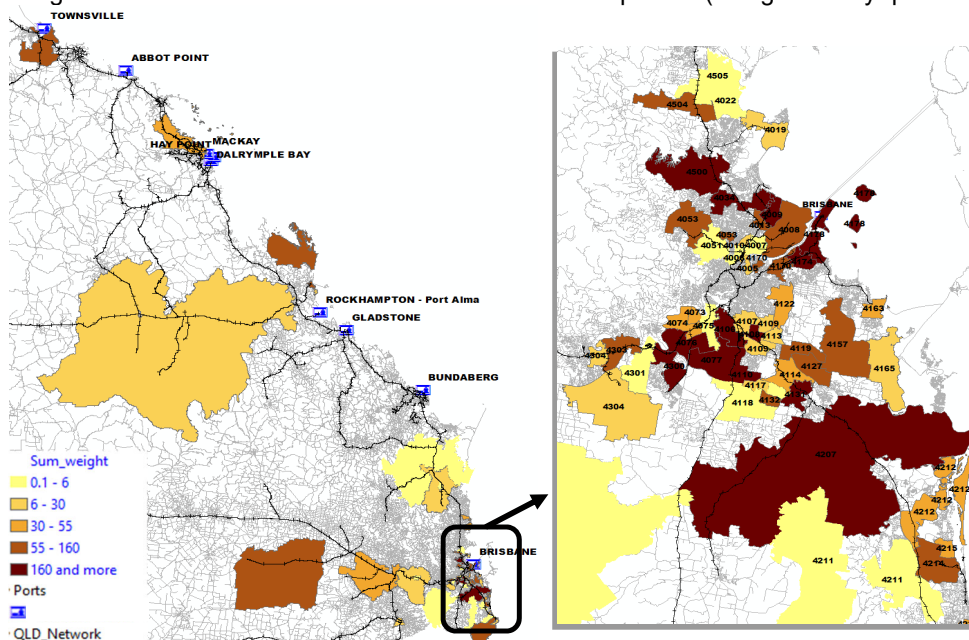


Figure 12 – Tonnage of containers destined for importers (categorized by quantile)

Figure 13 shows the datasets and derived parameters to be examined as explanatory variables in the choice model.

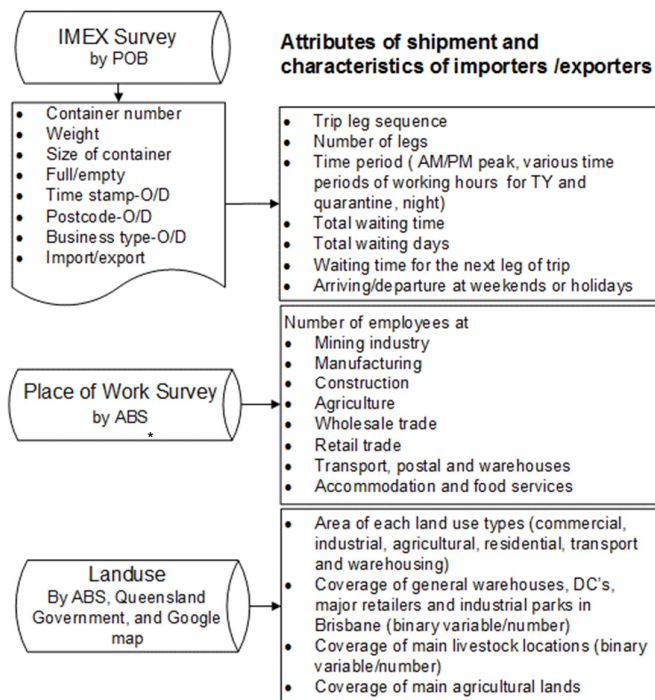


Figure 13 – Datasets available for the study

The import containers are disposed in one of three ways, as summarized in Figure 14: (A) they are unpacked at DCs located inside or close to the port (44%); (B) they are stored for a couple of hours or days and then are handled to the importers (28%); (C) they are directly delivered to importers (28%). There is no information on the final destination of shipments unpacked at DCs, but it can be inferred that those shipments are in smaller quantities which have been bundled with other shipments in one container. In options (A) and (B), it may also be possible to use land use information at the destination in interaction with the weight of a shipment to infer a type of commodity; then, one could relate the choice of using a DC with different commodity types.

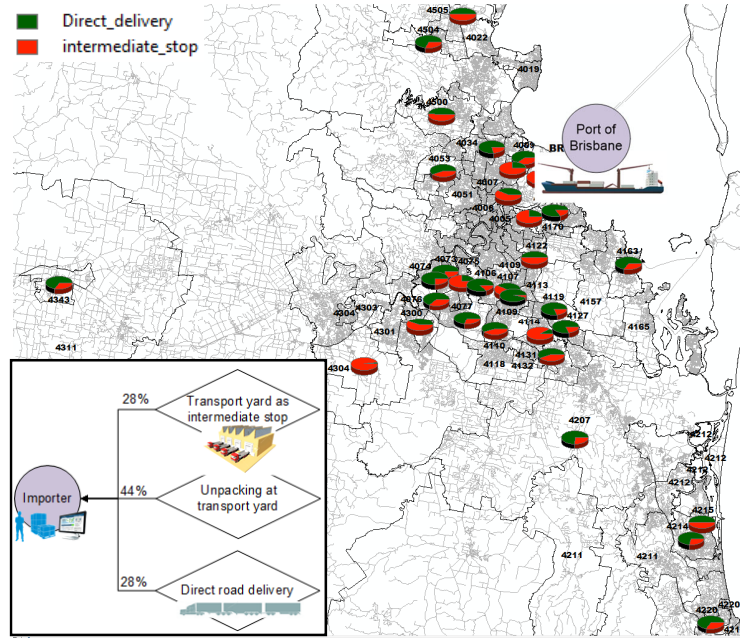


Figure 14 – Patterns of using DCs

3.3.2 Model formulation

We consider the choice of using a DC within the framework of a traditional random utility model where shippers seek to maximize their utility. The utility U_{in} of alternative i (either direct haul (choice A), storage at DC (choice B), or unpacking at DC(choice C)) for importer n is expressed as a function of a vector z_n of socio-economic characteristics of importer n and a vector x_{in} of attributes of alternative i for importer n :

$$U_{in} = V(z_n, x_{in}; \beta) + \varepsilon_{in} \quad (3.1)$$

where β is a vector of coefficients to be estimated and ε_{in} is a random error component.

The hybrid choice model (Walker (2001)) integrates latent variable models within the DC choice model, with the latent variables being partial or completely missing from the database. Consider a variable z_n with missing data; it is possible to express the variable as a latent variable α_n via a structural equation:

$$\alpha_n = g(z_n^*; \gamma^s) + \sigma^s \omega_n^s \quad (3.2)$$

where z_n^* is a subset of the vector of explanatory variables z_n (obviously excluding the variable of interest), γ^s is a vector of coefficients to be estimated, ω_n^s is assumed a normally distributed random error component, and σ^s is the scale.

It should be noted that the definition of latent variable is simply that the variable cannot be measured directly. In this case, we have a single indicator (PI_n) for each latent variable which would be given by the z_n values, in order to retrieve an estimate of the missing values (actually, it is used to retrieve the measurement of the variables for all values), as suggested by Sanko et al. (2014):

$$\begin{cases} PI_n(z_n) = g(\alpha_n, \varsigma_i) & \text{if } z_n \text{ is observed} \\ PI_n(z_n) = 1 & \text{if } z_n \text{ is not observed} \end{cases} \quad (3.3)$$

where ς_i is a vector of estimated parameters.

Since the latent variables are not fully observed, the choice probability is obtained by integrating over the distribution of the error components of the latent variables α_n :

$$L = \int_{\alpha_n} \sum_n \ln [PC_{in}(y_{in} | x_{in}, z_n^*, \alpha_n; \beta_{xi}, \beta_{zi}, \beta_{\alpha}) PI_n(z_n) \phi(\alpha_n) d\alpha_n] \quad (3.4)$$

where PC_{in} is the probability of the choice i made by importer n , ϕ stands for the normal density function, β_{α} is the parameter associated with z_n , latent variable α_n , and y_{in} is the indicator which equals one if it is the chosen alternative and zero otherwise. The probability of choosing to use a DC has a multinomial logit (MNL) formulation according to (3.5).

$$PC_{in} = \frac{\exp(\beta_x x_{in} + \beta_z z_n^* + \beta_{\alpha} \alpha_n)}{\sum_j \exp(\beta_x x_{jn} + \beta_z z_n^* + \beta_{\alpha} \alpha_n)} \quad (3.5)$$

Since the independence of choice observations over importers is an important assumption to estimate the log-likelihood function described in (3.4), the containers of the same shipping lines, the same origin and destination and within a 15-min threshold in both arrival and departure timestamps were assumed bundled together as one shipment. Thus, the shipment is the modelling unit, which can consist of one or more containers. The hybrid model is estimated by maximizing the simulated log-likelihood. Estimation was performed via Monte Carlo simulation using the PythonBiogeme software (Bierlaire, 2016) using Modified Latin Hypercube Sampling (MLHS) draws (number of draws: 1000) for the random component (Hess et al., 2006).

3.3.3 Model specification

In our case study, out of a sample of 8167 full containers in the import chain, the arrival time of containers at the port and also the reported weight of shipments were missing for 1552 (19%) and 3169 (39%) containers, respectively. The structural equation for the latent variable *weight* expresses the weight of the shipment in interaction with the commodity type, as a function of the characteristics of the ultimate destination of the shipment (for observed choices (A) and (B)), such as the area of commercial land use types in the destination suburb, and the number of employees per industry sector in the destination suburb. The structural equation for the latent variable *time of arrival* is expressed as a function of the number of employees in transport sector, and the area of commercial land use types in the destination zone (km²). These variables were the only statistically significant variables among other examined combinations. It should be noted that the unit of modeling is shipment which may consist of either several containers bundled together or a single container.

$$\log(Time_n) = \gamma_{t,Constant} + \gamma_{t,EmpTransp} EmpTransp_n + \gamma_{t,EmpManuf} EmpManuf_n + \gamma_{t,AreaCom} AreaCom_n + \sigma_t \omega_t \quad (3.6)$$

$$\log(Weight_n) = \gamma_{w,Constant} + \gamma_{w,AreaCom} AreaCom_n + \sigma_w \omega_w \quad (3.7)$$

where $Time_n$ refers the arrival time of the shipment handled from the stevedores, $Weight_n$ is the reported weight of the cargo, $EmpTransp_n$ indicates the number of employees (thousands) in the transport and warehousing sector, and $EmpManuf_n$ represents the number of employees (thousands) in the manufacturing sector at the final destination suburb. $AreaCom_n$ indicates the area of commercial land use (m²). The utility equations of the DC choice model are specified as follows, where the choice (C), unpacking at the DC, is considered as the reference alternative:

$$V_{A,n} = \beta_{1,Constant} + \beta_{1,EmpAgr} EmpAgr_n + \beta_{1,Weekend} Weekend_n + \beta_{1,EmpWholesale} EmpWholesale_n + \beta_{1,IndusPark} IndusPark_n \quad (3.8)$$

$$V_{B,n} = \beta_{2,Constant} + \beta_{2,LatentTime} \log(Time_n) + \beta_{2,Dist} Dist_n + \beta_{2,LatentWeight} \log(Weight_n) + \beta_{2,Retailers} Retailers_n \quad (3.9)$$

where V_A and V_B are the utilities of direct delivery and using DC as an intermediate stop, respectively; $Dist_n$ indicates the total distance on the shortest path from the port to the ultimate destination suburb; $Weekend_n$ is a binary variable which equals 1 if the arrival time

of the container was on a weekend or holiday; *IndustPark* and *EmpAgr_n* indicate the number of industrial parks and major DCs of general cargo at the destination suburb; and, *retailers_n* and *EmpWholesale_n* represent the number of major retailers and the number of employees (thousands) in the wholesaling sector in the destination suburb, respectively.

3.4 Results

Estimates of the hybrid choice model alongside the standalone choice model without latent variables (with and without missing values) are presented in Parameter estimates of employment and distance suggest that the probability of direct delivery also increases with an increase in the number of employees in the agricultural sector, which are mainly in rural areas, and also when the arrival date is on a weekend, while decreases by the higher distance between importer's location and the port. On the other hand, direct delivery is less preferred in the case that the arrival time of shipments is after 7am and if, as well as shipments destined to suburbs with a smaller number of major industrial points (such as distribution centers, warehouses and industrial parks), but higher number of employees at the wholesaling sector. However, the results imply that shipments are most likely to be stored at DCs with increasing numbers of major retailers, while larger shipments either are delivered directly or unpacked at DCs.

Turning to the structural equations for arrival time of shipments from stevedores, missing time values are explained by the number of employees in the manufacturing, transport and warehousing sectors, and by the area of commercial land uses in the suburb. The latent weight is explained by the number of employees in wholesale trade and the area of commercial land uses in the suburb. The estimates show that the weight of shipment increases when the destination of containers is located in a suburb with a higher wholesale trade sector and higher commercial land use area.

Table 4 implies that the inclusion of missing observations outperforms the choice model with only observed values. However, the inclusion of latent variables not only notably improves the goodness of fit measures, but also, by applying a joint maximum likelihood estimation across both model components, overcomes the bias inherent in removing missing data. When comparing the models, the first model in which missing values were excluded has a far lower number of observations, and this justifies the estimation of the remaining two models. The second model has a significant parameter for the missing

values (i.e. time and weight), which suggests that there is a bias in estimating only parameters based on the observed information while ignoring the missing data. Accordingly, this justifies the estimation of the third model.

This result confirms previous findings by Sanko et al. (2014) that, in a hybrid framework, the latent variable can be used to explain the missing information based on other characteristics, easily circumventing the endogeneity problem, selection bias and loss of efficiency which will occur due to imputation or removal of missing data.

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Table 4 – Estimation results for choice model

Parameters	Standalone MNL (excl missing values)	Standalone MNL (with missing values)	Hybrid Choice model	
			Choice model	Latent variable model
β1,Constant	-0.718 (-11.61)	-1.150 (-19.50)	-1.150 (-19.50)	yw,Constant -4.600 (-142.05)
β1,EmpAgr	0.027 (4.79)	0.030 (5.10)	0.030 (5.09)	yw,AreaCom 0.056 (3.14)
β1,Weekend	3.150 (5.15)	3.270 (6.20)	3.280 (6.28)	ow a 1.280 (33.10)
β1,EmpWholeSale	6.310 (4.26)	9.270 (4.04)	9.270 (4.05)	yt,Constant -0.078 (-13.75)
β1,IndusParks	-0.264 (-6.06)	-0.113 (-3.27)	-0.112 (-3.28)	yt,EmpTransp -0.028 (-4.88)
β2,Constant	-2.230 (-3.99)	-1.590 (-6.96)	-8.680 (-5.30)	yt,EmpManuf -0.056 (3.14)
β2,Dist	0.925 (2.00)	0.142 (4.48)	0.172 (4.02)	yt,AreaCom 0.064 (8.77)

β_2,ObservedWeight	-0.670 (-3.37)	-12.400 (-1.65)	-	ot a	0.261 (131.60)
β_2,WeightMissing	-	-1.590 (-7.09)	-		
β_2,LatentWeight	-	-	-0.924 (-3.29)		
β_2,Retailers	0.118 (2.08)	0.119 (2.06)	0.112 (2.40)		
β_2,ObservedTime	-0.188 (-2.38)	-0.474 (-1.88)	-		
β_2,TimeMissing	-	-0.168 (-2.31)	-		
β_2,LatentTime	-	-	-2.440 (-1.91)		
Number of parameters	10	12	18		
Number of observations	2698	5037	5037		
Null LL (choice of CT)	-2964.06	-5533.71	-5533.71		
LL (choice of CT)	-1524.94	-2509.75	-2499.03		
LL (measurement)	-	-	-7677.23		
Adjusted p2 w.r.t. to choice of CT	0.482	0.543	0.545		

a Normal distribution

3.5 Conclusions

Model estimation was undertaken on full container movements in import chain at Port of Brisbane, Australia. This study addresses the independence among observations by considering the shipment bundling, where a shipment can consist of one or several containers (5037 shipments consisting of 8167 containers).

The results of this study imply that instead of imputing or removing missing data, we can increase the model efficiency by explaining the missing information as a latent variable based on other characteristics. Considering the estimates, it appears that direct delivery is preferable when container arrives on weekends, and for agricultural products, while general cargoes and industrial commodities use DCs inside the port as an intermediate stop. The findings from this study show that importers who are located at shorter distances from the port prefer to deliver directly, while DCs facilitate long-distance transport by solving the problem of misalignment of business hours and increasing the reliability of on-time delivery. Expectedly, having more wholesale trade and higher commercial land use in a suburb has a positive impact on the weight of the shipment.

Furthermore, the probability of using DCs inside the port increases when the arrival time of containers is on the early hours of the day after 7am. Import containers destined to areas with a higher number of retailers and a larger area for commercial land use are more likely to travel through DCs either at the port or inland. This result indicates that retailers and smaller businesses use DCs as an extended component of their distribution system for storage and bundling to reduce their operating cost.

This study leads to an improved insight into the choice of the importers of using DCs versus direct haul delivery. As mentioned in the introduction, the practice of establishing new urban DCs often fails because of the lack of knowledge on the decision-making process. In this study we identified the main parameters which affect this decision, namely the arrival time and date of shipment, the distance traveled and weight, and the commodity type that can be inferred from the effects of land use area and number of employees of each industry sector. The importance of deriving a complete list of factors which affect these decisions is crucial for facility location planning, which can be investigated in future research.

Chapter 4: A joint hybrid model of the choice of container terminals and of dwell time

Paper published in the journal of Transportation Research Part E: Logistics and Transportation Review

<https://doi.org/10.1016/j.tre.2017.12.005>

Elnaz Irannezhad, Carlo G. Prato, Mark Hickman

4.1 Abstract

Container terminals (CTs) are important nodes that help port–landside interactions and improve efficiency and reliability of operations. CTs may be used for either consolidation (in export chains), deconsolidation (in import chains), or storage for subsequent delivery with more cost–effective and higher–utilisation vehicles. CTs help in overcoming mismatches between the arrival time of shipments and the working hours of port operators, as well as in managing delays or bottlenecks in the supply chain. This study investigates the determinants of the choice of using CTs, as either an intermediate stop or a location for packing/unpacking, as an alternative to direct haul delivery. Moreover, this study looks jointly at the decision on the dwell time of containers by proposing a joint copula–based discrete–discrete modelling framework, where the choice to use a CT and the choice of dwell time are estimated simultaneously. Last, this study treats missing information (often found in freight studies) as a latent variable by specifying a hybrid model to represent the choice to use a CT. The model is estimated for the case–study of import and export container transport for the Port of Brisbane (Australia).

Model estimates show the practicality of enriching a dataset with missing information via a robust econometric solution, and also demonstrate a strong correlation between the choice of using CTs and the decision of the dwell time in both import and export container transport. Relevant findings from the model are: (i) shorter distances increase the probability of direct delivery for both import and export shipments; (ii) larger industrial areas in both origin and destination suburbs increase the likelihood of storage at CTs; (iii) weekend or late

arrival of import shipments increase the probability of direct delivery; (iv) import shipments are more likely to be stored at CTs if destined to suburbs with a higher number of retailers and industrial parks, and to be delivered directly if destined to suburbs with a larger wholesale sector; (v) heavier export shipments are more probable to be delivered directly or stored at CTs inside the port; (iv) late night or early morning arrival of export shipments increase the likelihood of storage in inland or port CTs; (vi) export containers originating from suburbs with a higher number of mining, agricultural, and manufacturing employees are more likely to be stored at CTs; and, (vii) export containers originating from suburbs with a higher number of livestock-related businesses, distribution centres, and industrial parks are less likely to be stored at inland CTs.

4.2 Introduction

According to the World Bank, container traffic has more than tripled from 2000 to 2014 and it is expected to grow even faster in the future (The World Bank, 2016). As maritime containerised trade continues to grow, the role of container terminals (CTs) in improving the efficiency of logistics operations becomes paramount. By definition, a CT (also referred to as a transport yard, distribution centre, trans-shipment point, or warehouse) is a facility built to provide a trans-shipment point between sea and hinterland transportation for containers in import and export chains. In CTs, containers can be deconsolidated (in import chains), consolidated (in export chains), or stored for subsequent delivery with more cost-effective and higher-utilisation vehicles with more flexible time-windows. From the city managers' perspective, CTs assist in reducing negative externalities of freight movements such as pollution, congestion, and land use impacts, as well as in contributing to economic growth through faster, more reliable, and more efficient logistics operations. From the freight operators' perspective, even though CTs impose the extra cost of double handling and storage, they provide more reliability in trade and help solve problems among operators such as mismatches between arrival times of ships and the working hours of importers, exporters, stevedores, and customs officers. Also, importers and exporters use CTs as an extended component of their distribution system for the purposes of storage, bundling, or packing/unpacking to reduce shipping and hinterland transport costs (Rodrigue and Notteboom, 2007).

Considering the growth in maritime containerised trade, limited availability of land around ports, and the increase in vessel size, it is important to understand the circumstances

under which freight operators use CTs, in order to allocate their resources effectively. Factors influencing the choice of using CTs as intermediate stops or as packing/unpacking stations (versus direct delivery) could include: (1) the characteristics of the shipment (e.g., size, commodity type, arrival time, departure time); (2) the characteristics of the cargo owners that can be either importers, exporters or shipping lines (e.g., in terms of resource availability, working hours); and, (3) the attributes of the CT (e.g., cost, capacity, geographic location). These factors may also influence the dwell time, or how long containers stay in the CT before being delivered to an importer in an import chain or being loaded onto a ship in an export chain. It should be noted that the dwell time relates to the choice of using a CT, as the imposed rehandling and storage costs are an impedance for cargo owners using the CT in the first place.

However, it is uncertain whether the correct research question is, “How long is the optimum dwell time that the importer/exporter considers, if a container is to be stored at the CT?”; or instead, “Does the importer/exporter consider storage at the CT, if the containers need to be stored for a certain dwell time?”.

Joint models to address the endogeneity and simultaneity of decisions have been receiving increasing attention in the transport literature (Bhat and Eluru, 2009; Spissu et al., 2009; Portoghese et al., 2011; Born et al., 2014; Paleti et al., 2014). The logistics literature is also capturing the interplay between decisions such as shipment size and mode choice (De Jong and Ben-Akiva, 2007; De Jong and Johnson, 2009; Windisch et al., 2010; Pourabdollahi et al., 2013; Abate and de Jong, 2014; Irannezhad et al., 2017d). However, neither modelling the decision to use CTs nor modelling the duration of the dwell time at CTs has received attention, let alone the joint modelling of these decisions (Huber et al., 2014; Davydenko, 2016).

The choice of using CTs was studied in the German Federal Transport Investment Plan (2003), where a logit model was estimated to determine this choice as a function of the location of the available CTs, transportation costs, travel time, and the surrounding area of the terminals. Goodchild et al. (2008) minimised logistics costs to capture the underlying economic forces explaining the preference of direct versus indirect (i.e., through trans-shipment points) distribution. Relevant parameters were transportation costs, distribution costs, inventory costs, goods’ value, interest rates, transit times, and safety factors. Kim et al. (2010) estimated a logit model of the distribution channel choice, where the alternatives

were a direct channel, the channel through a wholesale store, the channel through a CT, and the channel through outsourcing logistics. Relevant parameters were the market characteristics (i.e., population and firm density), commodity type, average order frequency, company size, and annual sales.

The remaining body of literature concerning CTs is concerned with the design of efficient logistics and infrastructure networks, where the focus is on the optimisation of the location of the CT and/or its allocation to freight consumption points, either for a specific commodity (e.g. (Maurer, 2008; Friedrich, 2009), or a container chain (e.g. (Limbourg and Jourquin, 2009; Davydenko and Tavasszy, 2013; Gu and Lam, 2013; Zhang, 2013; Halim et al., 2016). Agent-based models are also used to analyse policy impacts on the use of CTs (e.g. (van Duin et al., 2012; Teo et al., 2015), but none of these researches investigated the factors underlying the preferences for CT usage.

Looking at dwell times, only a handful of studies have pursued a statistical analysis of dwell time choice, despite its impact on CTs' capacity and logistics efficiency. The optimum utilisation of CTs was modelled by imposing a pricing mechanism based on different dwell times (Merckx, 2005), while the influence of dwell time on the capacity of CTs was formulated as an empirical equation in (Dally, 1983; Hoffmann, 1985; Chu and Huang, 2005). The factors affecting dwell times at CTs were modelled only in two studies, one by applying a Genetic Algorithm (Moini et al., 2012) and the other by using regression and Artificial Neural Networks (Kourounioti et al., 2016). The most relevant factors include the port of origin, the location of the CT, the CT working hours, the day and month of discharge, the size and type of container, the commodity type, and the available hinterland connections and transport modes (Moini et al., 2012; Kourounioti et al., 2016).

The first contribution of this study is the analysis of preferences for the use of CTs by both importers and exporters, alongside the decision about the dwell time of the containers in the CTs. Specifically, this study proposes a novel joint model of the choice of using CTs and the duration of dwell time at CTs that relies on the joint cumulative distribution of the two error terms being expressed by a copula function. The estimation of the probability of ending the dwell time is modelled via a duration model that can be either continuous or discrete, and either fully-parametric, semi-parametric, or non-parametric (Hensher and Mannering, 1994). Given that the storage cost is calculated on a daily basis, in this study the dwell time at CTs is a discrete variable corresponding to the number of days. Hence, the

first contribution of this study is the formulation and estimation of a discrete–discrete copula–based model of the choice of using CTs and the duration of the dwell time at the CTs, while accounting also for unobserved heterogeneity for some variables.

The second contribution of this study addresses the issue of missing data that is quite common in freight survey data. In most choice models, records with missing data are removed prior to analysis, a practice that causes the parameter estimates of the models to be biased when the percentage of missing data is significant. The main body of literature on the non–response problem concerns imputation (Ramalho and Smith, 2002), but latent variable models to address non–response to attitudinal items have been applied in some social science studies (Knott et al., 1991; Albanese and Knott, 1992; Muirheartaigh and Moustaki, 1999). Notably, these studies were unable to handle more than two latent variables due to computational difficulties. Ramalho and Smith (2002) proposed a likelihood–based approach to deal with missing data in discrete choice models when there is either “unit non–response” or “item non–response”. Sanko et al. (2014) addressed missing responses for household income in travel surveys with hybrid choice models. Accordingly, the second contribution of this study is the formulation and estimation of a hybrid version of the discrete–discrete copula–based model that is able to treat missing data from full container movements in the import and export chains, with the aim of providing unbiased estimates of the determinants for the choice of using CTs.

The third contribution of this study is the estimation of the hybrid joint model to a real–world case–study by focusing on the Port of Brisbane (Australia) and analysing a considerable number of observations, where the weight of the shipment and the arrival time of import containers at the stevedores are missing. Therefore, two latent variables were specified, for the weight of the import/export shipments and the arrival time of the import shipments. Then, the discrete–discrete copula–based model was estimated to unravel the determinants of the choices of using CTs and the dwell time at the CTs.

The remainder of this paper is organised as follows. Section 2 presents the data and methodology of this study, with emphasis on model formulation and model specification for container transport in both the import and the export chains. Section 3 shows the estimates of the joint hybrid copula–based model and illustrates the relation between the optimal and the chosen alternatives. Section 4 draws conclusions from this study.

4.3 Methods

4.3.1 Data

The novel joint model is based on a case–study of container shipments trading through the Port of Brisbane (Australia). A dataset of import and export chains was collected for the Port of Brisbane Import/Export Logistics Chain Study (PBPL, 2013), and included the details of individual container movements: container identification number, timestamps of arrival and departure, postcodes of origin and destination, weight of the shipment, and size of the container. This study looks at the movements of full containers and contains 8167 records for import chains and 7748 records for export chains. The movements are destined to and originated from different suburbs, mainly in the city of Brisbane but also across the state of Queensland. Moreover, the movements between the port and the final destination include at times intermediate stops at CTs, where the import or export containers are stored for a certain amount of time before being handed to the importers, stevedores, or exporters.

Three alternatives exist for the transport of import containers (the shares of observations in the case–study): (1) direct delivery to importers (28%); (2) transport with an intermediate stop at a CT prior to handing to importers (28%); (3) unpacking at a CT located inside or close to the port (44%).

Five alternatives exist for the transport of export containers: (1) direct delivery from exporters to stevedores (23%); (2) transport with an intermediate stop at a CT inside the port prior to handing to exporters (19%); (3) transport with an intermediate stop at an inland CT outside the port prior to handing to exporters (15%); (4) transport with an intermediate stop at both a port CT and an inland CT (5%); (5) packing at a CT located inside or close to the port (38%). It should be noted that this study considers the shipment as the unit of modelling, and each shipment may consist of either a single container or several containers bundled together. Table 5 represents the number of shipments in each alternative for both import and export chains.

Table 5 – Number of shipments for the choice of CTs and dwell time								
Dwell time	Import chain			Export chain				
# of storage days	Direct delivery	Storage at CTs at port	Unpacking at CTs	Direct delivery	Storage at CTs at port	Storage at inland CTs	Double storage	Packing at CTs
Less than one full day	2199	42	2769	1272	666	581	113	2234

1 day	–	13	–	–	83	54	32	–
2 days and more	–	14	–	–	339	80	170	–

Regarding both the import and the export data, all alternatives contain information about the origin and destination of the container, with the exception of alternatives involving packing/unpacking at CTs. Also, for these latter alternatives, information about the commodity is not known. However, it is possible to use land use and census information about the origin and destination along with information about the weight of the shipment in order to infer a type of commodity. Then, it is possible to relate the choice of using a CT versus direct delivery for different commodity types. Figure 15 shows the datasets and attributes to be examined as explanatory variables in the choice models.

