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Behavioural Urban Freight Modelling: Exploring Effects of Policies on an Urban Freight Distribution System

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Abstract

The importance of freight systems to the economy, environment, and modern life necessitates study and research in this field. This paper presents a framework to gain insight into the behavioural underpinnings that affect decision making in the freight sector. The objective of this research is to investigate the interaction of key actors in the inland import/export container market in Brisbane. This study addresses several decisions made in the freight distribution system including optimising the shipment size, using distribution/consolidation centre, mode/vehicle and route choices.

In this framework, the supply chain is modelled using an agent-based approach, in which the decisions of the key actors are captured in an integrated, disaggregate, and distributed system. The agents include shippers, distribution/consolidation agents, rail carriers, road carriers, and customers. The proposed framework incorporates five major decisions in the supply chain. In the first model, shippers and customers negotiate on the size and frequency of shipments based on minimizing total logistics cost. In the second model, shippers' decisions on bundling several shipments are captured, in light of carriers' prices and services as well as shippers' storage costs if a shipment is not sent immediately. In the third model, a shipper's choice to use a distribution or consolidation centre can be modelled, in light of shipment bundling, handling costs, and economies that may be realised from carriers, for given commodities and within given time slots. This interacts with the fourth model, capturing the competition between road and rail carriers in the shipper's choice of transport mode. Finally, road carriers then face the decision of the routes for commercial vehicles that meet these time slots ("time-windows") for each commodity.