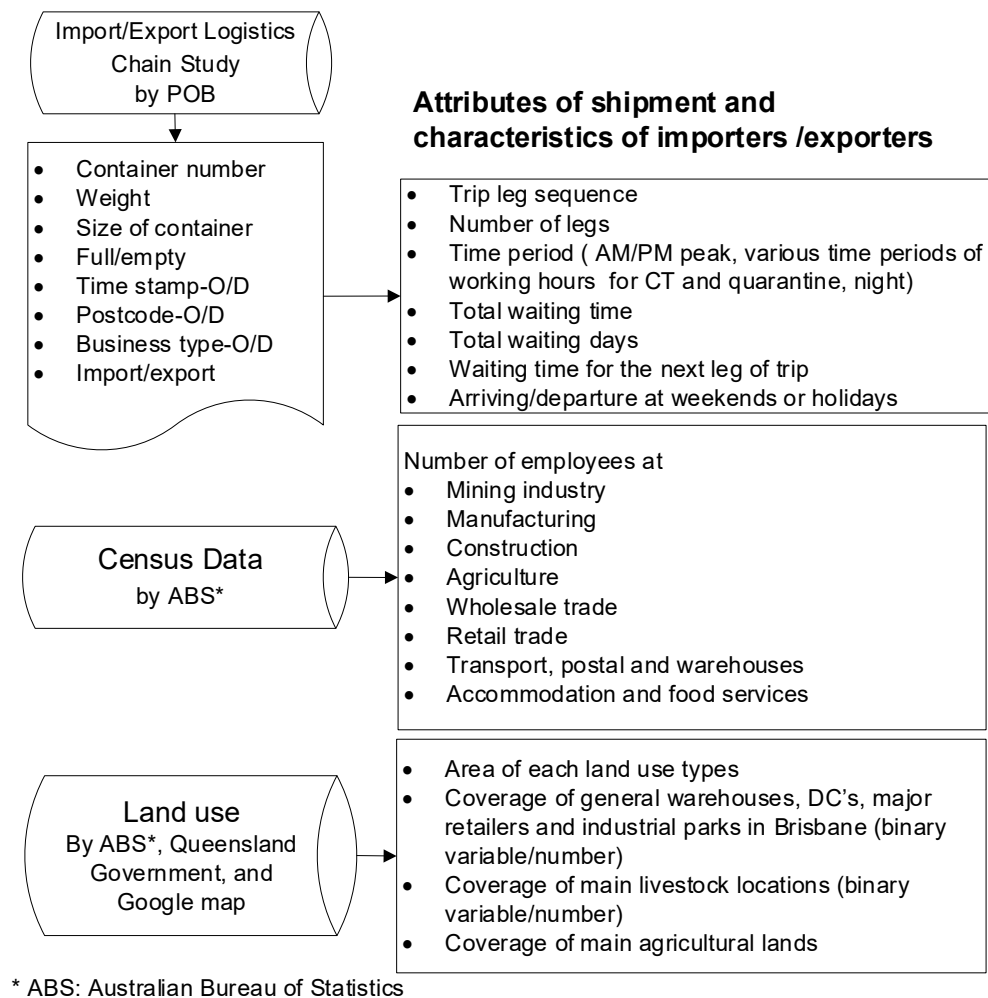


Figure 15 – Datasets available for the study

Exogenous variables that are considered in this study can be classified into two main groups: (i) shipment characteristics (e.g., weight, arrival time, distance from the port), and

(ii) land use and employment information of the origin and destination of export and import shipments, respectively. Table 6 provides descriptive statistics related to the variables that were found significant in the model specification discussed in section 2.3.

Attribute variable	Exogenous variables in import model	Statistics		Attribute variable	Exogenous variables in export model	Statistics	
		Average	SD			Description	Average
Weight	Weight (tonnage)	14.78	7.31	Weight	Weight (tonnage)	22.66	7.31
Dis	Distance (km)	21.04	106.84	Dis	Distance (km)	55.63	32.02
IndusParks	Industrial parks (number)	1.69	2.31	IndusParks	Industrial park (number)	2.18	2.33
Retailers	Retailers (number)	0.44	1.21	Livestock	Livestock businesses (number)	0.42	0.50
AreaCom	Area of commercial land use (km2)	0.70	1.74	AreaAgr	Area of agriculture land use (thousand km2)	0.49	0.38
AreaIndus	Area of industrial land use (km2)	4.01	4.20	AreaTransp	Area of transport land use (km2)	0.02	0.02
EmpTransp	Employment in transport (thousands)	0.61	0.94	AreaIndus	Area of industrial land use (km2)	3.93	5.99
EmpAgr	Employment in agriculture (number)	25.56	79.24	EmpAgr	Employment in agriculture (number)	114.89	84.28
EmpManuf	Employment in manufacturing (thousands)	0.97	1.80	EmpManuf	Employment in manufacturing (thousands)	1.04	2.01
EmpWholesale	Employment in wholesale (thousands)	0.49	1.27	EmpMining	Employment in mining (number)	22.72	59.56

An important aspect of the sample is that, out of 5037 shipments in the import chain, the arrival time at the port and the reported weight of the shipment were missing in 727 (14.4%) and 1852 (36.8%) observations, respectively. Similarly, out of 5624 shipments in the export chain, the weight of the shipment was missing for 3632 observations (64.6%), while only a small share of the origin (pickup) time was missing. Given the novel approach proposed to address missing information, these missing values were modelled as latent variables. The structural equations of shipment weight and arrival time in the import chain were estimated respectively on the remaining 4310 and 3185 observations. In the export chain, the structural equation for shipment weight was estimated on the remaining 2439 observations.

4.3.2 Model formulation

The choice of using a CT is modelled within the random utility maximisation framework where importers and exporters maximise their utility. The utility U_{in} of alternative i for the importer/exporter for shipment n is expressed as a function of a vector z_n of attributes of

observation n (i.e., characteristics of the shipment and of the importer/exporter), and a vector x_{in} of attributes of alternative i as perceived by the importer/exporter with regards to shipment n :

$$U_{in} = V_{in}(z_n, x_{in}; \beta) + \varepsilon_{in} \quad (4.1)$$

where V_{in} is the deterministic part of the utility function, ε_{in} is the stochastic part of the utility function, and β is a vector of parameters to be estimated.

The hybrid choice model (Walker, 2001) integrates latent variable models within the joint CT use choice model, with the latent variables being the missing variables from the dataset. If the vector z_n contains a variable with missing data, it is then possible to express the missing data as a latent variable α_n via a structural equation:

$$\alpha_n = g(z_n^*; \gamma) + \omega_n \quad (4.2)$$

where z_n^* is a subset of the vector z_n of explanatory variables (excluding the variable of interest), γ is a vector of coefficients to be estimated, and ω_n is a random error component that follows a distribution with density $f(\omega|\psi)$ where ψ are the parameters of the distribution (i.e., mean and standard deviation) of ω_n .

It should be noted that the definition of a latent variable is simply a variable that cannot be measured directly. In this case, in order to retrieve an estimate of the missing values, an indicator I_n is used for each latent variable α_n . The indicator is a function of the vector z_n^* and a vector of parameters ς_i , (see Sanko et al. (2014)):

$$\begin{cases} I_n(\alpha_n) = h(\alpha_n, \varsigma_i) & \text{if } \alpha_{nk} \text{ is observed} \\ I_n(\alpha_n) = 1 & \text{if } \alpha_{nk} \text{ is unobserved} \end{cases} \quad (4.3)$$

To calculate the probability P_{in} of choosing to use a CT, we consider a mixed logit (ML) structure that accounts for heterogeneity across observations:

$$P_{in} = \int \frac{e^{V_{in}(\alpha_n, z_n, x_{in}; \beta)}}{\sum_{j=1}^J e^{V_{jn}(\alpha_n, z_n, x_{jn}; \beta)}} f(\beta | \phi) d\beta \quad (4.4)$$

where the parameters β are distributed with density $f(\beta|\phi)$ and ϕ refers to the parameters of that probability density. Decisions regarding which parameters to model as random

parameters, as well as the statistical distribution to capture heterogeneity, are discussed in the following sections.

The dwell time at the CT is modelled as a discrete outcome, where U_{dn} represents the random utility of the dwell time being equal to a number of days d for observation n , κ is a vector of parameters to be estimated, and ε_{dn} is a random error component:

$$U_{dn} = V_{dn}(z_n, x_{dn}; \kappa) + \varepsilon_{dn} \quad (4.5)$$

Accordingly, the probability of a dwell time of d days at the CT is expressed with an MNL structure according to eq. (6). It should be noted that tests for taste heterogeneity were performed, but the absence of heterogeneity advised to retain the MNL structure.

$$P_{dn} = \frac{e^{V_{dn}(z_n, x_{dn}; \kappa)}}{\sum_{r=1}^D e^{V_{rn}(z_n, x_{rn}; \kappa)}} \quad (4.6)$$

The joint probability that storage at a CT is chosen, and for d days, is expressed in eq. (7), where y_{idn} is equal to one if the chosen alternative is storage at the CT, and $\varepsilon_{rn}, r \neq d$, and $\varepsilon_{in}, i \neq 2$ are the disturbance terms of the unchosen alternatives. It should be noted that the equation is written for alternative 2 in the import chain, which stands for the choice of storage at the CT, and it is similar for alternatives that involve storage for the export chain, namely alternatives 2, 3, and 4:

$$P(y_{idn} = 1) = \Pr \left(\varepsilon_{jn} - \varepsilon_{in} \leq (V_{in} - V_{jn}), \varepsilon_{rn} - \varepsilon_{dn} \leq (V_{dn} - V_{rn}) \right) = C_{\theta} \left(F_{\varepsilon}(V_{in}), F_{\varepsilon}(V_{dn}) \right) \quad (4.7)$$

To model the multivariate functional form of the joint distribution of two random variables in eq. (7), a copula-based approach is used. A copula is purely derived from the marginal distributions of each random variable. According to Sklar (1973), there exists a unique copula that ties two random variables $(\varepsilon_{jn} - \varepsilon_{in})$ and $(\varepsilon_{rn} - \varepsilon_{dn})$, and allows a multivariate distribution to be formed from several one-dimensional distribution functions. The parameters of these distribution functions can be estimated simultaneously.

Several copulas have been formulated in the literature and can be used, allowing for both positive and negative dependence, symmetric or asymmetric dependence structure, and specific multivariate distributions. In this study, we investigated the Archimedean class

of copulas that are very flexible, easy to construct, and popular in applications (Bhat and Eluru, 2009). Accordingly, we investigated two asymmetric copulas with different tail dependence structure and two symmetric copulas: (i) the Gumbel copula, which is well suited when there is a positive dependence with a strong right tail and weak left tail correlation (Gumbel, 1960); (ii) the Clayton copula, known as the reverse of the Gumbel with a weak right tail and strong left tail dependence (Clayton, 1978); (iii) the Frank copula (Frank, 1978); and, (iv) the Joe copula, which is symmetric and allows both positive and negative dependence (Joe, 1993).

Finally, the hybrid joint model was estimated by maximizing the simulated log-likelihood. Since the latent variables are not fully observed, the choice probability was obtained by integrating over the parameters of the distributions of the latent variables α_n and over the random parameters considered in the mixed logit model:

$$L = \int_{\alpha_n} \int_{\beta} \sum_n \ln \left[\left(y_{idn} P(y_{idn} = 1) + (1 - y_{idn}) y_{jn} \prod_{j \neq 2} P_{jn} \right) I_n(\alpha_n) \phi(\alpha_n) d\alpha_n \phi(\beta) d\beta \right] \quad (4.8)$$

where P_{in} is the probability of the choice i made for observation n that corresponds to the integral of standard logit probabilities over the density of random parameters β as shown in eq. (4); $\phi(\alpha_n)$ is the parametric density function associated with the latent variable α_n ; y_{idn} is equal to one if the chosen alternative is storage at the CT (choice 2 in import transport, and choices 2,3, and 4 in export transport) for d days, or zero otherwise; and y_{jn} is equal to one for the chosen alternative in the CT use choice model, or zero otherwise.

The selection of the distribution for the random parameters β should be a considered decision within some common functional forms, as choosing the wrong distribution may lead to inconsistent estimates or illogical signs. Given *a priori* expectations about the sign of parameters, bounded distributions appear preferable in this study, and hence five common distribution forms were considered for all parameters in the model: normal, lognormal, truncated normal, triangular, and truncated triangular.

It should be noted that the estimation of the log-likelihood function in eq. (8) was possible under the following reasonable assumptions: (i) independence of choice observations over importers/exporters; and, (ii) bundling of containers carried by the same shipping lines, having the same origin and destination, and being within a 15-min time-window in both arrival and departure timestamps. Again, the unit of observation was the

shipment and can consist of one or more containers. The hybrid joint model was estimated by maximizing the simulated log-likelihood and was compared to a standalone multinomial logit model (MNL) and a hybrid MNL model that does not consider the dwell time endogenously. All models were coded in PythonBiogeme (Bierlaire, 2016) and were estimated using Monte Carlo simulation with 1000 draws from a Modified Latin Hypercube Sampling (MLHS) algorithm for the random parameters (Hess et al., 2006).

4.3.3 Model specification

This section presents the specifications of the joint choice models for import container transport and export container transport. From all the information collected (Figure 15), all potential explanatory variables were added progressively in various forms to test whether they were statistically significant at least at the 10% level and, if they were significant, they were retained in the model. Finally, the best model specifications were determined after testing for all combinations of variables and checking for partial correlations.

4.3.3.1 Model for import container transport

As mentioned, out of a sample of 5037 shipments in the import chains, the arrival time at the port and the reported weight of the shipment were missing for respectively 14.4% and 36.8% of observations. These missing values were modelled as latent variables, where the structural equations of shipment weight and arrival time in the import chain were estimated respectively on the remaining 4310 and 3185 observations.

After specification testing, the structural equation for the shipment weight expresses the latent variable *Weight* as a function of the area of commercial land uses in the destination suburb as shown in eq.(4.9). The relation between weight and commercial land use area is likely because the majority of container import commodities are general cargoes for which weight can be explained as a function of consumption. It should be noted that the unit of modelling is the shipment, so the weight is the total weight of the bundled containers. The structural equation for the time of arrival expresses the latent variable *Time* as a function of the number of employees in manufacturing, transport, and warehouse sectors, and the area (km²) of commercial land uses in the destination suburb, as shown in eq.(4.10). It should be noted that the variable *Time* is considered as a continuous variable where 7am is chosen as the baseline (zero) value.

$$\log(Weight_n) = \gamma_{w,Constant} + \gamma_{w,AreaCom} AreaCom_n + \sigma_w \omega_w \quad (4.9)$$

$$\log(Time_n) = \gamma_{t,Constant} + \gamma_{t,EmpTransp} EmpTransp_n + \gamma_{t,EmpManuf} EmpManuf_n + \gamma_{t,AreaCom} AreaCom_n + \sigma_t \omega_t \quad (4.10)$$

where $Time_n$ is the arrival time of the shipment handled from the stevedores, $Weight_n$ is the reported weight of the shipment, $EmpTransp_n$ indicates the number of employees (thousands) in the transport and warehousing sector at the destination suburb, $EmpManuf_n$ represents the number of employees (thousands) in the manufacturing sector at the destination suburb, and $AreaCom_n$ indicates the area (km²) of commercial land use at the destination suburb. The last term of each equation captures the heterogeneity across observations by estimating σ_w and σ_t and considering the error terms ω_w and ω_t as distributed according to a standard normal distribution.

The choice model was estimated on the full sample data, where missing values of time and weight were modelled via the structural equations presented above. After specification testing, the utility equations of the CT use choice model were specified as shown in eq.(4.11) through eq.(4.13), where choice 3 (unpacking at the CTs) is the reference alternative. It should be noted that the error terms are Gumbel distributed, and the equations present the deterministic parts of the utility functions.

$$V_{1n} = \beta_{1,Constant} + \beta_{1,EmpAgr} EmpAgr_n + \beta_{1,Weekend} Weekend_n + \beta_{1,EmpWholesale} EmpWholesale_n + \beta_{1,IndusPark} IndusPark_n \quad (4.11)$$

$$V_{2n} = \beta_{2,Constant} + \beta_{2,LatentTime} \log(Time_n) + \beta_{2,Dist} Dist_n + \beta_{2,LatentWeight} \log(Weight_n) + \beta_{2,Retailers} Retailers_n \quad (4.12)$$

$$V_{3n} = 0 \quad (4.13)$$

where V_{1n} , V_{2n} and V_{3n} are the utilities of (1) direct delivery to importers, (2) storage at CTs as an intermediate stop, and (3) unpacking at the CTs, respectively, $Dist_n$ is the shortest path distance from the CT to the destination suburb, $Weekend_n$ is a binary variable which indicates whether the arrival time of the container was on a weekend or holiday, $IndusPark_n$ indicates the number of industrial parks and major distribution centres of general cargo, $Retailers_n$ is the number of big supermarkets and shopping centres, and $EmpAgr_n$ and $EmpWholesale_n$ are respectively the number of employees in the agricultural and wholesaling sector. All variables are related to the destination suburb, and the related β 's

are parameters to be estimated that are fixed, with the exception of $\beta_{2,Dis}$ that is assumed to be lognormally distributed.

After specification testing, the utility functions of the dwell time were specified as eq.(4.14) through eq.(4.16) where storage of less than one day is the reference alternative and differences for two or more days of storage at the CT were not observed. This created a three–alternative specification:

$$V_{0n} = 0 \quad (4.14)$$

$$V_{1n} = \kappa_{1,Constant} + \kappa_{1,AreaIndus} AreaIndus_n + \kappa_{1,EmpManuf} EmpManuf_n \quad (4.15)$$

$$V_{2n} = \kappa_{2,Constant} + \kappa_{2,AreaIndus} AreaIndus_n \quad (4.16)$$

where V_{0n} , V_{1n} , and V_{2n} are (respectively) the deterministic utilities of storage for less than a whole day, a whole day, and more than one day at the CT, $EmpManuf_n$ is the number of employees in the manufacturing sector, and $AreaIndus_n$ is the land area of the industrial sector in the destination suburb.

4.3.3.2 Model specification for export container transport

After specification testing, the latent variable *Weight* was expressed as a function of the agricultural, transport and warehouse land area (km²) of the origin suburb, as shown in eq.(4.17). The relation between the weight of the shipment and these land uses is likely because the major share of exported commodities via containers through the Port of Brisbane are agricultural products.

$$\log(Weight_n) = \gamma_{w,Constant} + \gamma_{w,AreaAgr} AreaAgr_n + \gamma_{w,AreaTransp} AreaTransp_n + \sigma_w \omega_w \quad (4.17)$$

where $Weight_n$ is the total reported weight of the shipments bundled together, and $AreaAgr_n$ and $AreaTransp_n$ represent the area (km²) of the agricultural land and of the transport and warehousing sector in the origin suburb, respectively.

The choice model was estimated on the full sample data, where missing values of *Weight* were modelled via the structural equation in eq.(4.17). The deterministic parts of the utility functions for the CT use choice model are presented in eq.(4.18) through eq. 4.22) where the choice of packing at CT is considered as the reference alternative in eq. (22):

$$V_{1n} = \beta_{1,Constant} + \beta_{1,LatentWeight} \log(Weight_n) + \beta_{1,IndusPark} IndusPark_n + \beta_{1,Livestock} Livestock_n \quad (4.18)$$

$$V_{2n} = \beta_{2,Constant} + \beta_{2,LatentWeight} \log(Weight_n) + \beta_{2,Time} Time_n + \beta_{2,Dist} Dist_n + \beta_{2,IndusPark} IndusPark_n + \beta_{2,EmpManuf} EmpManuf_n + \beta_{2,EmpMining} EmpMining_n + \beta_{2,EmpAgr} EmpAgr_n + \beta_{2,Livestock} Livestock_n \quad (4.19)$$

$$V_{3n} = \beta_{3,Constant} + \beta_{3,LatentWeight} \log(Weight_n) + \beta_{3,Time} Time_n + \beta_{3,Dist} Dist_n + \beta_{2,EmpManuf} EmpManuf_n + \beta_{2,EmpMining} EmpMining_n + \beta_{2,EmpAgr} EmpAgr_n \quad (4.20)$$

$$V_{4n} = \beta_{4,Constant} + \beta_{4,Dist} Dist_n + \beta_{4,DistInland} \log(DistInland_n) + \beta_{4,IndusPark} IndusPark_n + \beta_{4,EmpManuf} EmpManuf_n + \beta_{4,EmpMining} EmpMining_n + \beta_{4,EmpAgr} EmpAgr_n + \beta_{4,Livestock} Livestock_n \quad (4.21)$$

$$V_{5n} = 0 \quad (4.22)$$

where V_{1n} is the deterministic utility of direct delivery from the exporter n to the stevedores, V_{2n} is the deterministic utility of transport from the exporter n with an intermediate stop at the CT located at the port, V_{3n} is the deterministic utility of transport from the exporter n with an intermediate stop at the CT located outside the port, V_{4n} is the deterministic utility of transport using both inland CTs and port CTs, and V_{5n} is the deterministic utility of transport using the CT for packing.

After specification testing, the following explanatory variables for the utility functions were considered: $Livestock_n$ is the number of businesses related to livestock; $EmpAgr_n$, $EmpManuf_n$, and $EmpMining_n$ represent respectively the number of employees in the agricultural, manufacturing, and mining sector; $IndusPark_n$ is the number of industrial parks and major distribution centres of general cargo; $Time_n$ is the continuous departure time of the export container from the exporter, where 7am is specified as the baseline (zero); $Dist_n$ is the shortest path distance from the exporter to the port; and, $DistInland_n$ is the distance from exporter n to the inland CT, which is exclusive to the choices of inland storage and double storage in eq.(4.20) and eq.(4.21). All the variables are related to the origin suburb, and the related β 's are parameters to be estimated that are fixed with the exception of the parameters $\beta_{2,Dist}$ and $\beta_{3,Dist}$ that are assumed to be lognormally distributed.

After specification testing, the deterministic parts of the utility functions of the dwell time are specified in eq.(4.230 through eq.(4.25), where the three alternatives are specified as in the import case:

$$V_{0n} = 0 \quad (4.23)$$

$$V_{1n} = \kappa_{1,constant} + \kappa_{1,EmpManuf} EmpManuf_n \quad (4.24)$$

$$V_{2n} = \kappa_{2,constant} + \kappa_{2,AreaIndus} AreaIndus_n + \kappa_{2,EmpManuf} EmpManuf_n \quad (4.25)$$

where $EmpManuf_n$ represents the number of employees in the manufacturing sector and $AreaIndus_n$ indicates the area (km²) of industrial land use, both at the origin suburb of the exporter.

4.4 Estimation results

Table 7 and Table 8 present the estimates of four choice models for import and export container transport, respectively. Model 1 is a standalone MNL model excluding the observations where the shipment weight and the time of arrival present missing values. Model 2 is a standalone MNL model including all observations and estimating two parameters for the observations where the two variables present missing values. Model 3 is a hybrid model including the structural equation of the two latent variables. Model 4 is the hybrid joint copula-based model that represents the CT use choice and the dwell time choice.

While the rationale behind the hybrid model is the need to overcome the bias inherent in removing missing data, the rationale behind the joint model is the need to account for the simultaneous decision of using the CT and selecting the dwell time at the CT. The estimation of Model 4 was performed while testing for the most relevant Archimedean copulas allowing for both positive and negative dependence and having strong one-tail dependence (i.e., Gumbel, Clayton), or copulas with symmetric tail dependence (i.e., Frank, Joe). Ultimately, the best specification was found for the Gumbel copula that yielded the maximum likelihood. Accordingly, the tables report the results for the models with Gumbel copulas and present the estimates of the dependency parameter of the copulas.

The aforementioned specification testing meant that parameters were retained in Model 4 if they were statistically significant at the 10% level. However, a few parameters were retained in the other models purposefully regardless of their significance, both for the sake of comparison across the four models and for the possible relevance to the choice.

Firstly, model specifications may be compared. When comparing the models for the import container transport, Model 1 has a far lower number of observations, and this justifies the estimation of the remaining three models. Model 2 has a significant parameter for the missing values, which suggests that there is a bias in estimating only parameters based on the observed information while ignoring the missing data. Likelihood ratio tests show an improvement in Model 3 with respect to Model 2 for the CT use model ($LRT = 21.438$, $df=2$, $p<0.00001$), and similar tests show that the joint copula-based Model 4 is to be preferred to the two separate choices in Model 3 ($LRT = 298.14$, $df = 1$, $p<0.00001$). When comparing the models for the export container transport, likelihood ratio tests show again an improvement in Model 3 when compared to Model 2 for the CT use model ($LRT = 556.31$, $df=1$, $p<0.00001$), and similar tests show that the joint copula-based Model 4 is to be preferred to the two separate choices in Model 3 ($LRT = 411.45$, $df = 1$, $p<0.00001$). Moreover, the significance of the dependency parameters of the copulas confirmed the correlation of the two choices in both import and export container Model 4 and hence the need for a joint model to be estimated. It should be noted that both copula parameters were positive, which indicates that unobserved factors have the same directional effect on increasing and decreasing the probability of using a CT as an intermediate stop and on deciding the length of dwell time. The remainder of the presentation of results refers to Model 4 for both import and export container transport.

Secondly, parameter estimates may be examined. Looking at the two latent variables in import container transport, the weight of the shipment increases when destined to a suburb with a higher commercial land use area, while the time of arrival relates to the number of employees in the transport and manufacturing sectors as well as the area of commercial land use in the destination suburb. Looking at the only latent variable in export container transport, the weight of the shipment increases if it originated from a suburb with a higher area of agricultural land use, while it decreases with an increase in the area dedicated to the transport and warehousing sectors in the origin suburb. Given the five common distributional forms examined for the random parameters expressing heterogeneity (i.e., log-normal, normal, truncated normal, triangular, truncated triangular), the truncated normal distribution provided the best fit for both latent variables in the import container transport model, while the normal distribution gave the best fit for the only latent variable in the export container transport model.

In the import container transport model, the parameter estimates for the number of employees suggest that shipments related to the agricultural and wholesale sectors are more likely to be delivered directly, while shipments are more likely to be stored at CTs if they are destined to suburbs with a higher number of shopping centres, retailers, and industrial parks, as well as suburbs farther from the port. Furthermore, when the arrival date of import containers at the stevedores occurs on a weekend, the probability of shipment direct delivery increases, while the probability of storage at CTs decreases in the case that the shipment arrives later during the day.

Given that the majority of export containers from the Port of Brisbane concern bulk commodities (i.e., agricultural, livestock, mining, manufacturing, and chemical products), it is interesting that the choice of using CTs relates to the employment and land use areas of these sectors. Parameter estimates indicate that export shipments with a higher weight are more likely to be either delivered directly or stored at inland CTs, while shipments with a lower weight are more likely to be stored at a CT located at the port. The export shipments originating from the suburbs with a higher number of industrial parks are more likely to be transported directly to the stevedores or stored in a CT at the port, as either the only stop or their second stop in transit. The parameter estimates also suggest that storage at CTs (either at the port, inland, or both) is more probable for export shipments from the suburbs with a higher number of employees in the agricultural, mining, and manufacturing sectors. Moreover, the probability of using both inland and port CTs for export container transport decreases with a higher concentration of employees in the manufacturing sector, and does not relate significantly with the number of employees in the mining sector, while appearing as an attractive option for agricultural commodities. Last, the probability of direct delivery and storage at a CT in the port increases with the number of livestock-related businesses in the origin suburb.

In the export container transport model, the parameter estimates suggest that shipments headed to either port or inland CTs are more likely to be transported late at night or early in the morning. The effects of the distance between the importer/exporter and the port is similar for import and export container transport: direct delivery is more probable for the exporters located closer to the port, while storage at either port or inland CTs is more likely for greater distances from the port. Moreover, the probability of stopping at another CT at the port increases logarithmically with an increase in distance between exporters and

inland CTs. However, the preference for distance appears to be heterogeneous among observations for both import and export chains. Given the five common distributional forms considered, the log-normal distribution yielded a better fit for the distance between an importer and a CT, and the normal distribution provided the best fit for the distance being associated with stopping at an inland or port CT. It should be noted that the log-normal has an unbounded right tail, which makes sense when considering that some shipments are destined to remote areas.

The estimates of the dwell time model show that import or export containers from or to suburbs with a larger industrial area are more likely to be stored longer than one day. Also, one day storage is more probable for import containers destined to suburbs with a higher number of employees in the manufacturing sector, while the opposite relation is observed for export containers.

Table 7 – Estimation results for import container transport

		Model 1	Model 2	Model 3	Model 4
Alternatives	Parameters	MNL excluding missing values	MNL with missing values	Hybrid model	Hybrid joint copula-based model
Alt. 1 CT:	$\beta 1, \text{Constant}$	-0.718 (-11.61)	-1.150 (-19.50)	-1.150 (-19.50)	-2.500 (-34.72)
Direct delivery	$\beta 1, \text{EmpAgr}$	0.027 (4.79)	0.030 (5.10)	0.030 (5.09)	0.273 (7.16)
	$\beta 1, \text{Weekend}$	3.150 (5.15)	3.270 (6.20)	3.280 (6.28)	2.620 (2.00)
	$\beta 1, \text{EmpWholeSale}$	6.310 (4.26)	9.270 (4.04)	9.270 (4.05)	9.110 (8.70)
	$\beta 1, \text{IndusParks}$	-0.264 (-6.06)	-0.113 (-3.27)	-0.112 (-3.28)	-1.980 (-6.45)
Alt. 2 CT:	$\beta 2, \text{Constant}$	-2.230 (-3.99)	-1.590 (-6.96)	-8.680 (-5.30)	-30.500 (-2.20)
Storage at CT	$\beta 2, \text{Dist (mean)a}$	0.925 (2.00)	0.142 (4.48)	0.172 (4.02)	-3.320 (-1.99)
	$\beta 2, \text{Dist (st. dev.) a}$	–	–	–	-2.140 (-2.55)
	$\beta 2, \text{ObservedWeight}$	-0.670 (-3.37)	-12.400 (-1.65)	–	–
	$\beta 2, \text{WeightMissing}$	–	-1.590 (-7.09)	–	–
	$\beta 2, \text{LatentWeight}$	–	–	-0.924 (-3.29)	-4.030 (-1.98)
	$\beta 2, \text{Retailers}$	0.118 (2.08)	0.119 (2.06)	0.112 (2.40)	0.146 (3.14)
	$\beta 2, \text{ObservedTime}$	-0.188 (-2.38)	-0.474 (-1.88)	–	–
	$\beta 2, \text{TimeMissing}$	–	-0.168 (-2.31)	–	–
	$\beta 2, \text{LatentTime}$	–	–	-2.440 (-1.91)	-4.970 (-1.96)
	Alt. 3 CT:	Base alternative			
Unpack at CT					
Structural eq.	$\gamma w, \text{Constant}$	–	–	-4.600 (-142.05)	-4.600 (-140.47)
latent weight	$\gamma w, \text{AreaCom}$	–	–	0.056 (3.14)	0.064 (3.68)
	$\sigma w \text{ a}$	–	–	1.280 (33.10)	1.280 (33.06)
Structural eq.	$\gamma t, \text{Constant}$	–	–	-0.078 (-13.75)	-0.078 (-14.03)
latent time	$\gamma t, \text{EmpTransp}$	–	–	-0.028 (-4.88)	-0.028 (-4.79)
	$\gamma t, \text{EmpManuf}$	–	–	-0.056 (3.14)	-0.048 (-6.82)
	$\gamma t, \text{AreaCom}$	–	–	0.064 (8.77)	0.063 (8.65)

	ot a	–	–	0.261 (131.60)	0.261 (131.45)
Alt. 0 DT:	Base alternative				
Less than one day					
Alt. 1 DT:	$\kappa 1, \text{Constant}$	–	–	–	–0.696 (–1.64)
One day	$\kappa 1, \text{ArealIndus}$	–	–	–	0.618 (4.89)
	$\kappa 1, \text{EmpManuf}$	–	–	–	0.583 (1.80)
Alt. 2 DT:	$\kappa 2, \text{Constant}$	–	–	–	–0.803 (–1.72)
More than one day	$\kappa 2, \text{ArealIndus}$	–	–	–	0.474 (4.37)
Dependency	Copula parameter	–	–	–	39.900 (2.25)
Number of parameters		10	12	18	25
Number of observations		2698	5037	5037	5037
Null LL (choice of CT)		–2964.06	–5533.71	–5533.71	–5533.71
LL (total)		–1524.94	–2509.75	–10176.26	–10205.74
LL (choice of CT)		–1524.94	–2509.75	–2499.03	–2509.11
LL (measurement)		–	–	–7677.23	–7686.63
Adjusted p2 w.r.t. to choice of CT		0.482	0.543	0.545	0.544

Note: t–statistics are reported in parenthesis, *lognormal distribution

Table 8 – Estimation results for export container transport

		Model 1	Model 2	Model 3	Model 4
Alternatives	Parameters	MNL excluding missing values	MNL with missing values	Hybrid model	Hybrid joint copula–based model
Alt. 1 CT:	$\beta 1, \text{Constant}$	1.830 (4.01)	1.180 (1.94)	–1.320 (–1.42)	–1.670 (–4.63)
Direct delivery	$\beta 1, \text{ObservedWeight}$	–0.129 (–7.4)	–0.112 (–4.82)	–	–
	$\beta 1, \text{WeightMissing}$	–	–4.660 (–7.87)	–	–
	$\beta 1, \text{LatentWeight}$	–	–	–0.704 (–2.39)	–0.480 (–4.41)
	$\beta 1, \text{IndusParks}$	0.900 (20.47)	1.900 (22.74)	6.780 (11.54)	6.690 (1.97)
	$\beta 1, \text{LiveStock}$	2.240 (7.93)	1.920 (5.11)	26.400 (3.74)	26.600 (2.23)
Alt. 2 CT:	$\beta 2, \text{Constant}$	1.940 (2.16)	2.500 (3.34)	–1.230 (–3.34)	–1.370 (–5.84)
Storage at port CT	$\beta 2, \text{Dist (mean) a}$	0.810 (4.28)	0.933 (9.89)	1.520 (15.25)	1.161 (12.76)
	$\beta 2, \text{Dist (st. dev.) a}$	–	–	–	0.022(1.79)
	$\beta 2, \text{ObservedWeight}$	–0.167 (–4.97)	–0.157 (–5.14)	–	–
	$\beta 2, \text{WeightMissing}$	–	–3.570 (–5.04)	–	–
	$\beta 2, \text{LatentWeight}$	–	–	–0.198 (–1.97)	–0.259 (–4.31)
	$\beta 2, \text{Time}$	0.018 (0.07)	–1.220 (–9.17)	–0.902 (–6.18)	–0.742 (–5.77)
	$\beta 2, \text{IndusParks}$	0.257 (2.27)	1.460 (19.52)	6.400 (11.00)	6.410 (1.69)
	$\beta 2, \text{EmpManuf}$	–1.980 (–3.37)	–1.390 (–3.49)	–3.210 (–8.29)	–3.110 (–9.46)
	$\beta 2, \text{EmpMining}$	0.034 (2.14)	0.039 (3.58)	0.082 (7.23)	0.742 (7.82)
	$\beta 2, \text{EmpAgr}$	0.004 (1.80)	0.004 (6.20)	0.003 (4.34)	0.003 (5.59)
	$\beta 2, \text{Lifestock}$	5.340 (9.70)	3.980 (6.79)	28.600 (4.05)	28.600 (2.39)
Alt. 3 CT:	$\beta 3, \text{Constant}$	5.24 (7.17)	3.130 (4.35)	125.000 (4.45)	125.000 (6.66)
Storage at inland CT	$\beta 3, \text{Dist (mean) a}$	0.800 (4.26)	0.936 (9.92)	1.760 (16.74)	1.170 (12.76)
	$\beta 3, \text{Dist (st. dev.) a}$	–	–	–	0.046 (1.79)
	$\beta 3, \text{ObservedWeight}$	–0.253 (–9.42)	–0.157 (–5.14)	–	–
	$\beta 3, \text{WeightMissing}$	–	–3.570 (–5.04)	–	–
	$\beta 3, \text{LatentWeight}$	–	–	–9.490 (–5.31)	–9.480 (–7.46)

	β_3 ,Time	0.976 (2.70)	1.070 (4.49)	35.900 (3.16)	35.900 (2.07)
	β_3 ,EmpManuf	0.899 (2.37)	0.816 (4.88)	33.200 (6.01)	33.200 (4.80)
	β_3 ,EmpMining	-0.067 (-3.54)	0.002 (1.91)	-1.300 (-5.69)	-1.310 (-5.39)
	β_3 ,EmpAgr	0.008 (3.24)	0.008 (15.79)	0.290 (6.21)	0.300 (6.76)
Alt. 4 CT:	β_4 ,Constant	-14.600 (-290.75)	-6.090 (-17.53)	-6.77 (-27.18)	-6.730 (-20.96)
Storage at both	β_4 ,Dist	0.760 (4.02)	0.936 (9.64)	1.500 (15.07)	1.500 (7.91)
port and inland	β_4 ,DistInland	-0.233 (-1.49)*	0.492 (3.06)	-0.991 (-5.62)	-0.988 (-5.60)
CT	β_4 ,IndusPark	0.064 (8.94)	3.070 (15.41)	8.040 (13.42)	8.080 (2.11)
	β_4 ,EmpManuf	-0.240 (-0.90)*	-5.770 (-11.06)	-7.700 (-16.38)	-7.330 (-13.70)
	β_4 ,EmpMining	-0.0157 (-2.22)	0.087 (10.43)	0.113 (8.55)	0.085 (6.20)
	β_4 ,EmpAgr	-0.021 (9.91)	0.012 (14.79)	0.012 (23.3)	0.012 (18.96)
	β_4 ,Lifestock	-0.580 (2.36)	4.060 (5.60)	29.900 (4.23)	29.700 (2.44)
Alt. 5 CT:	Base alternative				
Packing at port					
CT					
Structural eq.	γ_w ,Constant	–	–	3.090 (109.18)	3.100 (63.57)
latent weight	γ_w ,AreaAgr	–	–	0.094 (13.97)	0.117 (14.30)
	γ_w ,AreaTransp	–	–	-4.440 (-10.62)	-5.370 (-2.91)
	$\sigma_w a$	–	–	0.993 (16.81)	0.987 (16.71)
Alt. 0 DT:	Base alternative				
Less than one					
day					
Alt. 1 DT:	κ_1 ,Constant	–	–		-1.550 (-16.72)
One day	κ_1 ,EmpManuf	–	–		-0.327 (-2.65)
Alt. 2 DT:	κ_2 ,Constant	–	–		-0.579 (-12.63)
More than one	κ_2 ,AreaIndus	–	–		0.014 (1.94)
day	κ_2 ,EmpManuf	–	–		-0.279 (-3.55)
Dependency	Copula parameter	–	–	–	5.180 (56.41)
Number of parameters		28	31	32	41
Number of observations		2045	5624	5624	5624
Null LL (choice of CT)		-3291.3	-9051.48	-9051.48	-9051.48
LL (total)		-1166.15	-4307.93	-7421.67	-7917.77
LL (choice of CT)		-1166.15	-4307.93	-4029.77	-4073.55
LL (measurement)		–	–	-3391.90	-3310.93
Adjusted p2 w.r.t. to choice of CT		0.637	0.521	0.551	0.555

Note: t-statistics are reported in parenthesis, * normal distribution

Figure 16 presents the scatterplot comparing the estimated systematic utility of the chosen alternative with the highest estimated systematic utility for import container transport across the alternatives for (a) Model 2 and (b) Model 4. Notably, 13.9% of the observations were estimated to have higher systematic utility in alternatives other than the chosen one for Model 2, while the outliers decreased to 11.4% of the observations for Model 4.

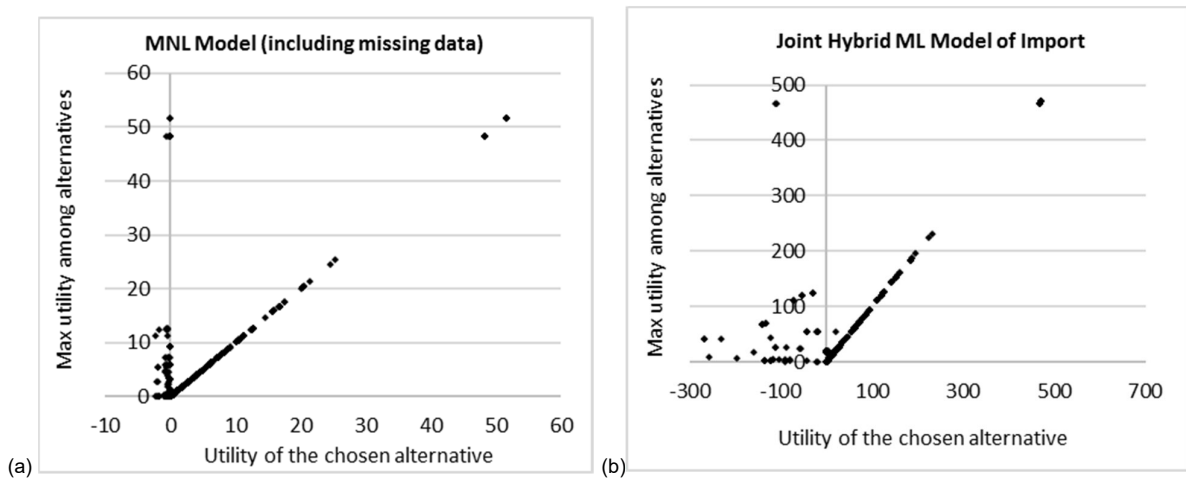


Figure 16 – Scatterplot comparing the estimated systematic utility of the chosen alternative vs. the highest utility across alternatives in import container transport for (a) Model 2 and (b) Model 4

Figure 17 presents the scatterplot comparing the estimated probability of the chosen alternative with the highest estimated probability for import container transport across all the alternatives for (a) Model 2, and (b) Model 4. Notably, 28.5% of the observations were estimated to be outliers for Model 2, while there was an improvement in that 21.3% of the observations had higher probability than the chosen alternative for Model 4.

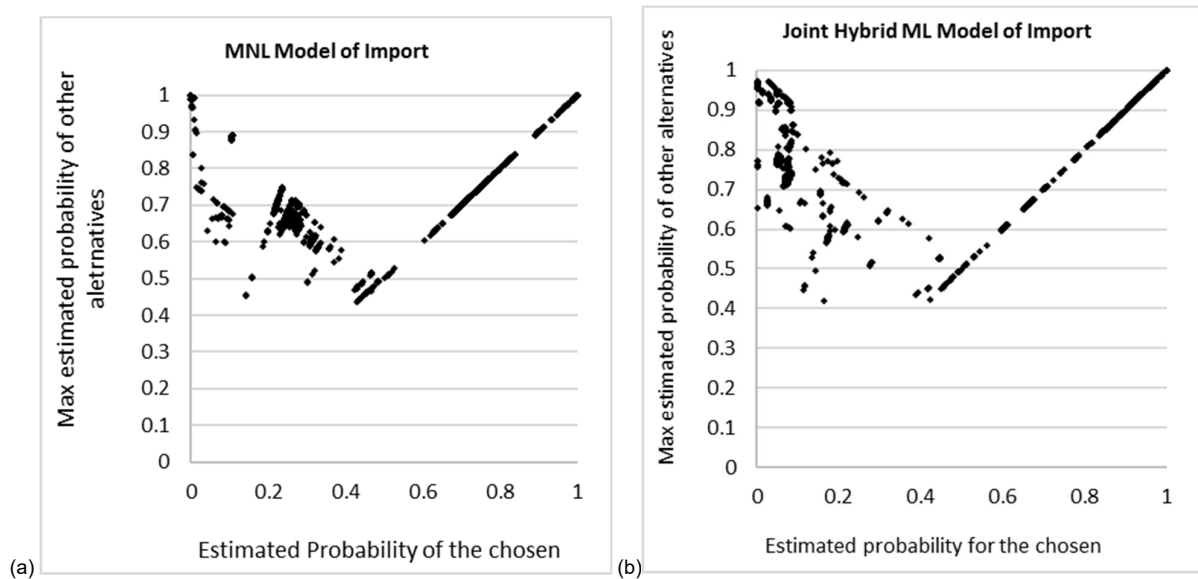


Figure 17 – Scatterplot comparing the estimated probability of being chosen vs. the highest probability across alternatives in import container transport for (a) Model 2 and (b) Model 4

Similarly, the joint copula-based hybrid structure of Model 4 for export container transport presents fewer outliers than the MNL structure of Model 2. In fact, in Model 4, 45.5% of the observations were estimated to have higher systematic utility in alternatives other than the chosen one, while the percentage was 49.4% of the observations for Model 2 (see Figure 18).

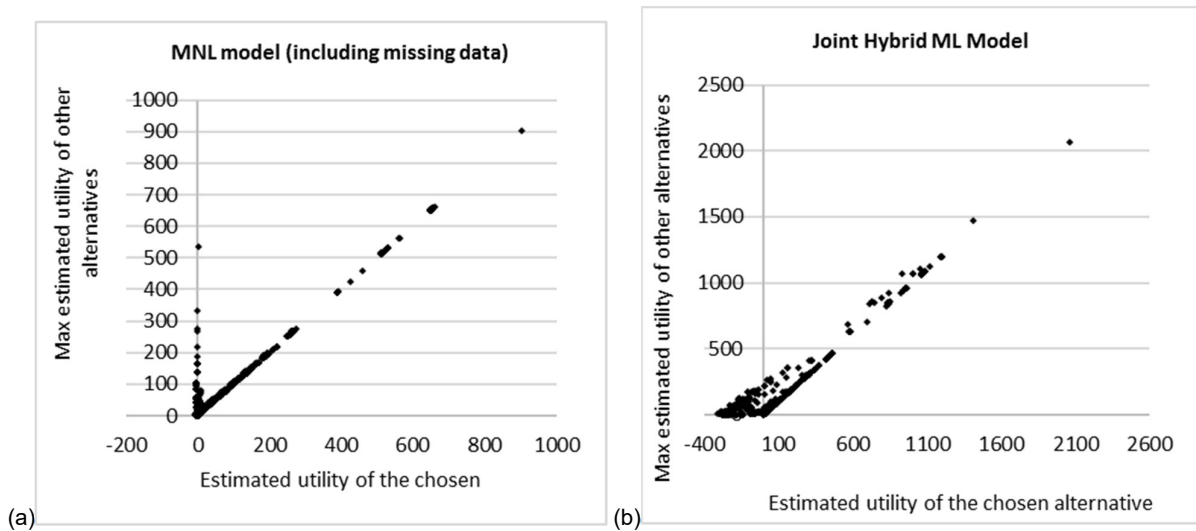


Figure 18 – Scatterplot comparing the estimated systematic utility of the chosen alternative vs. the highest utility across alternatives in export container transport for (a) Model 2 and (b) Model 4

Similarly, Figure 19 shows the comparison between the estimated probability of the chosen alternative versus the highest estimated probability for export container transport across all the alternatives. Notice that 22.2% of the observations are outliers, where the highest probability is estimated for an alternative other than the chosen one for Model 2. The joint copula-based model structure in Model 4 decreases this value to 18.5%.

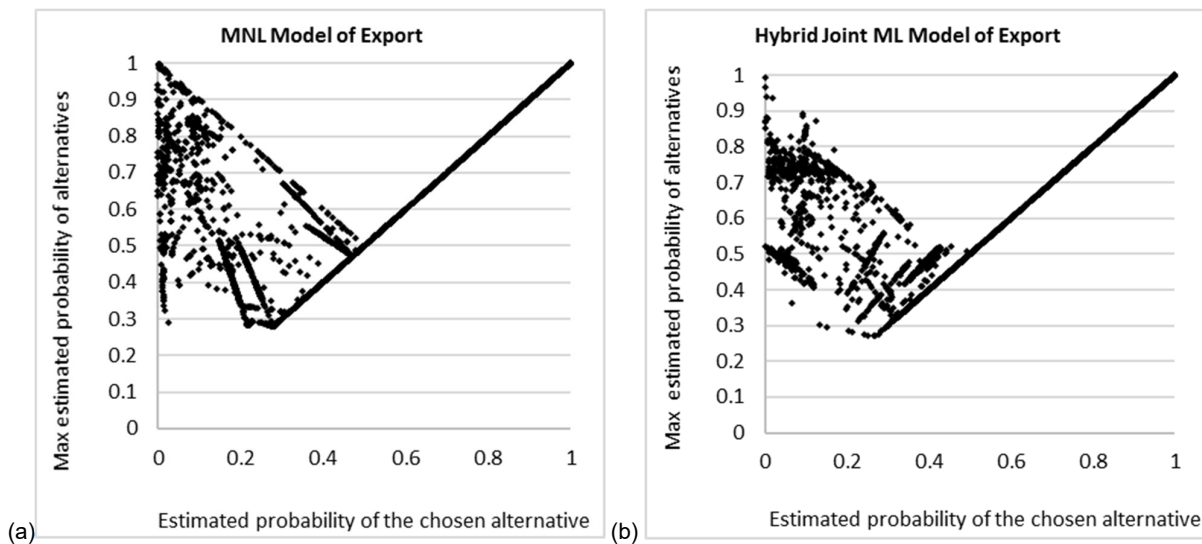


Figure 19 – Scatterplot comparing the estimated probability of being chosen vs. the highest probability across alternatives in export container transport for (a) Model 2 and (b) Model 4

In order to validate the robustness of these results, the model was estimated for 70% of the observations and applied to the remaining 30%. Also, in order to limit the effect of inherent randomness in the sampling of observations, this procedure was repeated 10 times. Table 9 shows the average number of outliers across the 10 different draws, for comparison

between the estimated probability of the chosen alternative versus the highest estimated probability across all alternatives, in Model 4 and in a constant-only model. The validation results show stability and confirm that the joint copula-based hybrid structure of Model 4 has fewer outliers and better choice reproduction when compared to the constant-only model that exactly replicates the market shares in the data. As an illustration, Figure 20 depicts the scatterplots of the estimated probabilities of the chosen versus the highest alternative for one of the validation subsets. Thus, we conclude that our model results are robust when validating the models using different subsets of the sample.

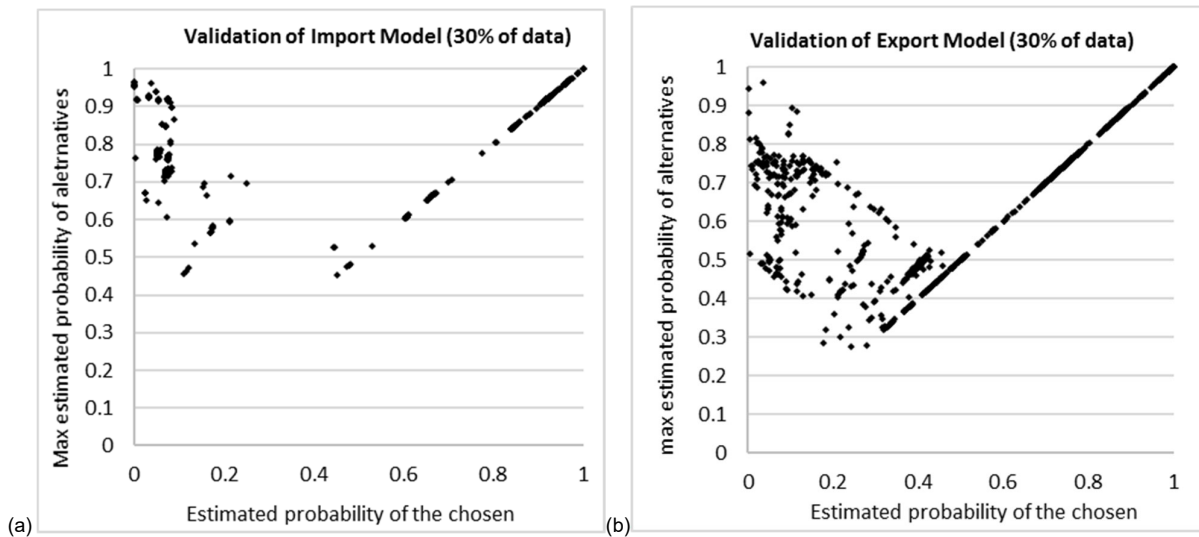


Figure 20 – Scatterplot of the estimated probability of the chosen vs. optimal alternative for a sample (30% of observations) with respect to (a) import chain, (b) export chain

Table 9 – Comparison of probability outliers between the joint copula-based hybrid model and the constant-only model reproducing the market shares

	Outliers of import chain	Outliers of export chain
Proposed Specification	34.50 %	30.04%
Constant Only	45.03 %	60.28 %

4.5 Conclusions

Given the continued growth in maritime containerised transport, the limited physical and logistical connectivity around ports, and the costs associated with the storage and rehandling of containers, there is a need to understand the factors affecting the choice of using CTs for freight operators to improve the efficiency of their operations. This study jointly analyses the choice of using a CT, as storage or for packing/unpacking purposes, and deciding the dwell time of containers at the CT. A joint copula-based model was specified

for a real-world case-study that focused on data collected in the Import/Export Logistics Chain Study of the Port of Brisbane (Australia) and was estimated for import and export container transport.

The first contribution of this study was the formulation and estimation of a joint discrete-discrete copula-based approach that captured the dependency between the use of the CT and the decision on the dwell time of containers. The copula parameters were significant and their positive sign showed that unobserved terms affect both the probability of using CTs as intermediate stops and the duration of the dwell time in the same direction. The second contribution of this study was the specification of a hybrid model in the context of freight and logistics, with the aim of correcting for missing information. Specifically, the model exploits the fact that variables with missing values are latent by definition. Hence, the hybrid formulation of the joint copula-based model allows circumvention of the bias inherent in removing observations or imputing values by expressing the value of the latent variables as a function of explanatory variables. The latent variables considered in this study are shipment weight and time of arrival in the import container model, and shipment weight in the export container model. The third contribution of this study was in the specific findings of the joint model, and certainly in particular the observation of heterogeneity in the sensitivity to distance, which was a factor found to be very relevant in the choice of using a CT.

The findings from this study show that both importers and exporters who are located at shorter distances from the port prefer to deliver directly, while CTs facilitate long-distance transport by solving the problem of misalignment of business hours and increasing the reliability of on-time delivery. The limited timeslots at the stevedores, and probable road work or accidents that cause congestion and delays for trucks, are common concerns of exporters, which in turn increases the probability of using CTs located close to or at the port for longer-distance travel.

Looking at the parameter estimates highlights the different characteristics of import and export supply chains concerning the usage of CTs and the duration of their use. Export containers originating from suburbs with a higher number of mining, agricultural, and manufacturing employees are more likely to be stored at CTs either inside the port or inland, whereas export containers originating from suburbs with a higher number of livestock-related businesses, distribution centres, and industrial parks are less likely to be stored at

inland CTs. The fact that a large number of packing facilities are located at or near the production/processing locations of the exporters, and that these facilities are considered as the industrial parks and distribution centres, can explain this result. Furthermore, considering that a significant proportion of export commodities through the Port of Brisbane are agricultural products (such as grain and cotton), pulp–paper, manufacturing, and mining products, the significance of these land uses on the choice of CTs can represent the impact of the types of commodity on these choices. Import containers destined to areas with a higher number of retailers and a larger area for commercial land use are more likely to travel through CTs either at the port or inland. This result indicates that retailers and smaller businesses use CTs as an extended component of their distribution system for storage and bundling to reduce their operating cost. The significant relationship between different land uses and the choice of CTs highlights the critical importance of the location of a CT, as international trade is highly dependent on quick and good access to transport and logistics services where goods can be stored or bundled or unbundled in a more efficient way.

The arrival on a weekend or a late arrival during the day is related to direct delivery for import containers, particularly if destined to suburbs with a larger wholesale sector. This may be a result of operating hours of CTs that do not work 24/7, or also the underlying fact that the wholesale sector has its own specific distribution centres for storage purposes. When looking at export containers, departure late at night or early in the morning is associated with a higher probability of storage at CTs either at the port or inland. We can hypothesise that exporters dispatch their shipments late at night or early morning and store at CTs for the purpose of on–time loading to ships for the next day and also avoiding the probable delays of daily roadway traffic. Also, the weight of the shipment makes for a higher likelihood of export containers to be delivered directly or stored at CTs inside the port.

The findings from this study show that larger industrial areas in both the origin and the destination suburbs increase the probability of storage at CTs for dwell times of at least one day. Also, while import shipments destined to the suburbs with a higher number of employees in the manufacturing sector are more likely to be stored at CTs for at least one day, export shipments originated from those suburbs have a shorter dwell time.

Notably, no cost data were reported in the dataset. Interestingly, an attempt was made to estimate costs associated with each alternative via quotes from freight operators working in import and export through the Port of Brisbane. However, using CTs inside the

port is the preferred option with respect to inland CTs, despite the high usage cost, including cartage, loading/unloading, and storage costs. This is possibly because of higher reliability for shorter hauling distances, or of larger availability of carriers and terminal capacity at the port. Further research could look into additional factors such as the availability of resources for the cargo owners, the relevance of owning land, the labour and machinery necessary for storage/packing/unpacking, the time–window constraints, the type of contract between buyer and seller (i.e., long–term vs. short–term), and the relevance of paying the costs associated with inland transport. Obviously, future research would benefit from richer datasets containing information such as commodity type, type of packing, and the value and volume of the container. Further research could also explore the dynamic aspect of transactions, as this study was estimated in a static context. As travel time, travel costs, and time–windows are dynamic in nature, and decisions about shipments are made on a case–by–case basis in a dynamic environment, a dynamic choice model could capture the maximum utility for each shipment on the basis of the dynamic explanatory variables over time periods.

Chapter 5: Modeling the efficiency of a port community system as an agent-based process

Published in the Procedia of Computer Science, Vol 109C, PP 918–923, Elsevier, 2017, and presented in the 6th International Workshop on Agent-based Mobility, Traffic and Transportation Models, Methodologies and Applications (ABMTrans 2017)

<https://doi.org/10.1016/j.procs.2017.05.422>

Elnaz Irannezhad, Mark Hickman, Carlo G. Prato

5.1 Abstract

We present an agent-based method which makes use of reinforcement learning in order to estimate the efficiency of a Port Community System. We have evaluated the method using two weeks of observations of import containers at the Port of Brisbane as a case study. Three scenarios are examined. The first scenario evaluates the observed container delivery by individual shipping lines and estimates the consignments allocated to the various road carriers based on optimizing the individual shipper's total logistics cost. The second scenario implies that, in the optimum case, all agents (shipping lines and road carriers) communicate and cooperate through a single portal. The objective of cooperation is in sharing vehicles and creating tours to deliver shipments to several importers in order to reduce total logistics costs, while physical and time window constraints are also considered. The third scenario allows for some agents to occasionally decide to act based on individual costs instead of total combined logistics costs. The results of this study indicate an increase in the efficiency of the whole logistics process through cooperation, and the study provides a prototype of a Port Community System to support logistics decisions.

5.2 Introduction

While billions of dollars are spent on infrastructure to move freight more efficiently, the complexity of the freight market and the lack of collaboration between the various agents

in this market often lead to sub-optimal use of that infrastructure. Freight agents mostly aim for profitable and safe operations, and they share or interact with the same infrastructure. These agents include shippers, carriers, terminal operators, and logistics solution providers such as freight forwarders. Yet, due to data confidentiality and competition among freight actors, there is poor information sharing, contributing to the sub-optimal use of infrastructure.

Ports are the primary interface in the import-export industry and play an important role in driving economic growth. Currently, many port authorities play a minimalist role as a landlord, only providing the necessary infrastructure to shippers and carriers in the port. Individual freight agents (e.g. shipping lines) optimize their own logistics process while not coordinating with other shipping lines, which may result in more truck movements than necessary and incurring higher transport costs. In this context, freight agents may be aided by the exchange of information concerning road traffic conditions, real-time availability of drivers and carriers, and opportunities for bundling of shipments into fewer vehicles. In the literature, this information exchange has been called a “Port Community System (PCS)”, formally defined as a holistic, geographically bounded information hub in a global supply chain that primarily serves the interest of a heterogeneous collective of port-related companies (Srour et al., 2008).

The PCS helps port authorities take the lead by providing a logistics solution to private actors, encouraging them to share information that may lead to lower logistics costs, to faster delivery/pickup in the import/export chain, and to higher customer satisfaction. Bringing all users together enhances the efficiency of the physical flow of freight, drives economic growth, and as a secondary result, assists in reducing externalities such as pollution, congestion, and land use impacts. For example, the PCS helps transport yards and container parks to predict and plan future shipments and helps carriers to better plan for their fleets. The benefits of the PCS have been seen in several examples (see Srour et al. (2008)), namely the Port of Rotterdam (Portbase), the Port of Hamburg (DIVA: Dynamic Information on Traffic Volumes), the Port of Antwerp (CCS Dakosy), the Port of Valencia, and the Port of Singapore (Portnet Trade Exchange).

The purpose of this study is to develop a multi-agent-based simulation model to examine an application of the PCS, allowing shipping lines to coordinate the delivery of import containers for shipment bundling and routing decisions. According to Malone and

Crowston (1994), coordination means managing the interdependencies among activities. Coordination here explicitly is defined as the ability to bundle shipments and to share vehicles for delivering containers to various destinations.

A multi-agent-based simulation consists of several agents who are interacting in an environment. This modeling technique captures the explicit decision-making of various actors, representing their management of resource and time constraints and their reaction to various policies. Agent-based models have been adopted in several domains, such as the interactions of economic agents in financial markets (e.g., Xu and Chi (2007), Bonabeau (2002) and Taghawi-Nejad (2013)), supply chain management for single firms, and the activities in fleet management including scheduling, dispatching or terminal management (e.g., Bouzid (2003), Burckert et al. (2000), Henesey (2006) and Dong and Li (2003)). For freight transport systems, this approach seems very suitable to illustrate competition and interaction among agents. INTERLOG (Liedtke (2009)) and TAPAS-Z ((Holmgren et al. (2013)) are examples of agent-based freight transport models at the regional level.

In addition to simulating the current situation, agent-based methods can be applied to examine various policies by changing the environment and observing how agents behave in the new environment. For example, Taniguchi et al. (2007) developed a multi-agent-based model (including shippers, carriers, and administrators) on a small test network to study the effects of road pricing on shippers' and carriers' strategies. Abdul-Mageed (2012) examined a coordinated truck assignment system for five trucking companies, comparing direct competition with cooperation by sharing vehicles. Results showed that the coordinated assignment system improved the transport process in terms of decreasing the number of empty trips and the number of late arrivals.

This study examines the impacts of the PCS on an inland container transport system in which shipping lines learn whether to act individually or to cooperate in order to deliver import containers, while maintaining the objective to minimize logistics costs. The total logistics costs consider time-based and distance-based operational costs, the capacity and fixed cost of vehicles, the road network operating constraints for larger trucks, and the fixed time windows for importers. This study contributes to the literature by implementing a reinforcement learning algorithm in a joint routing and vehicle type decision-making process through the PCS. Accordingly, three scenarios have been tested. In the first scenario, the choices of vehicle type and delivery routing are optimized individually by

shipping lines. In the second scenario, all deliveries are managed by the PCS. In the third scenario, each shipping line decides whether to cooperate with others through the PCS or to act individually. Shipping lines learn the optimal strategy through a Q-learning algorithm, which is a type of off-policy reinforcement learning method. In Q-learning, agent behaviors can be defined using a simulation system, allowing agents to perform independent actions but also to learn through experience to obtain specific objectives.

5.3 Methods

5.3.1 Model specification

A multi-agent-based system consists of agents and the environment where the agents are in interaction with each other. Each agent's actions follow predefined rules. Given the fragmentation of the container transport industry, a multitude of actors collaborate within a transport system, and significant time and budget are allocated to this interaction, as shown in Figure 21.a. Some of the actors provide physical transport, located in either the port or the hinterland (e.g., stevedores, carrier companies, distribution centers, container parks), while others provide logistics services (e.g., freight forwarders, shippers).

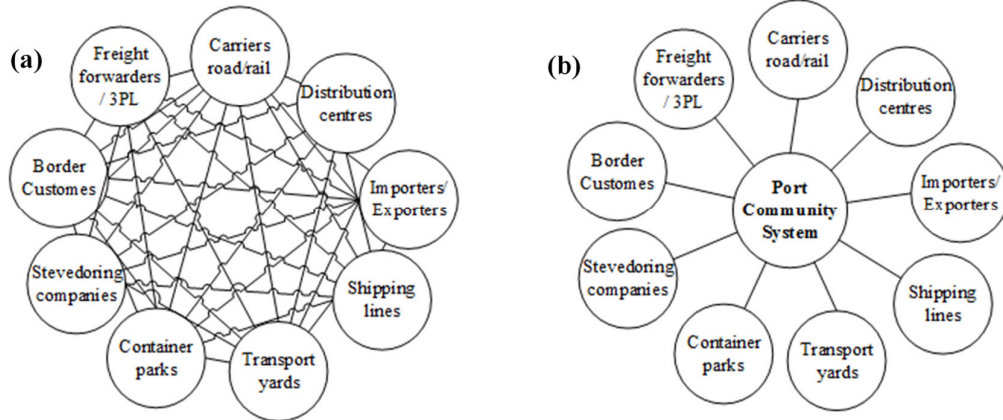


Figure 21 – Communication between individual port-related freight agents (a) without the PCS and (b) with the PCS

The agents in this model consist of importers, shipping lines, and road carriers. Importers/exporters, as the owners of shipments, have a given number of containers, the time-windows of delivery for those containers, and their origin/destination locations. There are two types of road freight vehicles, including semi-trailers and B-double trailers, which have different capacity and cost attributes. Shipping lines, as the main logistics providers, collect and distribute the import/export containers within the prerequisite time-windows and

choose an optimum vehicle and route. The environment consists of discrete states of the freight market (shipments to be delivered daily) and a physical road network in which B-doubles are not allowed to operate on some road segments.

In the first scenario (the current situation, shown in Figure 21.a.), the simulation outcome is achieved with individual shipping lines acting independently, while in the second scenario the simulation outcome is the result of full cooperation of all shipping lines to deliver their shipments through the PCS (shown in Figure 21.b). Notably, in the third scenario, in each of 50 discrete simulations (steps), each shipping line is given the opportunity to explore and exploit these two options (individual vs. cooperative delivery plans) for 14 days (with 1 day exhibiting 1 “state” of the environment) by learning through an off-policy reinforcement learning (RL) algorithm called Q-learning.

An RL algorithm is a computational method in which an agent is trained to take the optimal action through a learning process. The agent takes action based on a predefined policy, predicts a value for that action, experiences the actual outcome for every state (day), and then compares this prediction (expected) to the experience (observed). Q-learning is the most salient RL algorithm, and it is defined as (Watkins and Dayan, 1992):

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)] \quad (5.1)$$

where:

$Q(s_t, a_t)$: Value of taking action a_t in state s_t .

r_{t+1} : Reward from the environment in step $t+1$.

α : The learning rate, a value between 0 and 1, where a higher value represents faster learning.

γ : The discount factor, a value between 0 and 1, where a smaller value represents a more short-sighted agent, with the extreme 0 standing for an agent who only considers the current rewards.

$\max_a Q(s_{t+1}, a)$: The maximum reward that is expected to be achieved in the following state, if action a is chosen.

In this model, the action–value function $Q(s_t, a_t)$ is defined as the savings in the total logistics cost for action a_t compared to other actions, where the logistics cost are a summation of the cost due to time–windows violations, the operational costs attributed to travel time and distance, and the fixed costs of a road carrier. Travel time and distance are determined based on the result of the optimum routing in every state s_t (the environment on day t), where the optimum routing is obtained from the solution to the “capacitated vehicle routing problem with time–windows” (CVRPTW). The CVRPTW model is a combinatorial optimization problem which determines the optimal set of routes for a fleet of vehicles to traverse in order to deliver containers to a given set of customers considering vehicle capacities, delivery time windows, driver work rules, and network constraints for some vehicles. Accordingly, the optimum vehicle type is chosen within the solution to the CVRPTW. The algorithm for solving the CVRPTW is as follows:

Step 1: Initialize $Q(s_0, a_0)$ for each agent (137 shipping lines), where a_0 = individual action, s_0 = all shipments to be delivered in first day,
 $Q(s_0, a_0)$ = savings in total transport cost for all shipments for the first day, comparing each shipping line acting independently to all shipping lines cooperating
Repeat for each episode (50 simulations) until s_t is terminal:
Step 2: Initialize state s_t ($s_t = 1..14$ days)
Step 3: Choose a_t (independence or cooperation) using an action-taking policy. We use $\epsilon = 0.2$ which means 20% of the actions involve a random action and 80% of the actions the optimum action is taken. The optimum action is the action which has delivered the highest Q-value in the last 5 episodes.
Step 4: Observe the next state (s_{t+1} = all shipments in next day) and associated savings in total logistics cost (r_{t+1}) resulting from action a_t
Step 5: Update action-value function by $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)]$ where $\alpha = 0.7$, $\gamma = 0.3$
Step 6: Move to the next state $s_t \leftarrow s_{t+1}$;

Figure 22 – Q–learning algorithm of shipping lines

Python code was developed to implement the algorithm, calling the geo–processing tools of ArcGIS to solve the CVRPTW. It should be noted that, since each shipping line decides individually which action to take, the predicted value of action $\max_a Q_a(s_{t+1}, a)$ will not necessarily match what will be experienced in every episode (r_{t+1}).

5.3.2 Data

The case study focuses on container shipments entering the Port of Brisbane (Australia). The dataset was provided by the Port of Brisbane Import/Export Logistics Chain Study(PBPL, 2013) and includes details of individual container movements: identification number, timestamps of arrival and departure, postcodes of origin and destination, weight of shipment, and size of container. This study focuses on the movements of full containers

in import chains (1942 records) which are mainly destined into the suburbs of Brisbane. There are 137 agents (shipping lines) who delivered 1942 containers to 248 postcodes. The road network consists of 18,890 links and 22,700 nodes, from which only 5338 links allow B–doubles to operate.

5.4 Results

The principal measures of performance for the three scenarios, and the results, are shown in Table 10. The comparison between these measures confirms the benefits of cooperation through a PCS, in line with the literature (Abdul-Mageed, 2012). The analysis of the results reveals that, in cooperation, the number of visits in each tour increases by using larger vehicles, while the total distance traveled and consequently the total logistics cost decrease.

Table 10 – Simulation results of PCS for import containers

	Scenario 1: Individual action	Scenario 2: Full cooperation	Scenario 3: Q–learning result in 50th episode		
			Cooperating agents	Individual agents	Sum
Total logistics costs (\$)	2,238,925	1,947,616	1,603,323	367,158	1,970,481
Time–based operating costs (\$)	311,864	260,587	209,341	57,689	267,030
Distance–based operating costs (\$)	1,926,725	1,686,863	1,393,836	309,390	1,703,226
Number of trips by B–doubles	253	591	466	40	506
Number of trips by semi–trailers	1,174	747	550	296	846
Total number of trips	1,427	1,338	1016	336	1,352
Total travel time (hr)	3,448	2,929	2,406	558	2,964
Total distance (km)	159,343	135,222	111,143	25,770	136,913

Figure 23 indicates the Q–value function for ten major shipping lines (expressed by their name's acronym) who operate through the Port of Brisbane. Interestingly, the savings in logistics costs in cooperation are generally higher for shipping lines who have fewer shipments to deliver, while cooperation sometimes imposes a higher logistics cost upon the major shipping lines. This is why some shipping lines would prefer individual action over cooperation in the proposed RL algorithm, and leads to less total improvement compared to the full cooperation approach.

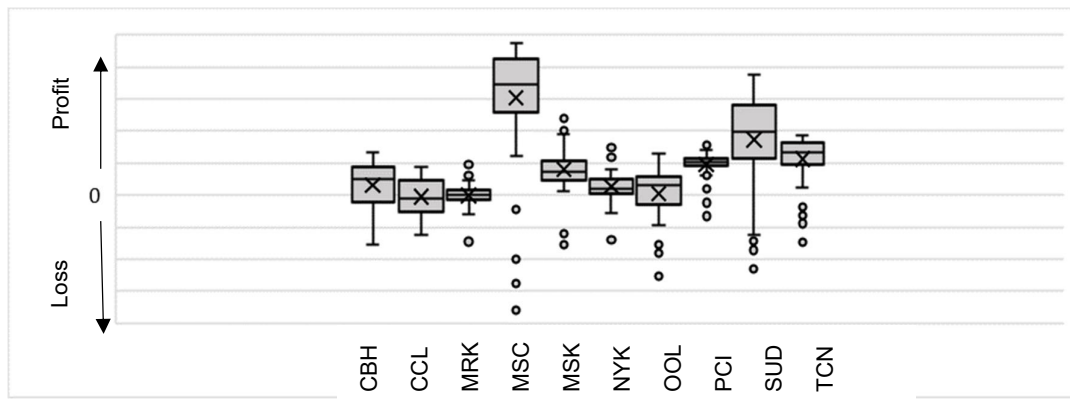


Figure 23 – Q-values for top ten shipping lines during 50 episodes ($\alpha = 0.7$, $\gamma = 0.3$, $\epsilon = 0.2$)

5.5 Discussion and conclusions

This paper provides insight into the benefits of adopting the PCS for private actors in terms of increasing efficiency, profit, and infrastructure utilization. The agent-based model developed in this study is based on the notion that freight markets are not usually in a stable equilibrium, as simplistically assumed in traditional modeling approaches (Friesz and Holguín-Veras, 2005), because agents are highly heterogeneous and should have a degree of freedom to choose non-optimum actions. The results prove that the cooperation between shipping lines in sharing vehicles through the PCS can decrease the total travel distance and total logistics cost as well as improve the vehicle utilization.

The results of Q-learning algorithm showed that the savings in logistics costs in cooperation are generally higher for shipping lines who have fewer shipments to deliver, while cooperation sometimes imposes a higher logistics cost upon the major shipping lines. The results of Q-learning implies that if PCS be provided as an optional solution by the port authority, the major shipping lines may not necessarily utilize the logistics cooperative scheme of PCS, while there still is a chance of using PCS as an integrated toolkit for administrative tasks.

Further avenues for research are foreseen based on the limitations of this study:

- Postcodes were the only information about the container destinations, and we assumed the same destinations for all containers sharing the same postcode.
- Travel time is assumed to be a function of only distance, while in reality it is a function of traffic volumes that vary dynamically by time of day.

- There is no information on time windows (working hours of agents and/or desirable receiving time for specific containers), nor of the costs of time window violations or late delivery. Thus, in this study, time windows for customers were assumed to be the observed destination timestamp plus or minus a 30 min threshold.
- The parameters used in the Q-learning algorithm should be chosen (or calibrated) based on the actual agent behavior. Calibration and sensitivity analysis for the parameter values (alpha, gamma, and epsilon) will be included in the future studies.

There are also a number of additional strategies to consider with the PCS. First, by taking into account the empty container and export chain, we can better plan to balance the empty and full container movements by having more efficient container movement in the hinterland. Second, by adding the truck mass restrictions on the road network, and also the dynamic travel time of links, routing will better match reality. Third, the probability of choosing each action (ϵ) can be obtained through developing a discrete choice model, using parameters from previous studies, developing a sample case-study, or developing a game (e.g. SMUrFS (Anand et al., 2016)). Last, about half of the import containers were stored at transport yards for several hours or days. By including the costs of storage and handling at transport yards, the choice of using transport yards can also be modeled jointly with vehicle type and routing.

Chapter 6: The effect of cooperation among shipping lines on transport costs and pollutant emissions

Paper published in the Journal of Transportation Research Part D: Transport and Environment, 65, Pages 312-323, (2018), also presented at the 97th Annual Meeting of the Transportation Research Board, January 7–11, 2018, Washington D.C.

Elnaz Irannezhad, Carlo G. Prato, Mark Hickman

6.1 Abstract

This study explores the effect of cooperation among shipping lines on transport costs and pollutant emissions. The quantitative benefits of the cooperation were measured via a simulation-based model that (i) optimized inland empty container reuse and (ii) considered a two-dimensional capacity (weight and size) for vehicle types and demands. Inland empty container optimization was integrated with a dynamic vehicle allocation and routing problem with time-window constraints, while the two-dimensional capacity considered minimising total transport costs in a time-varying network with road segment usage constraints by truck type. The simulation model was used to evaluate the status quo and the cooperation scenarios by analysing two weeks of import and export container movements for the port of Brisbane (Australia). The major findings from the study are: (i) the cooperation among shipping companies avoids a significant number of unnecessary truck movements and of storage days for empty containers; (ii) the cooperation translates into truck-sharing and utilisation of larger trucks, which are more environmentally friendly and cost-efficient choices when compared to smaller trucks; (iii) the introduction of a decision support system provides solutions to the freight actors regarding optimal routing and vehicle allocation, based on real-world constraints and dynamics. Remarkably, the savings in the cooperation scenario are substantial, yielding a 40% reduction of fuel consumption and pollutant emissions.

6.2 Introduction

International trade is a key component of sustainable development because of its contribution to the productivity of natural and human resources (Arntzen and Hemmer, 1992). However, it also entails environmental degradation because of the generated freight movements (Williams, 1993). International freight transport consists of maritime and inland transportation, where shipping lines are mainly responsible for the maritime movements, while road and rail carriers are mainly responsible for the inland movements. Nowadays, most shipping lines provide door-to-door transport services to customers in order to increase their competitiveness in the market and to control their container flows. Shipping lines may either sign long-term contracts with inland carriers and freight forwarders or own their inland transportation service. However, the imbalance of trade and economic needs in different regions implies that a significant volume of empty containers are repositioned through inland or seaborne services, with the consequent significant increase of logistics costs. Accordingly, shipping lines and shippers alike bear all associated landside handling and storage costs of empty containers and operations. Notably, empty container management consumes an equivalent amount of resources as full container movement, and, the separation of container operations between shipping lines entails the double handling of containers and imposes extra logistics costs.

Most of the landside container movements occur on the hinterland road network where container origins and destinations are located. Hence, container repositioning is not only costly for the shipping lines but also expensive for society, given negative externalities in terms of increased congestion, emissions, and energy consumption. As the transport sector accounted for 20.5% of the global CO₂ emissions in 2014 (The World Bank, 2014), it is crucial that ports, in their role as key freight generators, commit to protecting and sustaining the natural environment. Moreover, it appears to be essential that ports adapt to fundamental changes in the freight transport market resulting from competition, regulations, and growing trends towards IT-based systems. In contrast to the traditional focus on individual freight companies, an upward trend exists towards collaborative and real-time control systems aimed at increasing the efficiency of the whole logistics process. As a major actor, ports can play a key role in improving the efficiency of services and increase their competitiveness by facilitating these freight cooperation initiatives.

Accordingly, this paper presents a study undertaken for the Port of Brisbane (Australia) to analyse the environmental and economic benefits of horizontal cooperation among shipping lines in inland freight transportation. Australian port container traffic accounted for 7,635,620 TEUs in 2016 (The World Bank, 2016), where 1.2 million TEUs were handled through the Port of Brisbane (Port of Brisbane Pty Ltd, 2017). Forecasts of import/export growth indicate that the total container movements (full and empty) through the Port of Brisbane are expected to increase 2.3 times by 2040 (Port of Brisbane Pty Ltd, 2013). While the road transport sector accounted for 24.7% of the CO₂ emissions in Australia in 2014 (The World Bank, 2014), trucks (articulated and rigid) contributed to about 23.3% of the annual road transport emissions (Pekol Traffic and Transport, 2015), and truck Carbon Dioxide equivalent emissions (CO₂-e) were estimated to be more than 24 million kilograms per year in the Port of Brisbane precinct alone (Smit et al., 2010). Given these premises, this study focuses on inland container transportation to and from the Port of Brisbane with the aims of increasing the efficiency of land-based supply chain functions and of limiting their environmental impacts.

Inland container transportation consists of the allocation of containers and fleets between depots and customers. A typical container flow in an export chain is as follows: (i) the shipping line delivers an empty container to the exporter from an empty container park (ECP); (ii) the container is loaded by the exporter and carried to the stevedores at the port; (iii) the container is stored at either the wharf or the container terminals to be shipped. A typical container flow in an import chain is as follows: (i) the full container is unloaded by stevedores and stored at the wharf, typically between 3 and 7 days in Australian ports due to capacity constraints at the portside; (ii) the importers, who are informed about the arrival date and time of their shipments one day in advance, collect the full containers; (iii) the importers have usually a timeframe (between 7 and 10 days) to unload the container and then deliver it to the ECP; (iv) the empty containers at the ECP are either used for the export chain, returned to the port of origin, or leased to other shipping lines.

Given that only full container movements are paid by customers, container usage is directly linked to profits. Accordingly, the demand of an exporter for empty containers can be connected to the presence of nearby empty containers stored by an importer. This concept is termed “street-turn”, and maximizing this connection is an important objective from the shipping lines’ perspective. Specifically, coordination between shipping lines would

not only reduce the number of empty container movements but also increase profits. This coordination can be provided through an online market supported by a port authority, where information about the availability of containers becomes available to all actors. This web-based information exchange allows shipping lines to match empty container demand and supply without storing the containers in an ECP. This concept is also sometimes referred to as a “virtual container yard (VCY)” or “triangulation” and has been successfully applied as either a module of a Port Community System (e.g., Virtuele Haven in the Port of Rotterdam), or a standalone market (e.g., Ports of Oakland, Los Angeles, Long Beach, and Montreal) (Maguire et al., 2010).

It should be noted that bilateral outsourcing and partnerships are a relatively new practice in maritime container trade (Fink, 2002). For example, when a shipping line encounters a shortage of empty containers in port “A”, it may prefer to transport a full import container of another shipping line from port “B” instead of returning an empty container or leasing it from a container company. This decision entails additional transport and container double-handling, which translates into increased logistics costs. Rather, a partnership may be formed between the two shippers to increase efficiency and communication as well as to reduce operational costs. While such partnerships are not currently a common practice in inland container transport (Lun et al., 2010; Lee and Meng, 2015), they are expected to be a major future trend for smaller shipping lines to enable them to compete with emerging big alliances.

It should be also noted that only a few studies have analysed the potential benefits of shipper cooperation. A preliminary study investigated the feasibility of a VCY in the NY-NJ port region (Theofanis and Boile (2007), but under the assumption that no cooperation existed between trucking companies working with different shipping lines. Only one study (Sterzik et al. (2015) examined the potential benefits of cooperation while exploring the empty container repositioning problem integrated with the vehicle routing problem of road carriers. However, the study did not consider the effects of dynamic travel times in the road network on vehicle scheduling (although the time-window constraints of customers were considered), and the study allowed for only one container type (40-foot container) and one vehicle type.

This study overcomes the limitations observed in the existing literature by considering the dynamic nature of the problem of planning for empty container repositioning, given that

both demand and supply of containers are not deterministic. Time-dependent analysis is even more pertinent to the environmental evaluation of logistics operation, as emissions are a function of time and speed of the vehicles (Çimen and Soysal, 2017). Accordingly, this study contributes to the literature by integrating container repositioning within a dynamic supply chain where scheduling and routing of truck movements between various freight actors is considered. Moreover, this study overcomes the limitations observed in the existing literature by considering the multi-dimensionality of vehicle capacity, given that options exist in the weight and size of containers, as well as by considering the constraints imposed by the vehicle dimensions or by the road authorities. As a result, this study proposes the calculation of the levels of fuel consumption and the related pollutant emissions from inland truck-sharing and empty container repositioning. Considering that energy consumption and emission levels are highly relevant sustainability indicators, their assessment following the introduction of cooperation is of extreme importance (Haghshenas and Vaziri, 2012).

Summarising, this study evaluates the transport costs and the pollutant emissions when solving the problem of repositioning inland empty containers for reuse, while integrating vehicle allocation and routing and considering dynamic network travel times, heterogeneous vehicle types, network restrictions per vehicle type, and multi-dimensional capacity of vehicles and container demands. The evaluation was applied to a case study of the Port of Brisbane to show its applicability to a real-world problem. This problem was solved as a multi-dimensional capacitated vehicle routing problem with time-windows (CVRPTW) that considers the real-time network dynamics and network constraints for heavy vehicles. In the problem, each vehicle was assigned to multiple services, as long as the total service duration did not exceed the maximum working hours of the truck driver, and the containerised traffic interacted with the other vehicular traffic. The solution of the routing problem produced average travel speed and distance travelled by each vehicle for the calculation of the transport costs, the fuel consumption, and the pollutant emissions.

Two scenarios were considered: (i) the status quo scenario where the observed inland container movements were observed for two weeks; (ii) the cooperation scenario where the choice of repositioning empty containers directly from the importer to the exporter, the choice of vehicle type, and the delivery routing were optimised under the hypothesised cooperation. In the second scenario, a “virtual depot” allowed users to see the availability of both empty containers and road carriers in order to match supply and demand with regards

to the network dynamics for different days (i.e., weekend, weekdays) and different times of day (i.e., AM peak, off-peak, PM peak, night) where the planning horizon was one day (i.e., the information about shipments was available at the beginning of each day).

The remainder of the paper is organized as follows. The next section reviews the methods and data in terms of the model rationale, the model formulation, and a case study. Then, the results of the evaluation of transport costs and pollutant emissions for the status quo and the cooperative scenarios are presented, and the advantages from cooperation are illustrated. The last section draws conclusions from this study.

6.3 Methods and data

6.3.1 Model rationale

A simulation model was developed to evaluate the movement of containers for both the import and export freight markets. This simulation model was based on truck movements to manage loaded and empty containers in the inland market. Typically, the import containers would be carried from the port to customers in the hinterland, and export containers would be carried from the hinterland customers to the port.

The evaluation of the truck transport costs and pollutant emissions requires the formulation of a vehicle routing problem (VRP) within the simulation. This VRP manages the routing of trucks and containers within the supply chain. In evaluating the status quo and the impacts of cooperation among shipping lines, the VRP may have access to different trucks at different times.

The rationale of the VRP problem has its origin in the literature related to the operational container allocation problem, which considers the movements of both full and empty containers (White, 1972; Florez, 1986; Chen and Chen, 1993). The problem is commonly formulated for empty containers, which by and large are driven by the movements of full containers. Although interrelated, the optimization logic is different between maritime and inland containers: (i) maritime empty containers are repositioned from import-dominant ports to export-dominant ports; whereas, (ii) inland containers are exchanged between importers and exporters directly to avoid double-handling, trans-shipping and empty storage costs at ECPs.

Accordingly, the literature on empty container repositioning can be divided into two categories. The first category focuses on maritime empty containers, for either a single shipping route (Lai et al., 1995), or multiple ports (Shen and Khoong, 1995; Du and Hall, 1997; Cheang and Lim, 2005; Lam et al., 2007; Li et al., 2007; Feng and Chang, 2008; Dong and Song, 2009; Moon et al., 2010; Song and Dong, 2012). Only a limited number of studies about maritime repositioning of empty containers considers a dynamic context as either a network model connecting multiple ports while considering random demand and supply of empty containers (Raymond and Chuen-Yih, 1998), or a dynamic decision support system based on a minimum cost flow algorithm (Cheang and Lim, 2005). The second category concentrates on inland empty containers in either a static (Erera et al., 2005; Olivo et al., 2005; Wang and Wang, 2007; Chang et al., 2008; Bandeira et al., 2009; Furió et al., 2013; Zhang, 2014) or a dynamic context, modelled by using either a stochastic network optimization model (Crainic et al., 1993; Chen and Ma, 1995), or simulation models using heuristic search techniques (Lai et al., 1995; Furió et al., 2009). This study proposes a model of inland empty container repositioning that is not only in a dynamic context, but also considers multiple customers, as the unit of analysis is the container and not the vehicle. Accordingly, this study extends a previous study about dynamic empty container reuse that demonstrated a significant reduction in cost and congestion (Jula et al., 2006), as well as a previous study about a time-varying model that consisted of a cost minimisation model considering heterogeneity in container types (Olivo et al., 2013).

This study looks at the VRP in order to account fully for the movement of the containers and consequently to calculate transport costs, fuel consumption, and pollutant emissions. The VRP is a combinatorial optimization problem that determines the optimal set of routes for a fleet of vehicles to traverse in order to deliver containers to a given set of customers considering real-time constraints (Eksioglu et al., 2009; El-Sherbeny, 2010). Recently, environment-related VRP studies are on the rise because of the increasing awareness about the importance of accounting for environmental impacts and the attractiveness of businesses that care about sustainability (Çimen and Soysal, 2017).

The literature on the VRP accounting for environmental indicators can be divided into two categories (see, for a review, Demir et al., 2014). The first category focuses on "green" VRPs where a dual objective problem (cost and emission) is minimized (Kara et al., 2007; Bektaş and Laporte, 2011; Demir et al., 2011; Suzuki, 2011; Gaur et al., 2013; Kwon et al.,

2013; Zhang et al., 2015; Li et al., 2016; Soysal, 2016; Suzuki, 2016; Norouzi et al., 2017; Wang et al., 2017; Li et al., 2018). The second category concentrates on time-dependent VRPs where the optimum routes and plans are determined from shortest travel time searches in a time-varying network, but with a detailed environmental evaluation (Kuo, 2010; Figliozzi, 2011; Jabali et al., 2012; Franceschetti et al., 2013; Tajik et al., 2014; Setak et al., 2015; Wen and Eglese, 2015; Ehmke et al., 2016; Qian and Eglese, 2016; Xiao and Konak, 2016; Çimen and Soysal, 2017). This study aligns with the second category by considering a time-dependent VRP, but also considers time-windows and heterogeneous vehicle types. Accordingly, it extends existing literature that does not focus on these components of real-world problems (Imai et al., 2007; Caris and Janssens, 2009; Zhang et al., 2010; Sterzik and Kopfer, 2013; Braekers et al., 2014). Notably, only a few studies allowed for different vehicles to be assigned to service the pickup and delivery of a certain container (Smilowitz, 2006; Zhang et al., 2011; Xue et al., 2014; Jeong and Ritchie, 2017), accounted for customers' time-window constraints (Jeong and Ritchie, 2017), and considered time-varying travel times in the VRP (Ichoua et al., 2003; Fleischmann et al., 2004). This study not only considers the container movements explicitly, but also allows for the possibility of repositioning empty containers in a dynamic environment, thus extending a preliminary effort (Irannezhad et al., 2017) by solving an integrated vehicle routing and empty container repositioning problem while considering real-world constraints and dynamics.

Lastly, this study aligns with existing efforts in calculating traffic-related emissions with complex and detailed models. Different input variables may be considered in emissions models (see, e.g., Muñuzuri et al. (2018): (i) average speed, as in COPERT (Ntziachristos et al., 2009), MOBILE (US EPA, 2003), and EMFAC (CARB, 1996); (ii) traffic stream conditions, as in HBEFA (Colberg et al., 2005) and ARTEMIS (André et al., 2009); (iii) macroscopic traffic flow, as in TEE (Negrenti, 1996) and Matzoros (Matzoros and Van Vliet, 1992); (iv) instantaneous driving cycle, as in MEASURE (Guensler et al., 1998) and VERSIT+ (Smit et al., 2007); and, (v) engine and operating vehicle types, as in PHEM (Hirschmann et al., 2010), CMEM (Barth et al., 1996), and VT-Micro (Rakha et al., 2004). Only one study exists that estimates CO₂ emissions reduction as a result of maritime empty container repositioning (Song and Xu, 2012). This study estimates the emission reduction for the most important pollutants as a result of inland empty container repositioning and truck-sharing. Specifically, average speed was calculated for every segment of the route of every vehicle, and ecological footprints were estimated according to the COPERT model

calibrated for Australia (EMISIA; Commonwealth of Australia, 2016) that is a function of the average speed of travelled links and the Australian fleet vintage configuration registered in Queensland (Queensland Government, 2013).

6.4 Model formulation

Given the described rationale for the VRP, initially a dynamic capacitated VRP with time windows (DCVRPTW) was formulated to minimize the total travel impedance, while considering the capacity constraints of vehicles and the demand and time-windows of customers.

Consider a set of vehicles K over a directed graph G connecting $N+1$ nodes corresponding to N customers, and a vehicle depot z at the seaport which is the node $N+1$. A give set of customers is defined as N , and a set of customers plus depot z is referred to N_0 . The mathematical formulation of the DCVRPTW is as follows:

$$\min \sum_{k \in K} \sum_{i \in N_0} \sum_{j \in N_0} C_{ijk} x_{ijk} \quad (6.1)$$

subject to:

$$\sum_{k \in K} \sum_{j \in N_0} x_{ijk} = 1 \quad \forall i \in N \quad (6.2)$$

$$\sum_{i \in N_0} \sum_{j \in N_0} p_j x_{ijk} \leq q_k \quad \forall k \in K \quad (6.3)$$

$$\sum_{j \in N} x_{zjk} = 1 \quad \forall k \in K \quad (6.4)$$

$$\sum_{i \in N} x_{izk} = 1 \quad \forall k \in K \quad (6.5)$$

$$\sum_{i \in N_0} x_{ihk} - \sum_{j \in N_0} x_{hjk} = 0 \quad \forall k \in K, \forall h \in N \quad (6.6)$$

$$t_i^a \leq t_{ik} \leq t_i^b \quad \forall k \in K, \forall i \in N \quad (6.7)$$

$$t_k^a \leq t_{zi} + t_{ik} \quad \forall k \in K, \forall i \in N \quad (6.8)$$

$$t_k^b \geq t_{jz} \quad \forall k \in K, \forall j \in N \quad (6.9)$$

$$t_{ik} + t_{ij} - M(1 - x_{ijk}) \leq t_{jk} \quad \forall k \in K, \forall i, j \in N \quad (6.10)$$

$$\sum_{i, j \in N_0} t_{ijk} \leq t_k \quad \forall k \in K \quad (6.11)$$

$$x_{ijk} \in \{0, 1\} \quad \forall k \in K, \forall i, j \in N_0 \quad (6.12)$$

In the formulation, C_{ijk} is the operational time-based cost of a trip between nodes (customers) i and j for vehicle k , consisting of the cost associated with the waiting, service, and travel time between the nodes. When the feasible solution is obtained, the number of vehicles is defined and consequently the types and related fixed costs of the vehicles are

defined as well. The decision variable x_{ijk} is equal to one if vehicle k travels directly from node i to node j , and zero otherwise. Eq. (6.2) ensures that, in the given time horizon, all customers are visited only once by a vehicle. Inequality (6.3) implies that the total demand p_i of all customers loaded on a vehicle k must be less or equal than the capacity q_k of vehicle k . It should be noted that both capacity and demand in our problem have two dimensions (weight and size), and both dimensions of demand should meet the two capacity constraints. The depot z of the vehicles is assumed to be the port where most of the road transport carriers are located. Eq. (6.4) forces all vehicles to leave z and eq. (6.5) forces all vehicles to return to z . Eq. (6.6) imposes the constraint that vehicle k leaves each node after it is served.

Given the operating hours of stevedores at the port (24/7 in our case), the time-window constraints are imposed only on vehicles $[t_k^a, t_k^b]$ and customers $[t_i^a, t_i^b]$. Accordingly, some vehicles are assumed to work only on the night shift and others to work only on the day shift. The decision variable t_{ik} is defined for each customer i and each vehicle k and denotes the time when vehicle k starts to service customer i . The vehicle cannot be assigned before and after the working hours of vehicle k , as specified by constraints in eqs. (6.8) and (6.9), where t_{zi} is the travel time from depot z to customer i , t_{ij} is the summation of service and travel time between two consecutive customers, and t_{jz} is the travel time from customer j to depot z . Eq. (6.10) imposes the constraint that vehicle k cannot arrive at j before $(t_{ik} + t_{ij})$ when traveling from i to j , where M is a large scalar. Finally, eq. (6.11) ensures that the total service by the vehicle k does not exceed the allowable vehicle working hours t_k .

The repositioning of empty containers is modelled within the simulation as follows: if the time window of delivery of an empty container by an exporter matches the time window of a pickup request of an empty container from a nearby importer to the ECP, the first trip leg (i.e., from the importer to the ECP) is removed and instead a new request is created to transport an empty container directly from the importer to the exporter.

The simulation was coded in Python, calling the geo-processing tools of ArcGIS to solve the CVRPTW. The code was run on a Windows-PC having a 3.4 GHz i7 processor and 16 GB of RAM. The VRP solver in ArcGIS (ESRI, 2017) is based on a tabu search metaheuristic that is widely considered to be the best approach to solve large vehicle routing

problems (Gendreau, 2003). The estimated travel times at various times-of-day for a typical weekday and weekend were extracted for each roadway link by using the Google map distance matrix API (Google Maps Platform), using the “gmapsdistance” library developed for the R language (Melo and Zarruk, 2016).

6.5 Case-study

Having obtained the routes for each truck from the VRP solver, simulation was performed for the calculation of the transport costs and pollutant emissions. The use of historical data for the simulation ensures a realistic setting concerning the actual number of requests, the number of vehicles, and the dynamic travel impedance for each vehicle type. The case study consisted of two weeks of inland container movements through the Port of Brisbane (Australia) that were provided by the Port of Brisbane Import/Export Logistics Chain Study (PBPL, 2013). The dataset includes details of individual container movements: container identification number, arrival and departure timestamps, origin and destination postcodes, shipment weight, and container size. This data includes all shipments handled through the Port of Brisbane in that period, mostly originated or destined from/to Queensland and a few from northern New South Wales. The identification numbers of the containers refer to 277 shipping lines, which are involved in 23,833 full and empty container movements between various freight actors as shown in Figure 24.

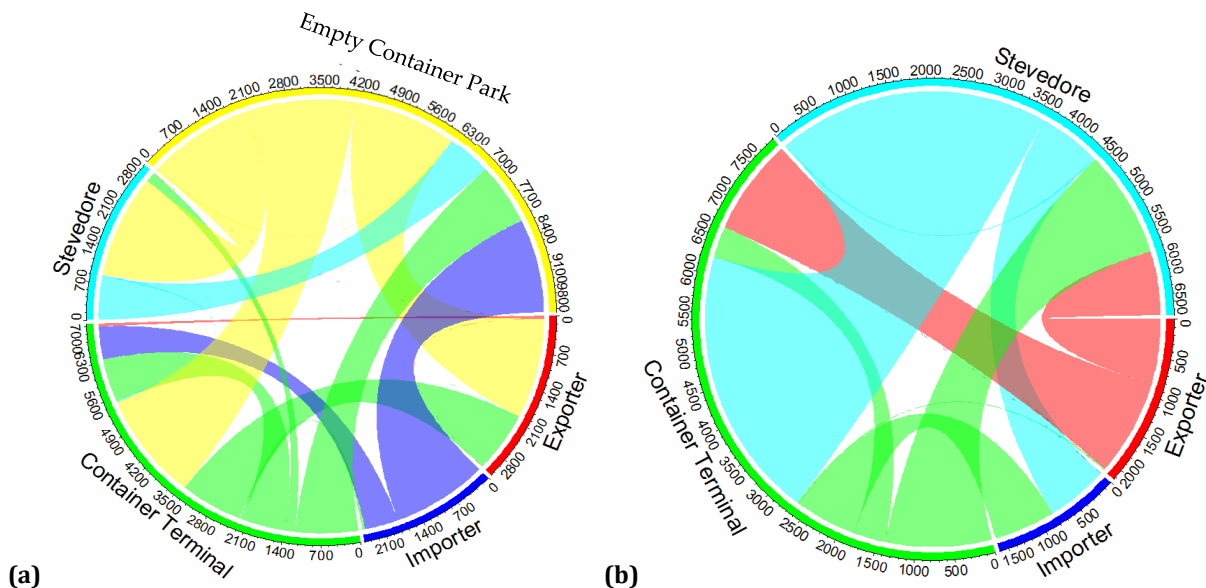


Figure 24 – Container flow between various inland freight actors for (a) empty containers, (b) full containers

The movements of empty containers in the container chain include: (i) from the importer to the ECP for staging; (ii) from the container terminals to the ECP after unpacking the import containers; (iii) from the ECP to the exporters; (iv) from the ECP to the container terminals for packing export shipments; (v) from the ECP to the stevedores. Because of the imbalance in Australian trade, there is a significant number of empty containers which are transported from the ECP to the stevedores to be exported. As a result, we could not investigate changes in movement (v) due to a lack of information on the international trade in this case study. Therefore, we only considered the repositioning of empty containers between importers, exporters, and container terminals.

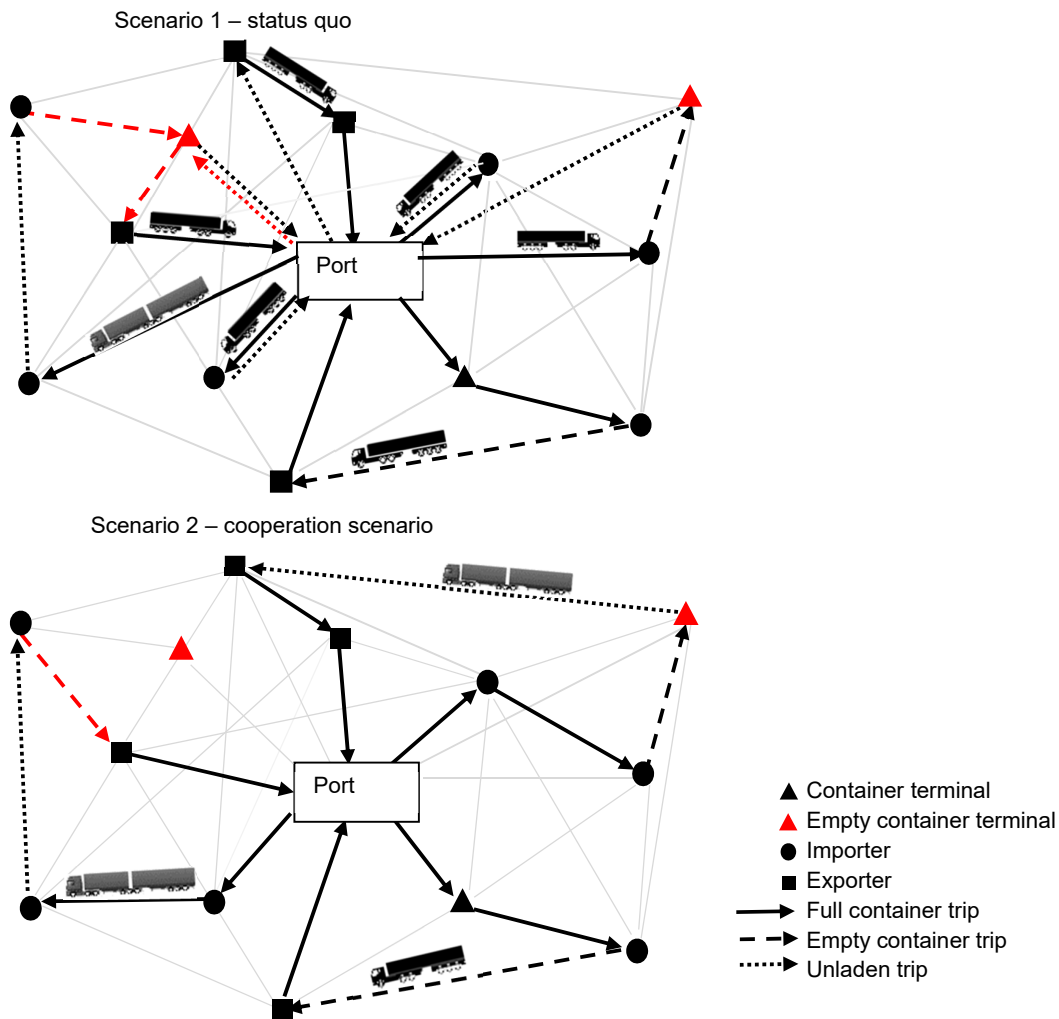


Figure 25 – Inland container transportation in two scenarios

Figure 25 shows a schematic inland container transportation. In the status quo, each shipping line only serves its own customers. Also, with no information on requests of other

shipping lines, vehicles cannot make a tour to serve the customers of other shipping lines. In the second scenario, shipping lines can cooperate in inland transportation by serving multiple requests with a single vehicle. Furthermore, empty containers can be delivered directly from importers to the exporters without being stored at the ECP, but only if the time-windows of both importers and exporters match. The algorithm for simulation of both scenarios is represented in Figure 26, where the differences between scenarios are underscored.

We considered one day as the time horizon for simulation and assumed that all decisions for shipments are made at the beginning of each day. The shipping lines, as the main logistics providers, collect and distribute the import/export containers within the prerequisite time-windows and choose the optimum vehicle and route. Two types of road freight vehicles are considered, namely semi-trailers and B-double trailers, which have different capacity and cost attributes. The road network consists of 10,915 links and 15,747 nodes, covering the primary road network in Queensland, on which only 49% of links allow B-doubles to operate. Given this, the trailer of a B-double has to be detached at a designated location and then handled in the next round (next day). Accordingly, travel-time and distance on unallowed links for B-double trailers were tripled to discourage their use.

The total transport cost considers time-based and distance-based operational costs as well as the fixed cost of vehicles. The rental cost of vehicles per unit time was assumed as the fixed cost of vehicle, and the working rate of drivers for a unit time and fuel price per distance were considered as the time-based cost and distance-based cost, respectively. Finally, we assume that the full containers must unload in the specific time-windows that were observed in the original data set.

Scenario 1 (status quo)

Step 1: Initialize all shipments for each shipping line that are to be delivered to customers i on day d . Set the “*weight TEU*” as two-dimensional demand of customers with time-windows specification of customers $[t_{1i}, t_{2i}]$, and locate the coordination of customers along the network (i.e., importers, exporters, transport yards, ECPs).

Step 2: Initialize the set K of available vehicles with two-dimensional capacity “*weight TEU*”, with time-windows specifications $[t_{1k}, t_{2k}]$, and the cost attributes (including fixed cost, time-based cost, distance-based cost).

Step 3: Initialize the network with the vector of link travel times for each time period and each day type (i.e., weekday, weekend).

Step 4: Update the travel time impedance on each link for each shipment, based on the time-windows.

Step 5: Generate the shortest-path cost matrix between all customers and depot for each vehicle type.

Step 6: Construct an initial solution by using the cost matrix by inserting the orders one at a time.

Step 7: Improve the solution by resequencing the orders on each route, as well as moving orders from one route to another, and exchanging orders between routes until the optimum solution is achieved.

Scenario 2 (cooperation)

Step 1: Initialize all shipments that are to be delivered to customers i on day d . Set the “*weight TEU*” as two-dimensional demand of customers with time-windows specification of customers $[t_{1i}, t_{2i}]$, and locate the coordination of customers along the network (i.e., importers, exporters, transport yards, ECPs).

Step 2: Initialize the set K of available vehicles with two-dimensional capacity “*weight TEU*”, with time-windows specifications $[t_{1k}, t_{2k}]$, and the cost attributes (including fixed cost, time-based cost, distance-based cost).

Step 3: Initialize the network with the vector of link travel times for each time period and each day type (i.e., weekday, weekend).

Step 4: Update the travel time impedance on link for each shipment based on the time-windows

Step 5: If a container is unloaded at customer i , and an empty container is requested at customer j with the same TEU within the same time-window, create a request from i to j by quantity “0 TEU”, and remove two movements from customer i to ECP, and from ECP to customer j .

Step 6: Generate the shortest-path cost matrix between all customers and depot for each vehicle type

Step 7: Construct an initial solution by using the cost matrix by inserting the orders one at a time.

Step 8: Improve the solution by resequencing the orders on each route, as well as moving orders from one route to another, and exchanging orders between routes until the optimum solution is achieved.

Figure 26 – Simulation Algorithm

6.6 Results

The model simulation results are presented as aggregate values for the two scenarios in Table 11. It should be noted that the status quo scenario represents the vehicle routing and allocation resulting from individual decisions by shipping lines each day, while the cooperation scenario represents the vehicle routing and allocation resulting from the possibility that not only a road vehicle can be shared between different shipping lines to service multiple customers, but also empty containers can be swapped between different shipping lines.

The analysis of the simulation results reveals that cooperation between shipping lines translates into an increase in the number of visits in each tour and the usage of larger vehicles, and a decrease in the total distance travelled and consequently the total transport costs. Notably, as a result of the cooperation 1711 empty containers were repositioned directly from importers to exporters without passing through the ECPs, with a consequent saving of 1777 storage days in total and 4468 unnecessary trips for the 277 shipping lines. Given the assumption of similar time-based and distance-based costs in both scenarios, the consequent decrease in the total transport cost is estimated to be more than 40%. Not only the repositioning and truck-sharing significantly diminished the number of movements and transport costs, but also the number of B-doubles increases in the cooperation scenario, a fact that leads to more productivity as well as fuel and environmental savings.

When considering that these results only reflect trip and cost savings over the 14 days under analysis, the savings in the long term is expected to be even more significant. It also should be noted that the storage cost of empty containers at the ECP was not explicitly considered in this study and is not included in the total transport costs, mainly because shipping lines normally negotiate a daily/weekly rate with the ECPs that varies for shipping lines of different market size.

Table 11 – Simulation results of truck-sharing and empty container repositioning

	Scenario 1: Status Quo	Scenario 2: Cooperation	changes in the second scenario
Total transport costs (m\$)	28.1	16.2	-42.3%
Time-based operating costs (m\$)	3.66	1.96	-46.4%
Distance-based operating costs (m\$)	24.44	14.25	-41.7%
Total number of trip legs	23,833	22,122	-7.18%
Total number of tours	16,777	10,598	-14.7%
Total travel time (hr)	13,425	7,225	-46.2%
Total distance ('000 km)	1,979.0	1,147.1	-42.0%

Number of trips by B-doubles	5,441	6,233	+792 vehicle trips
Number of trips by semi-trailers	11,336	4,365	-6,971 vehicle trips
Unnecessary trips, avoided in the second scenario as a result of repositioning			-1,711 trips
Unnecessary storage of empty containers, avoided in the second scenario			-1,777 days
Unnecessary storage of empty containers for 1 day			158
Unnecessary storage of empty containers for 2 days			76
Unnecessary storage of empty containers for 3 days			62
Unnecessary storage of empty containers for 4 days			37
Unnecessary storage of empty containers for 5 days			38
Unnecessary storage of empty containers for 6 days			46
Unnecessary storage of empty containers for 7 days			28
Unnecessary storage of empty containers for 8 days			25
Unnecessary storage of empty containers for 9 days			16
Unnecessary storage of empty containers for 10 days			6
Unnecessary storage of empty containers for 11 days			5
Unnecessary storage of empty containers for 12 days			1

Given the simulation results from the solution of the DCVRPTW, the result of the modifications in logistics operations was calculated in terms of pollutant emissions. Specifically, the emissions from the logistics solution in both scenarios were estimated on the basis of the calibrated COPERT guidelines for Australia (EMISIA, 2014). The advantage of using the geo-processing tools of ArcGIS to solve this optimisation problem is that the outputs are generated as sequences of routes on the network. Hence, it is possible to calculate the average speed of each link segment of the optimum route for the assigned vehicle, and consequently compute the fuel consumption and pollutant emissions.

Firstly, the fuel consumption was calculated depending on the truck type and the average speed of every segment in the optimum route. Then, the emission pollutants were estimated depending on the fuel consumption and the vintage year for the following pollutants: carbon dioxide (CO₂), carbon monoxide (CO), methane (CH₄), nitrous oxide (N₂O), nitrogen oxide (NO_x), non-methane volatile organic compounds (NMVOC), sulphur oxide (SO_x), and particulate matter (PM₁₀). Using the vehicle registration data from the Queensland Government (Queensland Government, 2013), the pollutant emissions were calculated for the routes of the semitrailers and B-doubles at each delivery plan during the two weeks that were analysed. As Table 12 summarises, the reduction in the emissions of the different pollutants and the fuel consumption in the cooperation scenario were estimated between 40 and 45%.

Table 12- Comparison of fuel consumption and pollutant emissions in the two scenarios

	Scenario 1 status quo			Scenario 2 cooperation		
	Semi-trailer	B-double	Total	Semi-trailer	B-double	Total
Fuel (million liters)						
Consumption	486.76	189.93	676.69	245.48	157.62	403.11
Pollutant emissions (kg)						

CO₂	1,300,245.12	507,340.26	1,807,585.38	655,736.78	421,039.58	1,076,776.36
CH₄	40.34	6.36	46.70	20.34	5.28	25.62
N₂O	17.52	6.27	23.79	8.84	5.20	14.04
NO_x	8,317.57	3,422.41	11,739.98	4,194.70	2,840.24	7,034.94
CO	4,291.25	1,792.09	6,083.34	2,164.15	1,487.25	3,651.40
NMVOC	711.77	164.97	876.73	358.96	136.90	495.86
SO_x	8.27	3.23	11.50	4.17	2.68	6.85
PM₁₀	528.54	120.40	648.94	266.55	99.92	366.47

Lastly, the use of the ArcGIS solver allowed to assess the interaction of the container truck traffic with the rest of traffic. The assigned truck movements resulting from the simulation for the AM peak period (7:00 – 9:00 am) in a typical weekday is shown in Figure 27, alongside the heavy vehicle flow and the traffic flow of all vehicles.

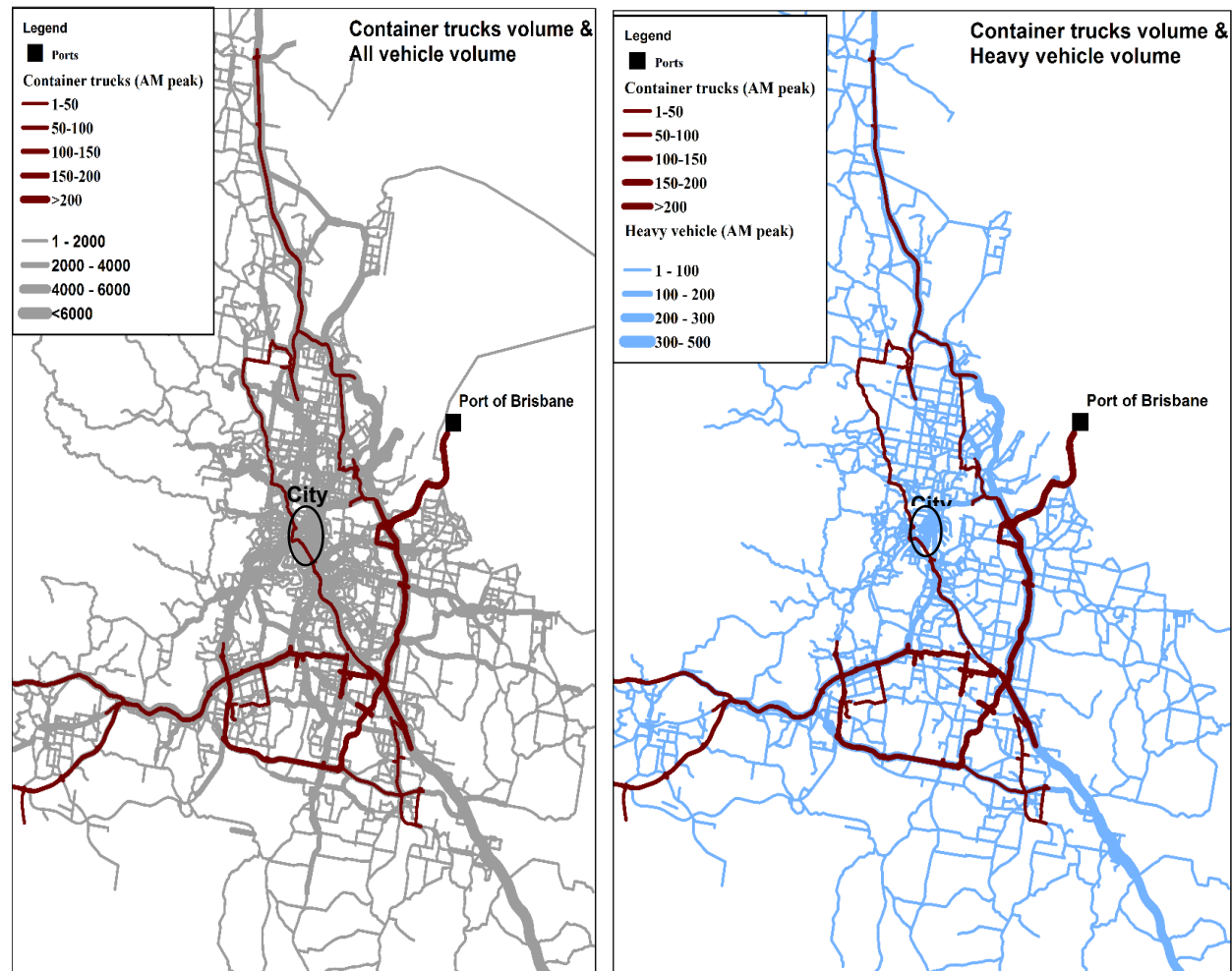


Figure 27 – Simulated container truck flow vs. the heavy vehicle and all vehicle flow for AM peak of a typical day

6.7 Discussion and conclusions

This paper provides insight into the benefits of cooperation between actors involved in the maritime container trade and quantifies the cost and emission reductions through economies of scope and scale. Considering real-world constraints and the dynamic nature of the problem, a closed-form analytical solution for the problem was not computationally appealing, and a simulation was developed in order to address these complexities.

The simulation was undertaken on a case-study of container trade through the Port of Brisbane (Australia). The use of a real-world case study proved the capability of the simulation in handling the real number of requests, the actual number of vehicles, and the dynamic travel impedance for each vehicle type. Accordingly, two scenarios were simulated: (i) a status-quo scenario under the assumption that shipping lines individually optimize the service delivery and pickup of containers on a daily basis; (ii) a cooperation scenario under the assumption that shipping lines cooperate to transport the full and empty containers across various locations, while also swapping the empty containers between importers and exporters. Depending on vehicle type and chosen route in the solution, the emission levels were estimated from the average speed of the route chosen by the specific truck.

Whilst this paper proves that the status quo results in inefficiencies and increased costs to shipping lines, importers, exporters and end users alike, it also shows that these inefficiencies can be overcome by the concept of horizontal and vertical integration. Coordination can be provided through an online marketplace where visibility, tracking and traceability are highly maintained. Such a marketplace, when developed, can become a key piece of the port infrastructure, which may be called a port community system, where the associated costs of each actor in each segment of the chain are shared. Accordingly, the visibility of the supply chain and the costs for every actor in the coordination scheme can be enhanced by using unique digital identifiers (electronic data interchange, EDI) for inter-organisational transactions across the chain. Automation, integration, operation, and maintenance of the system, however, comes at a cost for port authorities. However, facilitating the supply chain and increasing the efficiency of all actors is not only a driver of port competitiveness, but also a driver of economic growth by empowering local businesses.

It should be noted that the inputs to the proposed decision support system in the planning horizon (e.g. one week) include: (i) the import container list including information

of the expected arrival date, expected return date by importer, type, situation (cleaned, need to be washed, etc.), time-windows and location of the importer; (ii) the requested list of containers by exporters including information on weight of shipment, type, time-windows, location and other details; (iii) the fleet list including type of vehicle and availability plan. Several interviews¹ within a focus group of 15 representatives of shipping and transport companies revealed that each individual company has a well-defined empirical procedure to optimize their resources and will occasionally cooperate with others to meet their demands, but there exists a lack of integrated tools and systematic cooperation across companies. The aforementioned inefficiencies happen largely because of incompatible interfaces between the actors, the reliance on manual transactions, and the lack of interoperability between their systems. For example, the focus group showed that currently bilateral communication between parties occurs mostly with email communication, and in some rare occasions with dedicated user interfaces (e.g., <https://www.1-stop.biz/>). However, all parties were in favour of linking up one single interface in order to reduce their manual work and human errors.

Should the Port of Brisbane implement a decision support system (DSS) for empty container repositioning or truck-sharing, it would likely need to justify the benefits and saving of logistics costs. Several features play a key role in providing motivation for companies to adopt a DSS such as a user-friendly interface, smooth operation, and reporting capabilities in terms of logistics cost savings, environmental indices, unsatisfied demand, and unutilized fleet/containers.

The findings from this study highlight the benefits of cooperation among actors involved in inland container transportation, in terms of a reduction in the logistics costs and a higher utilisation of larger trucks, as well as a significant reduction in fuel consumption and pollutant emissions. While the results proved that the proposed simulation is capable of capturing the real-world constraints and components, further research is foreseen. Firstly, a longer duration could be selected for the planning horizon, so that if an empty container can be used by the same shipping line in the next couple of days, it is not swapped to another

¹ Several rounds of interviews were conducted by the Port of Brisbane, from 2017 to 2018, in a focus group chosen from freight operators and grain and cotton exporters. The back-and-forth individual interviews were completed in a “supply chain workshop” in June 2018, in which all actors participated and reviewed the results.

shipping line. Secondly, additional cost components could be included in the simulation, such as the costs of double-handling, storage at ECPs, and port community system administration. Thirdly, empty container swapping considerations could be taken into account, such as the time needed for cleaning and repairing a container. Fourthly, additional characteristics of containers could be considered in more detail such as open-top, refrigerated, or other specialized containers. Fifthly, inland empty container repositioning could be integrated with maritime transport and the back-loading (back-hauling) opportunities for non-containerized transport could be investigated. Given that the Port of Brisbane is the only port of call in Queensland for most shipping lines, and the last port in a vessel's route, back-loading is recognized as an opportunity for importers to minimize the transit time to overseas destinations and bears a great potential for Port of Brisbane to increase its competitiveness.

Lastly, the successful development of a cooperation scheme depends on the structure of the regional market. Major shipping lines, as the main actors, should see the benefit of collaborating with smaller shipping lines or their large competitors, without losing their market position. The simulation would benefit from the representation of this dynamic behaviour by various shipping lines using an agent-based simulation model where each agent decides to cooperate or quit the system.

Chapter 7: An agent-based model of hinterland container transport to evaluate cooperation efficiency

A manuscript submitted to the journal of Transportation Research Part E: Logistics and Transportation Review, in Dec 2017.

Elnaz Irannezhad, Carlo G. Prato, Mark Hickman,

7.1 Abstract

This study explores the savings in hinterland transport costs stemming from horizontal and vertical cooperation among freight agents as a value-added service of a Port Community System (PCS). This service is realised via a dynamic vehicle allocation and routing solution where real-world constraints and dynamics are taken into account. In particular, we answer to two specific research questions: (i) What is the likely impact of information sharing and cooperation strategies in hinterland container transport, as a value-added service of PCS? (ii) How the optimum cooperative strategy can be formulated to meet the dynamic demand and supply in hinterland container transport.

Addressing these research questions, we make two specific contributions to the research on cooperation strategies. The first contribution lies in developing of an agent-based simulation model in a large-scale and real case study, by using a reinforcement learning-based model based on probability matching theory that allows to simulate realistically the adaptive behaviour of agents. Furthermore, this research contributes to the literature on vehicle routing problem by solving a dynamic capacitated vehicle routing problem with time windows, and simultaneous pickup/delivery. Accordingly, this study incorporate the dynamics of this problem by considering time-of-day travel times in the road network, time-of-day constraints on the use of some road segments by larger trucks, and on the time-dependent service rate of the stevedores at the wharf. The results of the simulation of two weeks container movements indicate huge savings in total transport costs and distance travelled and higher utilisation of trucks from the resource sharing.

7.2 Introduction

Fragmentation in port-land operations and between hinterland logistics operators brings about extra trips, higher logistics costs, longer delays, and customer dissatisfaction. One consequence of this fragmentation is that logistics operators seek to ‘do their own thing’ in terms of planning and timetabling their operations, with little interest or ability to interact with their competitors. Given the numerous actors involved in joint logistical operations in import/export trade, an integrated logistics system helps in managing interdependencies among activities. Several studies and successful empirical cases showed that information sharing and inter-firm coordination brings about significant benefits across supply chain (Gavirneni et al., 1999; Lee et al., 2000; Sahin and Robinson, 2005; Zhou and Benton, 2007; Pathak et al., 2014; Kaipia et al., 2017). Accordingly, information sharing and value-added services delivered by ports can help integrate logistics operations, affect positively the end-users, and thus have a direct influence on the wider economy. As the primary interface in the import-export industry, ports can play an important role to reduce the inefficiencies in supply chains by providing an effective consultation mechanism and an efficient exchange of information with the different stakeholders (Córdova and Durán, 2014).

Currently, many port authorities play the minimalist landlord role by providing only the necessary infrastructure to shippers and carriers operating in the port. Individual freight actors optimize their own logistics process as they interact with the same infrastructure, regardless of possible opportunities for collaboration. However, freight actors might benefit from the exchange of information concerning road traffic conditions, real-time availability of drivers and carriers, and opportunities for the bundling of shipments into fewer vehicles. This information sharing can be provided via an online system called “Business Intelligence”, supported by a port authority where information becomes available to freight actors in a multi-level system. Business Intelligence is defined as an instrument that provides automated decision-making about business conditions and achieves competitive advantage by making the right decisions at the right time. In the context of this paper, the Business Intelligence is referred to as a Port Community System (PCS), with examples such as Virtuele Haven in the Port of Rotterdam, DIVA in the Port of Hamburg, CCS Dakosy in the Port of Antwerp, and Portnet Trade Exchange in the Port of Singapore.

Since developing a PCS is costly for a port, it is of the utmost importance to investigate this option carefully. Accordingly, organizations need models and approaches to

evaluate the capabilities of a PCS. Most existing studies investigating PCS either adopted a descriptive approach (Sweeney, 2005; Tsamboulas et al., 2012) or defined indicators to evaluate the efficiency of a PCS (Claudia and Felisa, 2012; Edvard et al., 2012). Other studies quantified the multiple features of a PCS by adopting a multiple-criteria decision-making method (Ghazanfari et al. (2014). Recently, Aydogdu and Aksoy (2013) estimated the time savings of various administrative processes after adopting a PCS, based on the average and the maximum time that were provided by various agents in the status quo. Even more recently, Carlan et al. (2016) conducted a review of cost-benefit studies of PCS and proposed a framework for further analysis.

The applications of a PCS have evolved during the recent years from serving as an information hub (Srour et al., 2008) to generating value-added logistics solutions, while the main objective remains encouraging horizontal and vertical cooperation among freight agents (Carlan et al., 2016). According to the European Commission (2011), horizontal cooperation is defined as the concerted practice between agents at the same level, while vertical cooperation is a form of integration between parties across the logistics chain. In the context of maritime and hinterland container transportation, horizontal cooperation enhances the service quality of shipping lines and carriers by increasing the geographic span of services while maintaining the optimum resources, and vertical cooperation provides well-integrated transport and logistics services across the supply chain.

The main body of the literature looks at optimizing the flow of information and customs activities (Van Oosterhout et al., 2007; Keceli, 2011; Córdova and Durán, 2014), mainly because port and customs-related document submissions are the most important reasons for users to adopt a PCS (Keceli et al., 2008), and are most likely considered as the early steps of PCS implementation. However, little documented proof of concept exists with regards to the role of logistics solutions in promoting cooperation. Given there is a need to quantify the impacts of such collaborations in hinterland transport, in light of the existing literature, this study takes a step further with an effort to investigate the impacts of cooperation among freight agents as a value-added service of a PCS.

The literature on the cooperation of maritime transport is gaining momentum, mainly because of emerging strategic alliances and acquisitions in the shipping industry (Heaver et al., 2000; Sheppard and Seidman, 2001; Cruijssen et al., 2007; Lun et al., 2010). Notably, quantitative studies on the hinterland cooperation are scarce (van de Voorde and

Vanelslander, 2010), and given that the hinterland transport costs are generally higher than the maritime costs and the most bottlenecks and delays occur on the landside, the limited attention paid to cooperation and coordination in hinterland container transport is surprising (Van Der Horst and De Langen, 2008).

A few existing studies have formulated mathematically the benefits of cooperation in hinterland transport and repositioning of empty containers as an optimisation problem. For example, Sterzik et al. (2015) examined the possible benefits of exchanging empty containers, simultaneously with solving a vehicle routing problem on an hypothetical static network, while assuming only one type of vehicle and one type of container (40-foot container). However, the agents' optimal decision depends on their gains resulted from economies of scale and scope in a dynamic market. Major freight agents (e.g. shippers or carriers), should see the benefit of cooperating with smaller agents or with their large competitors, without losing their market position.

Furthermore, the literature of vehicle routing and allocation problems often make simplified assumptions such as assuming homogenous vehicles (i.e. only one type of fleet), a static supply chain network or considering only one criterion for capacity (i.e. either weight, or size). Notably, the existing literature often are a prototype of a hypothetical or a toy network with limited number of supply and demands. Accordingly, it is of high importance to empirically show the capability of an optimisation model which is able to solve a real-size problem with more realistic assumptions.

To fill the aforementioned gaps, this research aims to quantify the likely impacts of decision support system implemented by PCS, on a real size hinterland container transport network. We focus on two salient questions:

- i. What is the likely impact of information sharing and cooperation strategies in hinterland container transport, as a value-added service of PCS?
- ii. How the optimum cooperative strategy can be formulated to meet the dynamic demand and supply of freight agents in hinterland container transport?

To address these two questions, a multi-agent system is simulated, where freight agents experience logistics outcomes from the PCS, and through a reinforcement learning method earn their gains and losses from the past experience, and then decide whether to use PCS service or not. To do so, we seek to make two key contributions.

The first contribution of this study is applying an agent-based simulation by using a linear reinforcement learning algorithm based on the probability matching theory in order to simulate the adaptive behaviour of freight agents to experience the benefits and costs of cooperation through a prototype of PCS. Agent-based simulations can assist to model the individual heterogeneous agents and determine whether cooperation brings about gains or losses in a dynamic environment. This modelling technique captures the explicit decision making of various agents in a dynamic environment, representing their management of resource and time constraints and their reaction to various policies.

In this study we consider two main RL strategies: (i) freight agents diversify in their first few choices and gradually converge to a single preferred option; (ii) freight agents learn the probabilities of different outcomes, and ultimately actions that were more successful in the past are more likely to be adopted in the future. In this latter approach, agents predict their future reward in a multi-step task while learning from their previous experiences. Accordingly, we assume the agents' beliefs change according to the accumulated knowledge based on their previous experiences of gains and losses. The result of individuals' decisions implies dynamism in the market and payoff variability. Accordingly, the decision of freight agents to use a PCS is determined based on the probability of saving in the logistics costs in past experiences on a similar day with similar shipment characteristics.

The second contribution of this study is an optimisation model, as a value-added service of PCS, where a dynamic vehicle allocation and routing problem with time-windows and real-time constraints is solved for the collaborative scenario. Accordingly, we adopt a dynamic capacitated vehicle routing problem with time windows (DCVRPTW) and simultaneous pickup/delivery. For our problem, the DCVRPTW with simultaneous pickup and delivery determines the minimum total travel impedance, while also selecting the fewest of two types of vehicles necessary to serve a set of pickup/delivery demands, considering the capacity constraints of vehicles and the pickup/delivery demand and time windows of orders. We consider the capacity for vehicles and for pickup/delivery demands in two dimensions, including both the weight and size of containers. We incorporate the dynamics of this problem by considering time-of-day travel times in the road network, time-of-day constraints on the use of some road segments by larger trucks, and constraints on the time-dependent service rate of the stevedores at the wharf.

Accordingly, we simulate four scenarios: (1) status quo scenario, where freight agents seek to optimise their own logistics in the absence of information sharing and cooperation strategies; (2) vertical cooperation scenario, where PCS provides an optimum delivery/pickup plan for freight agents, according to available timeslots of the stevedores at the wharf, carrier's fleets, transit time and daily demands of freight agents. This information sharing strategy through PCS enables agents to evaluate whether shifting the delivery time to the off-peak period can result in a significant saving of logistics costs, while the idle fleet and queue at the wharf gates are also optimised; (3) horizontal and vertical cooperation scenario, where PCS provides an optimum solution to serve delivery/pick up requests with less fleets assuming that all agents are required to use such service. In this scenario, various deliver/pickup requests might be served by one vehicle and each agent pay the partial transport cost of a tour instead of a two-way trip; (4) stochastic cooperation scenario, where it is unclear for every agent that what other agents' will do. Thus, agents are allowed to learn and to choose the best possible action through a reinforcement learning method in a dynamic environment. This scenario implies that using such PCS service is optional for users, and accordingly optimal solution is provided for only those who signed up. Thus, as more freight agents use the PCS, more resources, back-loading and shipment bundling opportunities become available for all users, and there will be more savings in the logistics cost. On the other hand, with the withdrawal of some big players from the PCS, the payoff for the other agents will be less than expected.

The remainder of the paper is organised as follows. Section 2 presents the data, model rational and the methodology of this study, with emphasis on the model specification and formulation. Section 3 shows the results of the model estimation. Section 4 provides managerial implications. Finally, Section 5 draws conclusions from this study.

7.3 Method

7.3.1 Data

The case study focuses on container shipments passing through the Port of Brisbane (Australia). The dataset was provided by the Import/Export Logistics Chain Study by the Port of Brisbane Pty Ltd (2013), and includes details of individual container movements: identification number, timestamps of arrival and departure, postcodes of origin and destination, weight of shipment, and size of container. This study focuses on the movements

of full and empty containers in import and export chains (23,833 records) belonging to 277 shipping lines.

7.3.2 Model rational

Agent-based models have been adopted in several domains, such as the interactions of economic agents in financial markets (Bonabeau, 2002; Xu and Chi, 2007; Taghawi-Nejad, 2013), fleet management including scheduling (Bouazid, 2003) and dispatching (Burckert et al., 2000), terminal management (Henesey, 2006), and intermodal transportation (Dong and Li, 2003; Baindur and Viegas, 2011). For freight transport systems, this approach seems very suitable to illustrate competition and interaction among various agents. INTERLOG (Liedtke, 2009), FREMIS (Roorda et al., 2010), and TAPAS-Z (Holmgren et al., 2013) are examples of agent-based freight transport models at the regional level.

In addition to simulating the current situation, agent-based models can be applied to examine various policies by changing the environment and observing how agents would learn and behave in the new environment. For example, Taniguchi et al. (2007) developed a multi-agent-based model (including shippers, carriers, and administrators) on a small test network to study the effects of road pricing on shippers' and carriers' strategies. Abdul-Mageed (2012) examined a coordinated truck assignment system for five trucking companies, comparing direct competition with cooperation by sharing vehicles. Results showed that the coordinated assignment system improved the transport process in terms of decreasing the number of empty trips and the number of late arrivals.

The aforementioned literature on agent-based modelling either assume a set of if-then rules or a probabilistic reinforcement learning methods to model agents' behaviour. Experiments in cognitive decision-making show that decision-makers have a toolbox of heuristics specific to each environment, and a learning rule may arise from simple heuristics, where the choice probability changes as a function of the encountered instances and of the payoff variability (Gigerenzer and Todd, 1999).

Reinforcement learning (RL) is a model of learning that captures these heuristics. RL has been found to be one of the main driving forces of human behaviour in iterative decision problems where the probabilities of "success" or "gain" are unknown to the decision maker. Experiments confirm that the percentage of adaptive behaviours is much higher than that of analytical behaviours (utility maximizers, loss avoiders or asset conservers) (Munier et al.,

1999). Specifically, probability matching is reported in experimental economics as an innate human heuristic whereby, if a strategy leads to a desirable outcome, the probability that it is used again increases, while an undesired outcome has the opposite effect (Rubinstein, 2002; Gaissmaier and Schooler, 2008). Inspired by probability matching theory, Rivas (2013) proved that, in environments where the payoff of the unchosen action is observed by an individual under RL, the probability of choosing an option converges to the probability of that option being the best alternative.

However, learning does not necessarily lead to the maximisation of gains for all agents and, particularly with the increase in payoff variability, choice behaviour tends to random decisions (Busemeyer and Townsend, 1993). Even though the optimal behaviour clearly is that they should follow a rational rule of “assess the chance of success of each action and choose the most likely one”, experimental results show that individuals diversify their choices. For example, Rubinstein and Tversky (1993) through an experiment observed that individuals employed rules to play the game while also diversified the rules they used during the sequence of games. Later on, Rubinstein (2002) reported the results of a multiple decision problems in a fixed set of alternatives. In these experiments, although the best strategy was choosing the action that is most likely to achieve success, individuals diversified their choices and diversification was stronger when faced with an uncertain situation where there was no explicit information about the chances of success, and was weaker for real life actions where individuals were aware of the action probabilities. Diversification can be explained as an instinct to seek information and learn about the environment. Accordingly, the RL implies the diversification in the decision-making by introducing a random decision under the probability concept. In the context of this study, as a higher number of freight agents use the PCS, more resources, bundling and back-loading opportunities become available for all users and there would be more saving in the logistics cost. On the other hand, with withdrawal of some big players of the system, the payoff for the other agents will be less than expected.

The agents in the proposed model consist of importers, exporters, road carriers, stevedores at the wharf, and freight agents. Importers and exporters are modelled as the owners of the shipments that must deal with a given number of containers, available time windows, and origin/destination locations of pickup and delivery. Road carriers are represented by two types of freight vehicles, namely semi-trailers and B-double trailers, with

different two-dimensional capacity and cost attributes. Notably, the two-dimensional capacity represents the weight of the shipment and the number of TEUs (Twenty-foot Equivalent Units). Practically, both the weight and size of the container are important where, for example, a 40-foot container does not violate the weight constraint imposed by either the vehicle itself or the road authorities. The environment consists of shipments to be delivered daily and a physical road network that considers time-dependent travel times and a limitation that only 49% of links allow B-doubles to operate. In some cases, this means that the trailer of a B-double has to be detached at a designated location and then moved separately; and accordingly, travel time and distance on links that do not allow B-double trailers are tripled to represent this real-world behaviour. The stevedores at the wharf are modelled at their port location as operating 24/7 with a limited service rate at the gates to load/unload the trucks.

7.3.3 Model formulation

The mathematical model of The DCVRPTW problem with simultaneous pickup and delivery presented in this section is based on the formulation proposed by Avci and Topaloglu (2016) and El-Sherbeny (2010).

Sets

N : set of all customers (delivery/pickup points)

N_0 : set of all customers and the port which is the depot of carriers and import /export containers

K : set of fleets, $\{1, 2, \dots, k\}$

Parameters

F_k : fixed costs of vehicle $k \in K$

C_{ijk} : operational costs of vehicle k for a trip between nodes i and j , consisting of the cost associated with the waiting, service, and travel time.

q_k : capacity of vehicle k

d_j : delivery of customer j loaded on vehicle k

p_j : pickup of customer j loaded on vehicle k

$[t_{1k}, t_{2k}]$: time-window constraint of vehicle k

$[t_{1i}, t_{2i}]$: time-window constraint of customer i

t_{ijk} : travel time of vehicle k between customers i and j

ts_{ik} : service time customer i by vehicle k which is proportional to deliver/pick-up loads

W_{max} : limited number of vehicles can be serviced simultaneously by stevedores at wharf

Decision variables

$x_{ijk} : \{1: \text{if vehicle } k \text{ travels directly from node } i \text{ to node } j, 0: \text{otherwise}\}$

y_{ijk} : total pick-up load by vehicle k while travelling between agents i and j

z_{ijk} : total delivery load by vehicle k while travelling between agents i and j

t_{ik} : arrival time of vehicle k to customer i

$$\text{Min} \sum_{k \in K} \sum_{j \in N_0} F_k x_{0jk} + \sum_{k \in K} \sum_{i \in N} \sum_{j \in N_0} C_{ijk} x_{ijk} \quad (7.1)$$

Subject to:

$$\sum_{k \in K} \sum_{j \in N_0} x_{ijk} = 1 \quad \forall i \in N \quad (7.2)$$

$$\sum_{i \in N_0} \sum_{k \in K} y_{jik} - \sum_{i \in N_0} \sum_{k \in K} y_{ijk} = p_j \quad \forall j \in N \quad (7.3)$$

$$\sum_{i \in N_0} \sum_{k \in K} z_{ijk} - \sum_{i \in N_0} \sum_{k \in K} z_{jik} = d_j \quad \forall j \in N \quad (7.4)$$

$$y_{ijk} + z_{ijk} \leq q_k x_{ijk} \quad \forall i \in N + z, \forall j \in N + z, \forall k \in K \quad (7.5)$$

$$\sum_{i \in N} \sum_{k \in K} y_{izk} = \sum_{i \in N} p_i \quad (7.6)$$

$$\sum_{i \in N} \sum_{k \in K} z_{Oik} = \sum_{i \in N} d_i \quad (7.7)$$

$$\sum_{j \in N} x_{z0k} = 1 \quad \forall k \in K \quad (7.8)$$

$$\sum_{i \in N} x_{i0k} = 1 \quad \forall k \in K \quad (7.9)$$

$$\sum_{i \in N} x_{ihk} - \sum_{j \in N} x_{hjk} = 0 \quad \forall k \in K, \forall h \in N_0 \quad (7.10)$$

$$t_{1i} \leq t_{ik} \leq t_{2i} \quad \forall i \in N, \forall k \in K \quad (7.11)$$

$$t_{1k} \leq t_{ik} + \sum_{i \in N_0} \sum_{j \in N_0} x_{ijk} t_{ijk} \leq t_{2k} \quad \forall i \in N, \forall k \in K \quad (7.12)$$

$$t_{ik} + t_{ik} + t_{jk} - M(1 - x_{ijk}) \leq t_{jk} \quad \forall i, j \in N, \forall k \in K \quad (7.13)$$

$$\sum_{k \in K} \sum_{j \in N} x_{0jk} \leq W_{\max} \quad (7.14)$$

$$x_{ijk} \in \{0, 1\} \quad \forall i, j \in N_0, \forall k \in K \quad (7.15)$$

$$y_{ijk} \geq 0 \quad \forall i, j \in N_0, \forall k \in K \quad (7.16)$$

$$z_{ijk} \geq 0 \quad \forall i, j \in N_0, \forall k \in K \quad (7.17)$$

$$t_{ik} \geq 0 \quad \forall i \in N_0, \forall k \in K \quad (7.18)$$

The objective function in eq. (7.1) minimises the fixed and operational costs of vehicles. Operational costs are the expenses incurred in the daily running of a business. Operational costs that are internal to a carrier include fixed and variable costs. Variable costs include the fuel, fuel taxes, oil, tires, maintenance, repair, crew wages, travel time, paid parking and tolls; while fixed costs include capital investment, depreciation, insurance, and registration fees.

The constraint in eq. (7.2) imposes that, in a given time horizon, all customers are visited only once. The constraints in eqs. (7.3-7.4) implies the flow equations for pick-up and delivery. The eq. (7.5) is capacity constraint and it should be noted that the capacity and demand in this study have two dimensions (weight and number of TEUs), and both should be matched to the demand and service supplied. The constraints in eqs. (7.6-7.7) guarantee that the sum of the inflow to the depot equals to the total pickup and delivery, respectively. The depot of the fleet is at the source node 0 (i.e., the port), so the constraints in eqs. (7.8-7.9) force all vehicles to leave the depot and return to depot, respectively. The constraint in eq. (7.10) forces each customer is visited and left by the same vehicle.

The constraints in eqs. (7.11-7.12) specify the time window limitations of customers and vehicle drivers, respectively. Given the operating hours of the wharf at the port (24/7 in our case), we only impose the time-window constraint on vehicles and customers.

Accordingly, some vehicles are assumed to work only during the night shift, and others to work only during the day shift. The constraints in eq. (7.13) implies that vehicle cannot arrive to the next customer before the minimum duration which is the summation of arrival time and service time of the first customer and travel time between two consecutive customers. Also, the stevedores at the wharf have a limited service rate where only a limited number of vehicles can be serviced simultaneously (W_{max}), and the constraints in eq. (7.14) represent this service rate (obtained from the observations of a typical day). Finally, the constraints in eqs. (7.15-7.18) represent the nature of decision variables.

In the status quo (the absence of cooperation), with no information on requests of other freight agents, Freight agents optimise their logistics by making a tour only among their own customers. In the second scenario (vertical cooperation), PCS provides a delivery/pickup plan for freight agents, which is optimized based on available timeslots of the stevedores at the wharf, carrier's fleets, transit time and daily demands of freight agents. This information sharing strategy through PCS enables agents to evaluate whether shifting the delivery time to the off-peak period can result in a significant saving of logistics costs, while the idle fleet and queue at the wharf gates are also optimised. In the third scenario (horizontal and vertical cooperation), PCS provides an optimum solution to serve all delivery/pick up requests with less fleets assuming that all agents are required to use such service. In this scenario, deliver/pickup requests of different agents can be served by one vehicle and each agent pay the partial transport cost of a tour instead of a two-way trip. In the fourth scenario (stochastic cooperation), agents are allowed to learn and to choose the best possible action through a reinforcement learning method in a dynamic environment. This scenario implies that using such PCS service is optional for users, and accordingly optimal solution is provided for only those who signed up. Accordingly, agents learn through the following reinforcement learning method, presented in Figure 28.

Consider an agent that, at every learning episodes $e = 0, 1, \dots, e_{max}$ (assumed $e_{max} = 100$), can choose to use the PCS to either shift the deliveries to off-peak period or bundle shipments with other agents. The payoff of a decision at episode e is the percentage savings in transport costs compared to the status quo, which considers time-based and distance-based operational costs as well as the time-based and distance-based operational costs as well as the fixed cost of vehicles. The rental cost of vehicles per unit time was assumed as the fixed cost of vehicle, and the working rate of drivers for a unit of time and fuel price for a

unit of distance were considered respectively as the time-based and the distance-based costs. The payoff $\pi_{bds(e)}$ of agent b from step e depends on the decision $d \in D = \{0: \text{individual operation in the status quo with hard time window, 1: vertical cooperation in the second scenario, 2: horizontal and vertical cooperation through the PCS in the third scenario}\}$, taken in the state $s_e \in S = \{1, \dots, 14\}$ and on other agents' actions, which are unknown. It should be noted that the number of learning episodes determine the long-term decisions whereas states represents the dynamic of the market regarding the varying number of shipments.

The payoff $\pi_{bds(e=0)}$ in the initial step is calculated on the basis of the status quo, while the payoff $\pi_{bds(e=1)}$ in the next step results from the full cooperation among all agents. In the following learning steps (up to e_{max}), we assume that agents adopt a learning rule suggested by Rivas (2013) which is a generalisation of linear reinforcement learning pioneered by psychologists Bush and Mosteller (1951). Let $P_{bds(e)}$ be the probability with which agent b takes the decision d in state s at the learning step e . Then, the learning rule in any state s for the agent b at the next learning step $(e+1)$ is given by the probability $P_{bds(e+1)}$ in eq. (7.19), where α is the learning speed ($0 \leq \alpha \leq 1$) and $\text{argmax}_d(\pi_{bds})$ is the decision d having the highest payoff among all other three decisions.

$$P_{bds(e+1)} = \begin{cases} P_{bds(e)} + \alpha(1 - P_{bds(e)}) \frac{e^{\text{argmax}_d(\pi_{bds})}}{\sum_{d \in D} e^{\pi_{bds}}} & \text{if } \pi_{bds} = \text{argmax}_d(\pi_{bds}), \quad d \in D \\ P_{bds(e)} - \alpha P_{bds(e)} \frac{e^{\text{argmax}_d(\pi_{bds})}}{\sum_{d \in D} e^{\pi_{bds}}} & \text{otherwise} \end{cases} \quad (7.19)$$

The simulation was coded in Python, calling the geo-processing tools of ArcGIS to solve the DCVRPTW with simultaneous pick-up and delivery. The software was run on a Windows-PC having a 3.4 GHz i7 processor and 16 GB of RAM. The VRP solver in ArcGIS (ESRI, 2017) is based on a Tabu search algorithm. Tabu search method is widely considered to be the best approach to solve large vehicle routing problems (Gendreau et al., 1994; Gendreau, 2003). The estimated travel times at various times-of-day for a typical weekday and weekend were extracted for each roadway link using the Google Map distance Matrix API `(())(())(())(())(())(())`, using the “gmapsdistance” library developed for the R language (Melo and Zarruk, 2016).

Simulation algorithm: Pseudocode

-
1. $e \leftarrow 0$; initial learning step(episode)
 2. **Initialize** OrderList [O_n]; {a set of two-dimensional demands “*weight TEU*” with time-windows specification of customers [t_{1i}, t_{2i}], and pickup/delivery locations along the network (i.e. coordination of importers/exporters/container terminals) considering the observed sequence of pickup and delivery orders}
 3. **Initialize** the stevedores specification; {location, working hours, hourly service rate}
 4. **Initialize** VehicleList [V_k]; {a set of two-dimensional capacity “*weight TEU*”, with time-windows specifications [t_{1k}, t_{2k}], and cost attributes (including fixed cost, time-based cost, distance-based cost)}
 5. **Initialize** time-varying network $G(L, N)$; {a vector of travel time of each link L per four time periods for weekdays and weekends (i.e. AM peak, noon, PM peak, night)}
 6. $d \leftarrow 0$; individual action in the status quo with hard time window (1 hour threshold of the observed time)
 7. **Initialize** States [S_{bd}] $\leftarrow [O_{na}]$; {a set of delivery/pickup shipments n if n belongs to the freight agent b on the day a }
 8. **Solve DCVRPTW (Tabu Search algorithm): while** not termination **do** (where termination is to service all orders satisfying all constraints)
 9. Set the constraints of time-windows of orders, capacity of vehicles, network constraints on B-doubles, sequence of orders, max operating hours of vehicles, and service rate of stevedores
 10. Generate the shortest-path cost matrix between all OrderList [O_n] and stevedores for VehicleList [V_k]
 11. Construct an initial solution by using the cost matrix by inserting the orders one at a time
 12. Improve the solution by resequencing the orders on each route, as well as moving orders from one route to another, and exchanging orders between routes until the optimum solution is achieved
 13. **End while**
 14. Calculate CostList [C_{bd}]; {cost of freight agent b based on the travel time and distance travelled and fixed cost of vehicle on a time-varying network}
-

-
15. $d \leftarrow 1$; individual action in the status quo with soft time window (anytime during the observed day)
 16. **repeat steps (7-14)**
 17. $d \leftarrow 2$; cooperation scenario
 18. **Initialize** States $[S_{bd}] \leftarrow [O_{na}]$; {a set of delivery/pickup shipments n for all agents on the day (a)}
 19. **Solve DCVRPTW: while** not termination **do**
 20. Set the constraints of time-windows of orders, capacity of vehicles, network constraints on B-doubles, sequence of orders, max operating hours of vehicles, and service rate of stevedores
 21. Generate the shortest-path cost matrix between all OrderList $[O_{na}]$ and stevedores for VehicleList $[V_k]$
 22. Construct an initial solution by using the cost matrix by inserting the orders one at a time
 23. Improve the solution by resequencing the orders on each route, as well as moving orders from one route to another, and exchanging orders between routes until the optimum solution is achieved.
 24. Calculate CostList $[C_{bd}]$; {cost of agent b based on the travel time and distance travelled and fixed cost of vehicle on a time-varying network}
 25. Calculate the PayoffList $[\pi_{bds}]$; {a set of the percentage of saving in logistics cost compared to CostList $[C_{bd}]$ if $d=0$ }
 26. $e \leftarrow 1$; **stochastic cooperation**
 27. Calculate the ProbabilityList $[P_{bds(e+1)}]$; (the probability of using PCS for agent b according to formula (14) for the current learning episode)
 28. **While** not termination **do**; (where termination is the maximum learning episodes)
 29. $e \leftarrow e+1$
 30. Calculate the ProbabilityList $[P_{bds(e+1)}]$; (the probability of using PCS for agent b according to formula (14) for the current learning episode)
 31. Update States $[S_{bd}] \leftarrow [O_{na}]$ for each $d=\{0,1\}$ following the probability $P_{bds(e+1)}$
 32. **If** $d = 2$ **solve** CVRPTW for $[S_{bd}]$;
 33. **Update** CostList $[C_{bd}]$, PayoffList $[\pi_{bds}]$, and ProbabilityList $[P_{bds(e+1)}]$
-

7.4 Results

The performance measures of four scenarios (i.e., status quo, status quo with soft time windows, full cooperation, stochastic cooperation from reinforcement learning) are shown in Table 13 and Figure 29. Measures concerned the total transport costs (including the split between time-based and distance-based costs), the total time and distance, the number of the two types of vehicles (measuring the shipment bundling), and the total number of trips. The comparison between these measures confirms the benefits of PCS, as a result of either shifting the shipments to the off-peak period or adopting cooperation. The status quo scenario represents the individual operation by shipping lines within a hard time-window that is within a one-hour threshold of the observed time-window. It should be noted that, while the PCS can facilitate the cooperation among agents, it can also provide the logistics solution for each individual agent such as shifting the shipments to off-peak period. This is the reason why the scenario of the status quo with soft time windows examined the effect of shifting the shipments to the off-peak period assuming that shipments have a soft time-window during the day. The soft time window not only helps to shift the deliveries to the off-peak period, but also enables the bundling of the shipments and consequently facilitates the decrease of the time-based costs and total logistics costs.

Interestingly, the best results are obtained in the full cooperation scenario where all shipping lines use the PCS to bundle the shipments and share the trucks. In this scenario, the number of visits for each tour increases by using larger vehicles (B-doubles), while the total distance travelled and the total logistics costs are at their minimum values. The stochastic cooperation scenario represents the result of reinforcement learning where, after the learning period, some shipping lines would continue cooperating through PCS, while others would prefer individual operation over cooperation but still are more likely to use the PCS to get a higher profit as a result of shifting to the off-peak period. Notably, the stochastic scenario leads to less total improvement compared to the full cooperation approach.

Table 13 – Simulation results of PCS for import and export

Parameters	Status quo	Status quo with soft TW	Full cooperation	Stochastic cooperation
Total transport costs (hundred thousand \$)	60,698	32,130	27,871	29,711

Time-based costs (hundred thousand \$)	40,408	11,965	8,537	10,018
Distance-based costs (thousands \$)	20,290	20,165	19,334	19,693
Total travel time (hr)	17,463	16,253	10,697	13,097
Total Distance (hundred thousand Km)	27,384	25,617	17,058	20,756
Number of trips by B-doubles	2,734	2,740	7,944	4,766
Number of trips by semi-trailers	44,874	44,725	34,487	38,582
Total number of trips	47,608	47,465	42,431	43,349

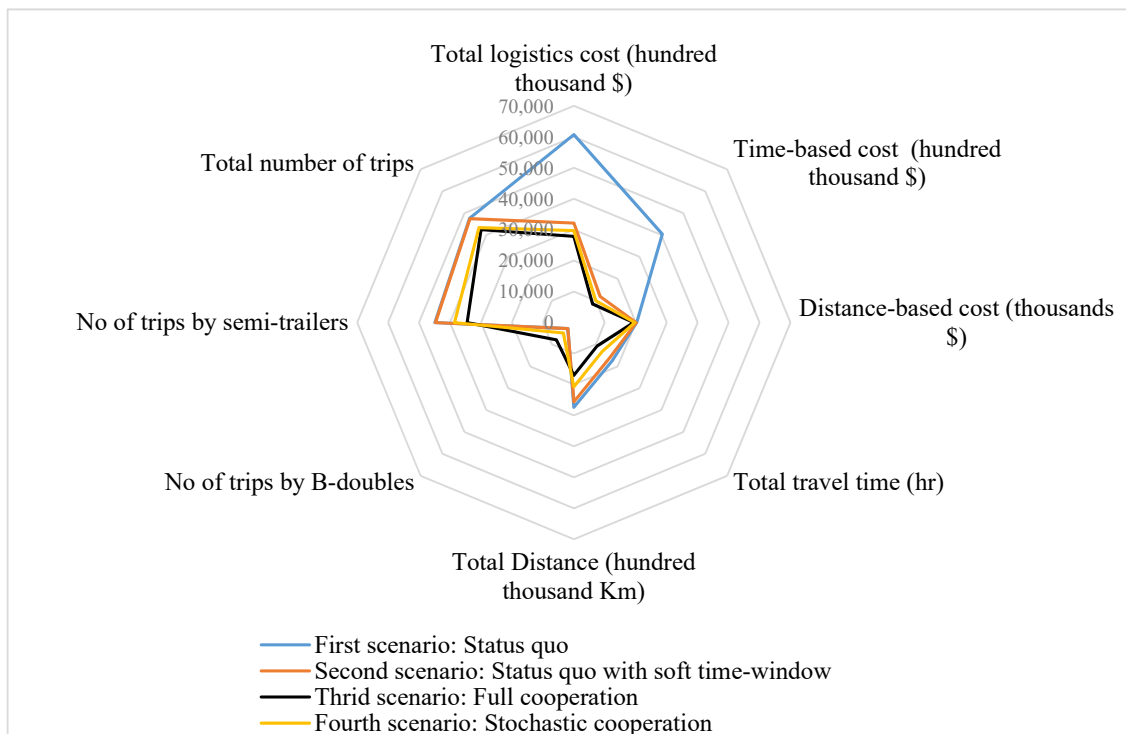


Figure 29 – Performance measures

Given that the time-based and distance-based cost were calculated in the same way for both scenarios, the decrease in costs associated with the distance and time, and consequently the total transport costs, is estimated to be more than 50% for the cooperation scenario. Considering these results reflect changes across only 14 days, the savings in the long term are expected to be major. Moreover, it should be noted that many other logistics processes are not considered explicitly in this research, and it is possible that introducing

the PCS would improve these processes as well. In order to fully evaluate the economic feasibility of the PCS, other considerations such as costs associated with delay and administrative costs could also be taken into account.

Figure 30 shows the transition of the probability of using the PCS during the learning period with various learning rates (specifically, $\alpha = 0.2, 0.5, 0.8$). Even though the PCS does not give a direct benefit regarding the transport costs for some shipping lines, other indirect economic benefits can be further explored in future research.

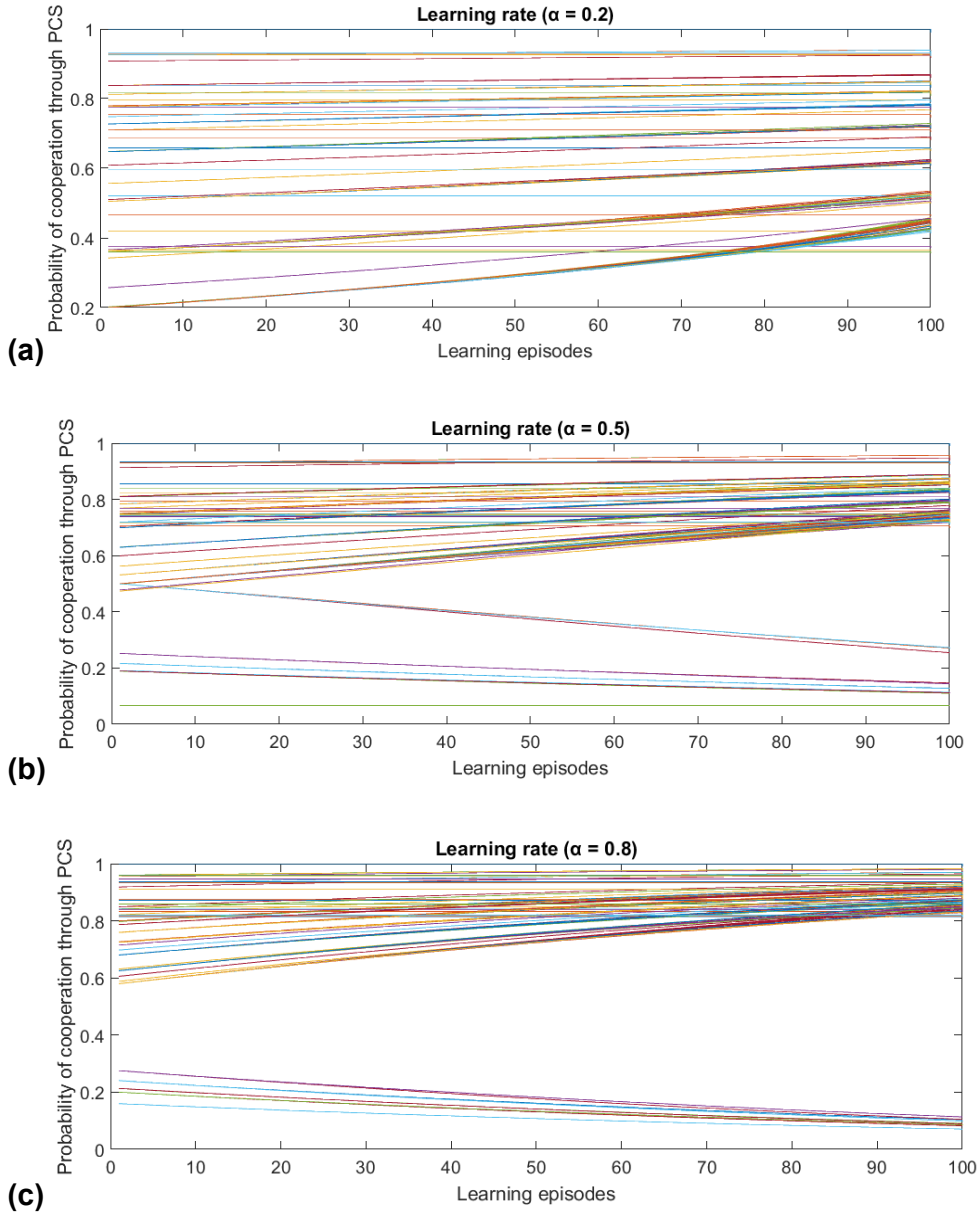


Figure 30 – Transition of probability of using PCS during the learning period with different learning rates (a) $\alpha=0.2$, (b) $\alpha=0.5$ and (c) $\alpha=0.8$

7.5 Managerial implications

This study offers practitioners several managerial insights about the role of horizontal and vertical cooperation in hinterland container transport. First, PCS provides a holistic optimum solution for all involved freight agents and improves supply chain performance if different aspects of integration is taken into account.

Second, it is important to identify and quantify the inefficiencies at early stages of developing PCS. The current hinterland container transport suffers from lack of visibility, manual work, mistakes, inefficiencies, penalty charges, and lack of coordination among agents. Freight agents (e.g. shipping line, road and rail carrier, shipper, container park, customs) seek to 'do their own thing' in terms of planning, timetabling their operations and using different platforms, with little visibility and coordination with the rest of the chain. This brings about several unexpected costs across supply chain such as penalty charges of cancelled bookings, amendment fees of not valid permits, and detention fees (i.e. penalty charges of containers outside of their time-windows allowed by shipping lines), late arrival costs, manual booking costs, and costs associated with idle fleets and containers. The financial impacts of lack of coordination and visibility can be classified into reduction in revenue, extra operational costs and capital cost for all parties and should be separately investigated in every case study.

Third, this study offers the greater benefits of both horizontal and vertical cooperation where all parties participate. However, investigation on the ultimate choice of collaboration through a PCS requires looking at the relationship among multiple interdependent variables. Supply chain mapping, identifying and quantifying inefficiencies are the necessary steps to provide motivation for freight agents to use PCS. This is particularly of high importance in landlord ports where port authorities cannot leverage these cooperation strategies among freight operators.

Fourth, from a psychological point of view, decision-making behaviour is highly adaptable and context-dependent, and the way a new service or a new technology is presented can influence the decision-making behaviours (Gifford and Checherita-Westphal, 2008). Accordingly, evaluating whether the freight actors see a benefit in adopting cooperation strategies through a PCS needs to be investigated in a broader concept of their strategic behaviour which can be explored in focus group interviews in the case study.

Fifth, integration is not necessarily required to be provided by a centralized web portal. PCS could be hosted by emerging technologies such as distributed ledger technology. Distributed Ledger technology (DLT) is an open-source decentralized platform that allows a more efficient, transparent and trustworthy flow of transactions between companies and individuals by removing the middleman and cutting out the costs, time lapses, and inter-parties lack of trust issues, while also maintains the privacy, immutability and business data confidentiality. One form of distributed ledger design is the blockchain system, which can be either public or private. DLT characteristics can assist a business structure which involves many parties that need trust transparency, as well as efficiency in inter-party transactions, contracting, and data management.

Supply chain and international trade are examples of those fragmented and complex systems that provide a great promise for DLT adaptation. End-to-end supply chain (e.g. from raw material to finished products, or from importer/exporter to international seller/buyer) needs track and trace that can be re-engineered by the adaptation of DLT. The use of DLT can help particularly on shipments or commodities with digital identifiers such as container trade. It can improve the process coordination by increasing knowledge and information sharing among the stakeholders. This technology can not only overcome international trade hurdles and disputes among agents for incurred unexpected costs by digitizing peer-to-peer collaboration tools and payments but also widen trade possibilities by providing the easy access to the services and infrastructure for all businesses.

With traditional supply chain and international trade, often the significant number of transactions can be impacted with data discrepancies and disputes due to lots of paperwork, multiple stakeholders, and human mistakes through passing through multiple systems. Additional costs emerge when shipments are entitled to delay in payments, and mutual contracts. DLT provides the smart contract without human intervention, where an encrypted, immutable and seamless transaction can be seen by everyone in the supply chain, ensuring a transparent and efficient supply chain. Moreover, the distributed and encrypted data structure of DLT and the absence of a central server increases the security of the system and eliminates the risk of cyber attack or hacking. Thus, the potential of DLT to lower the operating costs, boost the service quality, and consequently improve the organization and the entire supply chain competitiveness, is significant.

One may claim that this is also doable by digitizing the transactions and an integrated database. However, what makes DLT different from a database, which has existed for a while, is its assured immutability/irreversibility of the imputed original content due to its complex cryptographic verification, making it nearly impossible to alter fraudulently the state of the ledger. While a centralized system is vulnerable against cyberattacks, and possibly untrustworthy by freight operators, DLT provides privacy by hiding the information in the blocks. The sender can only send the information to the recipient may wish to know to finalize the transaction. The immutability aspect of DLT and the fact that they are distributed among multiple nodes (computers) means that it is extremely hard for a hacker to tamper with them and as a result, it is not hackable. Accordingly, sharing, updating and reacting on information types of activities can be almost instantly automated with a high degree of security which correlates directly to the efficiency. Using a hashing system and a distributed database can also protect the malware attack by issuing a new hash, while also many copies of the transaction are stored in other nodes of the network that are immutable.

7.6 Conclusions

Although a PCS is often initiated to serve as an information hub and a tool to facilitate the exchange of information and administrative tasks, the main objective remains to encourage the cooperation amongst freight agents to increase efficiency, profit, and infrastructure utilisation. A PCS can provide both horizontal integration through collaboration across agents of the same type, and vertical integration between different logistics providers across the supply chain. This study provides insights into the benefits of the horizontal and vertical integration across agents.

The decision of the logistics providers to use the PCS should consider some kind of a pilot project, experiencing the gains and losses in a dynamic market, where heterogeneous agents have a degree of freedom to experience their output through the system, learn and decide whether use the service. The agent-based model developed in this study enables the heterogeneous actions as a result of an adaptive reinforcement learning algorithm inspired by human decision-making strategies. The results prove that the cooperation between agents in sharing vehicles through the PCS can decrease the total travel distance and total logistics cost as well as improve the vehicle utilization. Although, this result is explicitly expected, but the amount of savings in logistics cost is required to be quantified in order to provide a robust proof of concept for managers.

However, it is often difficult to draw conclusions solely based on a single service without considering other benefits, costs, concerns, the dynamism of the market, and other agent characteristics. Due to the lack of information about the other involved costs, such as administrative and delay costs, this study looks at the savings in the logistic costs as a criterion to use a PCS. Furthermore, the lack of empirical evaluations of the existing PCSs imposed a limitation upon this study, meaning the evaluation of agents' decisions towards the PCS was remained in a simulated environment.

Chapter 8: Research opportunities in behavioral freight transport modelling

Paper submitted to the Journal of Transport Reviews in February 2018

Elnaz Irannezhad, Carlo Prato, Mark Hickman

8.1 Abstract

This paper presents a research agenda in behavioural freight transport modelling stemming from an extensive literature review. While recent developments in disaggregate freight modelling have made substantial moves towards a rich behavioural description of freight transport agents, this review clarifies that there are domains that still remain understudied. Arguably, the majority of existing studies in freight transport has disregarded the nature of interrelated decisions, the plurality of actors, and the mutual relations between different agents. Moreover, most freight transport models have been limited to an overly narrow interpretation of macro-economic theories, ignoring the dynamism of freight markets and the roles of cooperation, competition, and information sharing.

8.2 Introduction

While stimulating economic growth and enhancing markets for goods at the regional, national, and international levels, freight transport also imposes staggering negative externalities in terms of congestion, safety, land use degradation, noise, and air pollution (Gonzalez-Feliu, 2018; Muñuzuri et al., 2018). Inducing behavioural changes in freight supply chains, as well as promoting infrastructure changes and innovative freight policies, could provide improvements in economy and efficiency as well as alleviate or reduce these negative impacts. Thus, the crucial role of freight transport in the regional and national economies necessitates a broader understanding of the market for freight shipments and the tools that can interpret and forecast freight flows.

Freight vehicle movements are the result of interactions amongst various agents in the freight market. Each agent has its own nature (e.g., shipper, carrier) and characteristics in terms of resources (e.g. fleet, employees), geographic scope, market coverage, business strategies, and preferences over various types of logistics operations. Agents continuously adapt to the market within which they interact and coordinate with others within their respective supply chains. Furthermore, several freight transport decisions are made at the firm level and arguably some of them are interrelated, including buyer-supplier matching and distribution channel, shipment size, and mode of transport, and the choice of route. The results of these decisions are freight transport markets which are observable through the physical freight flows and activities.

However, freight traffic flows cannot simply be reverse-engineered to understand and replicate the agents' decisions and desires nor their adaptations to demand-oriented policies. Notably, ex-ante evaluation of urban freight policies and city logistic schemes requires a more fundamental investigation of the underlying behavioural mechanisms of the various actors, which result in freight traffic flows. Accordingly, disaggregate freight transport models rest upon the realisation that these actors are heterogeneous in their decision making process and should be modelled individually. In the last few decades, disaggregate freight transport modelling has stimulated interest by researchers and transport organisations. The study of disaggregate decision-making has also spanned many analytic methods that range from conventional multinomial logit models to more advanced econometric models.

Disaggregate freight models have been particularly useful in reaching out to practitioners, who are interested in evaluating freight-related public policies. Examples of these practices are regional freight transport models with disaggregate components that have been developed for Chicago (Outwater et al., 2013b), Florida (Chase et al., 2013), Portland/Oregon (Donnelly, 2002), Netherlands (Tavasszy et al., 1998; Bovenkerk, 2005; Davydenko and Tavasszy, 2013; Davydenko et al., 2014; Davydenko, 2015; Davydenko, 2016), and Tokyo (Wisetjindawat et al., 2012). However, a general lack of data, the proprietary nature of freight shipment data, the wide range of commodities with various specifications, and the complex nature of goods/service delivery has caused disaggregate freight modelling to be still far behind the passenger transport (Schröder and Liedtke, 2017).

We reviewed about 500 relevant studies in the freight transportation realm among textbooks, refereed journals, conference proceedings, and dissertations, which present literature review, data collection, and conceptual or analytical models. The search has been done in the Google Scholar search engine and other databases such as Science Direct, Proquest, Scopus, Emerald, the Web of Science, Transportation Research Board compendiums, and City Logistics Conference proceedings. Keywords used for the search not only include freight-related keywords such as 'freight transport', 'city logistics', 'freight distribution', 'behavioural freight model', but also cover policy, environment, and decision-making realms such as 'sustainable transport', 'choice modelling', and 'integrated transport network'. Furthermore, additional studies were added to the database if they were not retrieved through the preliminary search, but they were cited in the search results. Using the perspective from existing literature reviews (Woudsma, 2001; Regan and Garrido, 2002; NCHRP, 2008; Wang, 2008; Samimi et al., 2009; Chow et al., 2010; Anand et al., 2012; Gonzalez-Feliu and Routhier, 2012; Tavasszy et al., 2012; De Jong et al., 2013; Holguín-Veras et al., 2013; Liedtke et al., 2013; Friedrich et al., 2014; Mostert and Limbourg, 2016; Agamez-Arias and Moyano-Fuentes, 2017; Lee and Song, 2017), and an extensive survey of related literature, we identified areas that have not been deeply investigated in the freight transport realm. Accordingly, we identified a research agenda focusing on three major research directions.

Firstly, the omitted variable problem is a long-lasting issue of freight studies, mainly as a result of either neglecting non-transport related factors in freight surveys or removing important variables due to significant missing records. Furthermore, behaviours in freight transport studies have been conceptualized as choices, and choices are formalised as optimisation problems to be solved by freight agents where they are perfectly adapted to the environment, they are aware and familiar with all possible alternatives and, most importantly, they are able to determine and select the optimal choice. However, there is a growing literature testing the validity of those assumptions and examining the role of choice anomalies and heterogeneous decision-making strategies that sometimes contradict the axioms of traditional choice models using utility maximization. Several heuristics and biases affect decision-making such as risk attitude, projection bias, reference-dependent preference, inertia, bargaining, and oligopoly (Tversky and Kahneman, 1986; Caplin and Leahy, 2001; Kőszegi and Rabin, 2009; Kőszegi, 2010). These studies are the foundation of behavioural research which bridges the gap between economics and psychology and

looks at the process that agents adopt to assist them in reaching a decision, rather than simply analysing the outcomes of choices. Surprisingly, there is no study in freight transport that looks at the “decision process” paradigm, despite its importance.

Secondly, a decision maker is often modelled as an individual taking one decision at a time, while an outcome in real life may be a result of interactions among various agents or a result of multiple interrelated decisions. Accordingly, ignoring the interdependency of decisions may result in endogeneity problems. Although there have been a handful of studies that have captured multiple interrelated decisions, the majority of relevant articles focused only on the combined choice of shipment size and mode choice. Moreover, research efforts to parse the distinctive roles of various agents in a decision have been quite limited. Considering that some decisions in freight transport directly involve a variety of freight agents, it is necessary to study how such decisions are made, who makes them, and what happens as a result of the interactions between agents.

Thirdly, freight agents are reflexive actors that are situated within the context of a specific market, with specific market competitions, and technological trends. Classic freight models rest upon an assumption that all freight agents are homogeneous in their decision-making, and as a result the freight transport system is in equilibrium. This, however, has been proved to be in contrast with reality (Friesz and Holguín-Veras, 2005). Recent developments in agent-based modelling have made substantial moves towards a rich behavioural description of agents in dynamic environments. However, we contend that these models are still limited to a narrow interpretation of macro-economic conditions. Moreover, there are domains that remain understudied, such as the dynamism of the freight market, agent cooperation and competition, and the role of advances in information systems.

Accordingly, in this paper we set out three reference points in the following sections. Section 2 summarises the research gaps outlined from previous literature reviews. Section 3 explains the current practices of disaggregate freight choice models, and research avenues considering other aspects of decision-making. Section 4 presents the previous attempts of modelling interrelated decisions and a plurality of decision-makers, and also highlights future trends. Section 5 illustrates the modelling attempts that have considered the dynamism of market and interactions among various agents, and proposes future directions. Finally, Section 6 concludes and summarises the research agendas.

8.3 Research agendas from existing reviews

Two main research gaps are found in existing reviews of the freight transport literature (Woudsma, 2001; Regan and Garrido, 2002; Taniguchi and Thompson, 2002; Taniguchi et al., 2003; NCHRP, 2008; Wang, 2008; Samimi et al., 2009; Chow et al., 2010; Anand et al., 2012; Donnelly et al., 2012; Gonzalez-Feliu and Routhier, 2012; Tavasszy et al., 2012; De Jong et al., 2013; Holguín-Veras et al., 2013; Liedtke et al., 2013; Aljohani and Thompson, 2016; Mostert and Limbourg, 2016; Agamez-Arias and Moyano-Fuentes, 2017; Lee and Song, 2017; Taniguchi et al., 2018).

Firstly, the importance of gaining a better understanding of various freight agents and their interrelationships has been identified in several literature reviews. Anand et al. (2015) reviewed city logistics studies and argued that vehicle flow and carriers are the main focus of most studies, while other stakeholders and activities are underrepresented. They also identified a gap wherein the interrelation between various stakeholders, activity descriptors (e.g., commodity flows, vehicle trips, and freight generation), and environmental objectives have not been properly investigated.

Secondly, existing literature reviews highlighted the necessity of integration of logistics schemes both in global trade and across supply chains. Freight transport actors usually adapt themselves to the transport market structure and regional regulations in their operational region, which implies the necessity of integration of urban goods movement models and regional or even international trade models (Chow et al., 2010; De Jong et al., 2013). Accordingly, the integration of modelling components has also been identified as an important research gap (De Jong et al., 2013). This review asserted that most developments at the national level concern multiregional input-output economic analysis, while there are seven research gaps concerning various aspects of the integration: (i) a lack of analysis of the impacts of policies on logistics indicators such as shipment size, load factor, or empty trips; (ii) a lack of integrated models of the location of suppliers and receivers and the associated economic analysis; (iii) a lack of integration of production behaviour modelling with inventory and transport behaviour; (iv) a lack of modelling of timing of freight trips; (v) a lack of integration between national/international freight models and urban models; (vi) a lack of integration of freight and passenger movement models with joint assignment to the road network; and, (vii) a need to include more explanatory variables in models. The lack of integration of freight transport problems (e.g., terminal location, transport mode, vehicle or

vessel type, pricing and pickup-delivery decision problems) with the consideration of environmental issues was also pointed out by Mostert and Limbourg (2016), while there are only a few integrated passenger demand models with urban commercial vehicle models, as shown by Schröder and Liedtke (2017). Agamez-Arias and Moyano-Fuentes (2017) highlighted the importance of information sharing among intermodal freight agents, as well as the necessity for research about information technologies in integrated intermodal freight and international trade activities. This gap was also pointed out in the context of ocean container transport by Lee and Song (2017), who identified some areas that were understudied, including contracting, pricing, and information sharing.

The aforementioned research gaps from existing literature reviews, and an extensive survey of existing freight modelling efforts, we identified a research agenda in three major directions namely decision process paradigm, inter-related decisions and plurality of decision-makers, and advances of agent-based models.

8.4 Decision process paradigm

The fast-moving trend from aggregate to disaggregate methods illustrates the researchers' desire to understand individuals' behaviour and to enable better predictions. Hence, several developments have been made to address different aspects of the black box of choice behaviour with a few promising studies in freight transport.

Firstly, taste heterogeneity can be captured by introducing random parameters that account for the differences in agents' preferences towards some attributes, assuming those preferences vary continuously across the population of agents. The mixed logit model has been applied in various logistics choices such as off-peak delivery (Holguín-Veras et al., 2008), mode choice (Arunotayanun and Polak, 2011), distribution channel (Wisetjindawat et al., 2006), and use of container terminals (Irannezhad et al., 2017b). Latent class models offer an alternative approach where the continuous distribution of parameters over the sample population is replaced by a discrete distribution. For example, Piendl et al. (2017) specified a latent class model for the choice of shipment size on the basis of the commodity type.

However, heterogeneity may be the result of adopting different attribute processing strategies (APSSs), where the decision maker does not process all information given to them

with equal strategy. As the only study in this direction, Puckett and Hensher (2008) studied APSs through a stated preference (SP) survey of the preferences of freight transport providers and their customers in Sydney across a range of attributes, while also considering the roles of more than one agent in the decision-making process. This study showed that accounting for APSs' heterogeneity among various interdependent freight stakeholders results in different marginal disutilities and different willingness-to-pay for time-related attributes.

Moreover, heterogeneity may arise from different decision makers since logistics decisions are not always made by the same agent in every situation (Holguin-Veras, 2002). While segmentation of the population has been applied in a few examples (e.g. developing separate models for shippers and carriers (Irannezhad et al., 2017c), separate models for each commodity type, (de Jong et al., 2010; Kawamura et al., 2010), and exogenous segmentation (Piendl et al., 2017)), researchers are yet to fully capture the distinctive role of decision makers in freight surveys. Accordingly, despite the growing body of freight studies accounting the heterogeneity and APSs, there is a need for further improvements in freight surveys and models.

Secondly, while random parameter models are able to capture unobserved heterogeneity, they do not provide any insight about what factors have translated into that heterogeneity. In most disaggregate freight models, logistics decisions are commonly explained by variables including characteristics of decision makers (e.g., company size, type, service area, fleets), shipments (e.g., commodity type, size, time-windows specifications), and distribution channels (e.g., transport distance, cost, mode, tour specifications). However, there is a range of other attributes that are commonly omitted from freight models such as non-economic and psychological attributes as well as other aspects of the supply chain on a global scale (e.g., international trade, inventory of commodities, market specifications). One approach to address explicitly this issue is to use proxy variables instead of unobserved variables that are not directly relevant, but serve in place of an unobserved variable, such as using the value of time instead of the monetary value of transport time variability (reliability). Latent behavioural factors can also be represented by a latent construct through indicator equations that, alongside observed explanatory variables, better explain the decision maker's preferences toward different alternatives. Furthermore, omitted variables sometimes arise from the issue of missing data, which is

quite common in freight surveys. Estimating missing data as a latent variable is a more robust alternative than removing records with missing data, imputation, or excluding the variable. As the only attempt, Irannezhad et al. (2017b) specified and estimated a hybrid choice model to study the simultaneous decision of using container terminals and container holding time, where missing information about import and export containers was treated by a latent construct. While omitting influential variables may lead to misspecification and inconsistent estimation of parameters, future freight research should take this into account.

Thirdly, a great deal of studies have investigated cognitive processes and perceptions where the basic axioms of utility theory seem to be violated. Regret theory was first proposed by Loomes and Sugden (1982) as an alternative theory of rational choice under uncertainty, hypothesizing that individuals aim to minimize the anticipated regret when making choices. Random regret minimisation (RRM) was introduced to discrete choice modelling by Chorus (2010), and Boeri and Masiero (2014) were the first to study the application of RRM in freight mode choice while also considering taste heterogeneity. The results confirmed the hypothesis that a negative shift in reference point has an impact on freight agents' approach to choice. Later, Irannezhad et al. (2017c) applied a hybrid RRM-RUM structure for the choice of vehicle type for two separate models of carriers and shippers, considering a regret form for the attribute of vehicle hire cost. Results revealed that carriers try to maximize their total utility when considering various vehicle types based on the hire price of the vehicle. However, this was not the case for shippers, likely because they might already own the vehicle and therefore do not have to pay any hire costs. These promising results call for an explicit consideration of different behavioural paradigms in future freight studies.

Fourthly, decision mechanisms not only include utility maximization or regret minimisation, but may also incorporate the bounded rationality of the decision-maker. In the last century, it was noticed that economic agents do not make complex calculations prior to making a choice. Decision making behaviours simply rely on rules or analogies in peoples' minds rather than quantifying every alternative (Knight, 1971). Bounded rationality was first discussed in a seminal work by Simon (1955), hypothesizing that decision-makers consider some threshold of satisfaction rather than purely maximising their expected utility. Later, Simon (1978) presented another interpretation of bounded rationality, explaining that the behaviour of an economic agent is a result of a "process of thoughts" rather than "a product of thoughts"; hence, economic agents follow simple heuristics rather than complex

computations which are beyond their cognitive capacities. Day and Pingle (1991) suggested that economic behaviours could be described by seven different models: (i) experimentation or trial-and-error search when the cost of decision making is low; (ii) imitation and mimicking other agents' decisions; (iii) following an authority; (iv) habitual behaviour; (v) unmotivated search which is driven by the sense of adventure; (vi) hunch and intuitive actions which may be against rational decision making; (vii) procedural optimisation or a search for approximate optimality. However, current behavioural modelling practices appear to assume rational utility maximisation as the choice rule. This assumption might be effective in long-term policy assessments, but when it comes to short-term policies there is a need to investigate if freight agents are prone to any kinds of heuristics such as self-fulfilling expectations, impulsive or inconsistent behaviours.

Fifthly, logistics choices are subject to a degree of uncertainty, while some attributes are very risk-prone such as the variability in travel time and cost. Evidence from psychology and behavioural economics suggests that marginal utilities can decrease, increase or remain unchanged according to risk attitudes (risk averse, risk loving, or neutral). Li and Hensher (2012) were the first to model empirically the risk attitudes of carriers and shippers with regards to travel time. Moreover, the evidence presented by Kahneman and Tversky (1979) contradicted the axiom of expected utility maximisation under uncertainty by introducing the Prospect Theory, which breaks down decision-making heuristics into gain and loss domains relative to a fixed prospect. Experiments by Tversky and Kahneman (1992) revealed that a power-law utility function better reflects the relative rank of gains and losses. Despite applications of Prospect Theory in behavioural passenger transport studies in recent years, there has been no comparable practice in the field of logistics. Additionally, there has been no research into the extent of knowledge that agents have about possible choice alternatives, even though this is a prerequisite of behavioural modelling.

Lastly, all existing DCM in freight studies were estimated in a static context. As travel time, travel costs, and time-windows are dynamic in nature, and logistics decisions are made on a case-by-case basis in a dynamic environment, a dynamic choice model could capture decision-making on the basis of dynamic explanatory variables over time periods. Thus, further research should explore the dynamic aspect of decisions.

8.5 Inter-related decisions and plurality of decision makers

Freight agents make logistics choices that are clearly interrelated in that their outcome are mutually influential. For example, a shipper chooses the vehicle type and the route while considering the mass or size limitation on some road segments. In most cases, there is no clear causality and/or sequence between these decisions. Arguably, these interrelated decisions most likely result from a learning process and aim at minimising cost and/or maximising level of service. As a result, there is no clear-cut explanation about which one is conditional upon the other.

For a few decades, researchers have come to recognise the simultaneity of freight decisions. For example, McFadden et al. (1986), Abdelwahab and Sargious (1992), and Abdelwahab (1998) applied the switching regression technique to model the binary choice of transport mode and shipment size. The computationally intensive estimation of simultaneous equations, however, has caused several alternative modelling approaches to become common practice.

One approach is sequential modelling, where one decision is used as an explanatory variable to estimate the other decision(s). For example, Combes (2012) modelled the shipment size using the economic order quantity, by adding dummy variables for mode of transport and for direct or tour-based delivery. To avoid the bias resulting from the potential correlation of interrelated decisions, some studies have applied a sequential modelling approach, wherein one of the decisions is estimated independently with exogenous variables, with the resulting decision entering another model to estimate the second decision. Studies by Holguin-Veras (2002), De Jong and Ben-Akiva (2007), and Abate and de Jong (2014) are examples of sequential modelling of mode choice (first) and shipment size (second). However, the precision of sequential modelling approach is clearly lower than the one of simultaneous models (Mannering and Hensher, 1987).

Alternatively, several combinations of discrete categories are estimated jointly, for example joint mode and shipment size models by Chiang et al. (1981), De Jong and Johnson (2009), and De Jong and Ben-Akiva (2007). However, the superimposed discretisation of a variable with a continuous nature (e.g. shipment size) may lead to different estimated behavioural responses, as was proven by De Jong and Johnson (2009).

Recently, copula-based models have received increasing attention in the transport literature to address the endogeneity and simultaneity of decision. A copula is a parametrically-specified joint distribution of random variables derived purely from their marginal distributions, as proposed by Sklar (1973). Copula-based models have two main advantages. First, they overcome the computational difficulty of simultaneous equation modelling with easier estimation by maximum likelihood. Secondly, they allow for the marginal distributions in the discrete and continuous equations to take any parametric distribution (Bhat and Eluru, 2009). However, there are only three freight studies applying this approach to model two interrelated decisions namely a discrete-discrete mode and shipment size model (Pourabdollahi et al., 2013), a discrete-continuous vehicle type and shipment size model (Irannezhad et al., 2017c), and a discrete-discrete model of using container terminals and container dwell time (Irannezhad et al., 2017b). Regarding the existence of several other interrelated decisions in freight transport and possibly simultaneity of more than two decisions at a time, the researcher have only scratched the surface by modelling only a two joint choices, and mostly focused on mode and shipment size decisions.

Lastly, logistics decisions are likely the result of interactions between multiple agents, none of which have full power or control over the market (Bolis, 1998). Considering such interactions in behavioural freight modelling is critical. Hensher and Puckett (2007) developed a theoretical framework to address the behavioural processes associated with negotiations among multiple agents leading to a choice outcome. Hensher et al. (2007) investigated also the interaction of two agents in a retail distribution chain through the ideas of concession and power: they conducted a two-stage experiment and found that agent power varies across the alternative attributes including on-time reliability, variable charges, and transit time. However, the main body of existing DCM studies is based on the notion of utility maximisation for individual agents, and group utility maximisation is less studied. An important step to develop a deeper understanding of group decision making would be to design a specific survey method to capture the underlying interactions among various agents.

8.6 Advances of Agent-based models

Agent-based models (ABMs) are the most advanced disaggregate models in the freight realm, enabling different types of market structures to be considered. Grounded in

reinforcement learning, in an ABM framework we may not know the behaviour of the full system, but we have insight into how the system's agents behave. So, we can start modelling by identifying the agents and defining their behaviours. From these behaviours, the characteristics of the full system emerge at the aggregate level. Accordingly, a set of decision-making rules are defined for each individual agent based on their endogenous characteristics and other exogenous variables. The analyst may then track the agents over an entire network for a certain time period, and may experiment with the variations in behaviour due to implementing different policies. In recent years, the number of studies in traffic and transportation that have applied this technique has grown enormously. Given that many diverse agents are involved in the supply chain and freight transport system, agent-based modelling seems very suitable.

INTERLOG (Liedtke, 2009), TAPAS (Holmgren et al., 2012), and FREMIS (Cavalcante and Roorda, 2013) are examples of regional, agent-based, freight transport models. In the literature, there are also a few models of auctioning and bidding among shippers and carriers in which carriers are able to compete over the proposed price, adopting either a rule-based model (Van Duin et al., 2007) or game theory (Thorson, 2005; Friesz et al., 2013).

ABMs can also assist in examining various policies by introducing changes into the market environment, such as introducing tolls, subsidizing a transport mode, or establishing a new distribution centre. Taniguchi et al. (2007) and Tamagawa et al. (2010) developed a multi-agent model (shippers, carriers, and administrators) on a sample test network to study the effects of road pricing on shippers' and carriers' strategies. Using ABMs, mode shift behaviour was studied by Baindur and Viegas (2011), and the impacts of truck sharing on hinterland container transport was studied by Irannezhad et al. (2017a). The aforementioned studies adopted reinforcement learning methods where agents learned the best action in a dynamic environment through experience. In reinforcement learning, an agent moves towards the best alternative based on resultant feedback from the environment after each action. This is slightly different from game theory studies, where, for example, in a Cournot-Nash equilibrium it is assumed that no player has any reason to change unilaterally its behaviour.

Nonetheless, a few challenges in ABM studies should be addressed. *Firstly* the aforementioned attempts in ABM are either at a microscopic or macroscopic scale. A review

of the literature highlights a critical micro-macro gap: there is a need to bridge between the logistics activities of a single firm and the macro level of goods flow in regional or urban areas (Liedtke et al., 2013).

Secondly, ABMs can be improved by integrating with DCM. Accordingly, logistics behaviours in ABM follow the probability function obtained from DCM, while the interaction between all key decision-makers in a supply chain are also taken into account.

Thirdly, existing ABMs either model market orientation as supply-based or demand-based according to the logistics terms of a “push” or “pull” strategy. In a supply-based market structure (the “push” strategy), flow is modelled from the perspective of the producers of goods, and producers determine their shipping needs, including shipment size and commodity origins and destinations, by considering economies of scale and scope (Liedtke, 2009). However, in a demand-based market structure (the “pull” strategy), the supply chain is determined by consumers who choose the quantity of each commodity that minimises their total cost of ordering, transport, and inventory (Holmgren et al., 2012). The interface between these two strategies in logistics is called the push-pull boundary, which represents the equilibrium in the market resulting from production and consumption. Although spatial price equilibrium models based on this market structure have been applied in freight studies (Harker and Friesz, 1986), it is necessary to consider this concept in future ABM approaches.

Fourthly, the importance of dynamism in the freight transport market should receive more attention in ABM studies. While conventional aggregated freight studies assume the existence of an equilibrium concerning either cargo price or freight flow, several studies declare that urban freight markets are not usually in a stable equilibrium and are highly dynamic (Friesz and Holguín-Veras, 2005). Dynamism in freight transport markets results from an oligopolistic or a competitive market structure, where freight actors set up new strategies either as they are influenced by market rules and regulations or as they try to keep up with rivals (Nagurney, 2010; Lee et al., 2014).

Fifthly, many freight actors have realized that sustainable competitive advantage requires greater openness and commitment to horizontal and vertical cooperation instead of mistrust and rivalry within the supply chain (De Martino et al., 2015). Emerging cooperation and even creation of alliances among ocean and inland carriers are a result of

this mindset of bilateral outsourcing (Fink, 2002). The literature on the cooperation of maritime transport agents is gaining momentum (Heaver et al., 2000; Sheppard and Seidman, 2001; Cruijssen et al., 2007; Lun et al., 2010). However, as also pointed out by van de Voorde and Vanellander (2010), quantitative studies in this field are scarce, with few existing studies that investigate or calculate the benefits of cooperation in hinterland transport or that attempt to minimize costs in empty container repositioning (Sterzik et al., 2015; Irannezhad et al., 2018). Moreover, cooperation, alliances, and competition in an oligopolistic market of freight transport perhaps demands new concepts of equilibrium that take agents' strategies into account. Accordingly, the "Imitation Equilibrium", proposed by Björnerstedt and Weibull (1994), offers an alternative perspective to the standard Nash or Cournot equilibrium concept. The imitation equilibrium model features agents who imitate a rival's success; theoretical work by Vega-Redondo (1999) shows that such behaviour in the market converges to a competitive equilibrium. Research on alliance structural choices also assists in examining the structure of firms and markets, quantifying the value creation for firms by combining their resources, particularly sharing knowledge.

Sixthly, ABMs should accelerate with advances in information systems. A review of the literature in current logistics practices reveals some central problems that can be assisted by advances in information system technologies (Zhang et al., 2016). Currently, there are various information systems, both separate systems among different companies but also sometimes numerous systems inside each organization. Then, all information exists in small fragments hosted by individual companies, with no incentive to share among others in the supply chain. While a local optimization at the firm level can be a first step to improve efficiency, the supply chain necessitates a holistic optimisation across all levels. The practical failures of some logistics strategies such as empty container repositioning (triangulation), which result from mistrust in information sharing, highlight the importance of having a holistic view. For example, technologies such as the "smart contract" proposed by Szabo (1997), the Blockchain, the Internet of Things (IoT), and "port community systems" in maritime transport, provide a secure platform that enables a better integration of informational, physical, and financial flows on a global scale. Such information sharing strategies allow for more efficient, transparent and trustworthy flows of transactions between companies and individuals by removing the middleman and cutting out the costs, time lapses, and issues with lack of trust between parties. Accordingly, future research can look at the impacts of these digital supply chain scenarios.

Lastly, aligned with previous literature reviews, we also suggest that freight transport models should explicitly consider both public sector performance measures (such as safety, efficiency, reliability, environmental sustainability, and economic indices), and private sector performance metrics (such as operations, financial, and safety) that emerge from the behaviours of freight actors.

8.7 Conclusions

The challenges of freight transport modelling have led to discounting and simplifying the interactions between freight agents. In contrast, more recent studies and examples of current practice attempt to model individual interactions between agents and to consider multiple facets of individual freight flows. Nonetheless, only a few studies have addressed the entire supply chain or the dynamism of the freight transport market. Attempts to integrate all interactions have been frustrated by computational complexity, the difficulty of amalgamating human behaviors with economic concepts, and, arguably, the substantial complexity of the freight transport market. Accordingly, these frustrations lead to limited generalizability of the findings of existing studies in order to test future freight-specific policies and strategies.

In this review, we have presented a research agenda in behavioral freight transport modelling. We argue that the majority of existing studies has disregarded the choice heuristics, plurality of actors, and the mutual relationships between these actors. Moreover, the growing use of new information systems and cooperative strategies is creating significant dynamism in the freight transport market. While conventional static modelling approaches only model the consequences of these changes, ABMs provide an opportunity to adopt such dynamic and behaviourally rich perspectives on freight actor behaviours.

However, it should be noted that not every research agenda discussed in this chapter has been addressed in this PhD thesis.

Chapter 9: Conclusions and future research

Based on the existing literature reviews in freight modeling, this research addresses the identified research questions in order to provide insight into behavioural decisions in freight transportation. The first research question was answered by modelling the joint choices of vehicle type and shipment size, and the joint choices of using container terminal and dwell time simultaneously. In both models, the dependency parameter of these interrelated choices was statistically significant which confirmed the initial hypothesis (i.e. these choices are correlated).

Model estimation of two choices of shipment size and vehicle type was undertaken on a dataset of 550 shippers' observations and 1484 carriers' observations in Mashhad, Iran. The findings from this study reveal that using heavier vehicles in longer trips by both operators (shippers/carriers) as well as increasing shipment size proves the economies of scale and distance. Furthermore, carriers' preferences for heavier vehicles over vans for intercity movements and night deliveries, as well as for smaller shipment size during afternoon peak hours, appear as the result of passage restrictions of heavy vehicles in the congested urban network, particularly during the daytime hours.

Regarding estimates of the effects of commodity type in an urban transportation system, the results show that commodity types play a role in these joint decisions, as some commodities are more likely to be transported by for-hire carriers while others are more likely to be transported by shippers (ancillary carriers). Accordingly, for-hire carriers tend to ship construction and industrial commodities with heavier vehicles, while perishable foods and household commodities are mainly transported by vans. However, the positive sign in the shipment size model reveals that household items and furniture are among the most voluminous commodities, whereas perishable foods and fuel products are transported in smaller sizes by for-hire carriers.

Considering the estimates of the shippers' model, commodities such as fuel, food and beverages, industrial and manufacturing commodities, as well as services, are shipped

in larger sizes, particularly when the time of delivery is not during daytime hours. Also, light trucks seem to be a more efficient alternative than vans for carrying food and agricultural products, as well as for those shippers who have extended working hours at night. Conversely, light trucks are less likely to be used for industrial and manufacturing commodities.

As mentioned before, the interrelationship between vehicle type and shipment size is validated in the empirical results by obtaining a significant dependency parameter of the copula function. Looking at the variables and the estimated level of significance also proved the validity of different decision-making behaviors between shippers and carriers. Another important finding reveals that carriers compare the hourly hire price of various vehicle types explicitly, as well as the total utility they get from each vehicle type, based on the shipment characteristics.

The model estimation of two choices of using container terminal and dwell time was undertaken on import and export containers trading through the Port of Brisbane. The findings from the study on inland container transportation show that both importers and exporters who are located nearer the port prefer to deliver directly. Looking at the variables highlights the different characteristics of the import and export supply chains about the usage of container terminals (CTs) or the duration of their use.

Export containers originating from suburbs with a higher number of mining, agricultural, and manufacturing employees are more likely to be stored at CTs either inside the port or inland, whereas export containers originating from suburbs with a higher number of livestock-related businesses, distribution centres, and industrial parks are less likely to be stored at inland CTs. Import containers destined to areas with a higher number of retailers and or with larger areas for commercial land use are more likely to travel through CTs either at the port or inland. Arrival on a weekend or late arrival during the day is related to direct delivery of import containers, particularly if destined to suburbs with a larger wholesale sector. When looking at export containers, arrival late at night or early in the morning is associated with a higher probability of storage at CTs either at the port or inland. Also, a greater weight of the shipment makes for a higher likelihood of export containers to be stored in twice off-site and on-site CTs or be packed at CTs inside the port.

Findings show that larger industrial areas in both the origin and destination suburbs increase the probability of storage at CTs for dwell times of at least one day. Also, while import shipments destined to suburbs with a higher number of employees in the manufacturing sector are more likely to be stored at CTs for at least one day, export shipments originating from those suburbs have a shorter dwell time at the CTs.

The second research question was addressed by estimating a hybrid model with the aim of correcting for missing information. Building based on the applied model by Sanko et al. (2014), this research address the common issue of missing values in freight studies. Specifically, the model exploits the fact that variables with missing values are latent by definition. Hence, the hybrid formulation allows circumvention of the bias inherent in removing observations or imputing values by expressing the value of the latent variables as a function of explanatory variables. The latent variables considered in this study re shipment weight and time of arrival in the import container model, and shipment weight in the export container model.

Moreover, heterogeneity in the sensitivity to distance was observed as a result of applying a random parameter model, which was a factor found to be very relevant in the choice of using a CT.

The third research question was addressed by simulating an agent-based model where agents (i.e. shipping lines) are allowed to learn and to choose the best possible action (i.e. between individual action and cooperation) through a reinforcement learning method in a dynamic environment. This simulation environment implies that using such PCS service is optional for users, and accordingly, optimal solution is provided for only those who signed up.

Given the simulation results from the solution of the model, the result of the modifications in logistics operations was also calculated in terms of pollutant emissions. Specifically, the emissions from the delivery solution in both scenarios were estimated on the basis of the calibrated COPERT guidelines for Australia (EMISIA and Queensland Department of Science). Firstly, the fuel consumption was calculated depending on the truck type and the average speed of every segment in the optimum route. Then, the emission pollutants were estimated depending on the fuel consumption and the vintage year for the major pollutants. Using the vehicle registration data from the Queensland Government

(Queensland Government, 2013), the pollutant emissions were calculated for the routes of the semitrailers and B-doubles at each delivery plan during the two weeks that were analysed. Accordingly, the reduction in the emissions of the different pollutants and the fuel consumption in the cooperation scenario were estimated between 40 and 45%.

The findings from this study highlight the benefits of cooperation among actors involved in inland container transportation, through a reduction in the logistics costs and a higher utilisation of larger trucks, as well as a significant reduction in fuel consumption and pollutant emissions. Accordingly, results reveal that there is a significant number of unnecessary truck movements and storage days of empty containers which can be avoided via cooperation among shipping companies. Furthermore, the results proved that the proposed simulation model is capable of capturing the real-world constraints and components.

However, integration is not necessarily required to be provided by a centralized web portal. PCS could be hosted by emerging technologies such as distributed ledger technology (DLT) to allow a more efficient, transparent and trustworthy flow of transactions between companies and individuals by removing the middleman and cutting out the costs, time lapses, and inter-parties lack of trust issues, while also maintaining the privacy, immutability and business data confidentiality. The use of DLT can help particularly on shipments or commodities with digital identifiers such as container trade. It can improve the process coordination by increasing knowledge and information sharing among the stakeholders. This technology can not only overcome international trade hurdles and disputes among agents for incurred unexpected costs by digitizing peer-to-peer collaboration tools and payments, but also widen trade possibilities by providing the easy access to the services and infrastructure for all businesses.

With traditional supply chain and international trade, often the significant number of transactions can be impacted with data discrepancies and disputes due to lots of paperwork, multiple stakeholders, and human mistakes through passing through multiple systems. Additional costs emerge when shipments are entitled to delay in payments, and mutual contracts. DLT provides the smart contract without human intervention, where an encrypted, immutable and seamless transaction can be seen by everyone in the supply chain, ensuring a transparent and efficient supply chain. Moreover, the distributed and encrypted data structure of DLT and the absence of a central server increases the security of the system

and eliminates the risk of cyber attack or hacking. Thus, the potential of DLT to lower the operating costs, boost the service quality, and consequently improve the organization and the entire supply chain competitiveness, is significant.

9.1 Contributions and uniqueness

Considering the policy relevance of the third research question presented in this PhD thesis, it was necessary to better understand the behaviours of freight transport actors in the status quo and look at their needs. In the course of this research, IMEX data (Port of Brisbane Pty Ltd, 2013) became available, making the empirical modelling possible. Although simplification of logistics processes has been done to make the modelling task less challenging, the applicability and practicality of model are confirmed due to using a real dataset in a real case study.

The utmost impact of this study has been providing a proof of concept for developing a PCS in the Port of Brisbane by quantifying the benefits of integration of freight actors. Accordingly, the Port of Brisbane is now investigating the development of a PCS by implementing distributed ledger technology to assist its stakeholders to reduce supply chain costs and inefficiencies.

Given previous modeling efforts, this study contributes to the literature from several perspectives. First, this study proposes a copula-based discrete-continuous model of vehicle type and shipment size that recognizes the need for modeling these two decisions jointly while considering the nature of the two choices and, in particular, the continuous nature of shipment size. This study argues that different freight actors (i.e., carriers and shippers) have different preference structures because fleet ownership and the operating frequencies are different, and the study accommodates these differences by estimating two different models. This study has explored model formulations where different attributes might have either a utility maximization or a regret minimization expression that suggests how freight actors might process attributes differently.

Furthermore, this study explores the preferences of importers and exporters regarding the use of container terminals (CTs) as a transshipment point, as well as adding the decision for the dwell time of the containers. Accordingly, this study proposes a joint model of the choice of using CTs and the duration of dwell time at CTs, relying on the joint

cumulative distribution of the two error terms being expressed by a copula function. The joint model is a discrete–discrete copula–based model that also accounts for unobserved heterogeneity for some variables.

Another contribution of this research is a demonstration of the means to tackle the issue of missing data that may be found in freight survey data. In most choice models, records with missing data are often removed before the analysis. However, this practice causes the parameter estimates of the models to be biased, especially when the percentage of missing data is significant. Accordingly, this study presents a hybrid version of the joint copula–based model for treating missing data from full container movements in the import and export chains, with the aim of providing unbiased estimates of the determinants for the choice of using CTs.

This study also contributes to the overall body of research by introducing an integrated model of vehicle allocation and routing considering various vehicle types, dynamic network travel times, constraints on the use of some network links for selected vehicle types, and the multi–dimensional capacity of vehicles and container demands. This study attempts to fill this gap by incorporating these constraints and simulating a real–world problem. Making use of the existing solution algorithm in the ArcGIS software to solve the multi–dimensional capacitated vehicle routing problem with time–windows (CVRPTW), real–time network dynamics (dynamic travel times) and constraints for heavy vehicles are considered. Accordingly, the effects of a “virtual depot” are simulated where users can see the availability of both empty containers and road carriers and then match supply with demand. While the observed hinterland container movement is simulated as the status quo, the choice of repositioning empty containers directly from the importer to the exporter, the choice of vehicle type, and the delivery routing are optimized jointly.

This study presents an agent–based simulation in which shipping lines learn whether to act individually or to cooperate in order to deliver transport inland containers while maintaining the objective to minimize logistics costs. This study contributes to the literature by implementing two different reinforcement learning algorithms in a joint routing and vehicle type decision–making process through information sharing in a real-size case study.

9.2 Future work related to this study

One important avenue of future research is an investigation of the significant factors affecting other choices in the freight transport supply chain. While various decisions about hinterland transportation are investigated in this dissertation, one can argue that these decisions are affected by other aspects of the supply chain such as maritime transportation, international trade, and inventory of commodities.

Further research also could look into additional factors such as the availability of resources for freight owners, the relevance of owning land, the labour and machinery necessary for storage/packing/unpacking, the time–window constraints, the type of contract between buyer and seller (i.e., long–term vs. short–term), and the relevance of paying the costs associated with inland transport. Other considerations in empty container swapping should also be taken into account, such as the time needed for cleaning and repairing. Furthermore, in the study of container transportation, only two generic types of containers were considered (20– and 40–foot), while the type of container should be considered in more detail; e.g. open–top, refrigerated, or other specialized containers.

Further research could also explore the dynamic aspect of transactions, as this study estimates models in a static context. As travel time, travel costs, and time–windows are dynamic in nature, and decisions about shipments are made on a case–by–case basis in a dynamic environment, a dynamic choice model could capture the maximum utility for each shipment on the basis of the dynamic explanatory variables over daily or weekly time periods.

Whilst the results prove that the proposed copula–based model is capable of estimating two joint choices very well, modelling more than two interrelated choices can be investigated in the future.

Lastly, the true logistics cost includes many more components which should be included in the simulation, such as the costs of double–handling, storage, and administration. Accordingly, future research would benefit from richer datasets containing information such as commodity type, type of packing, the value and volume of the container, and true logistics costs.

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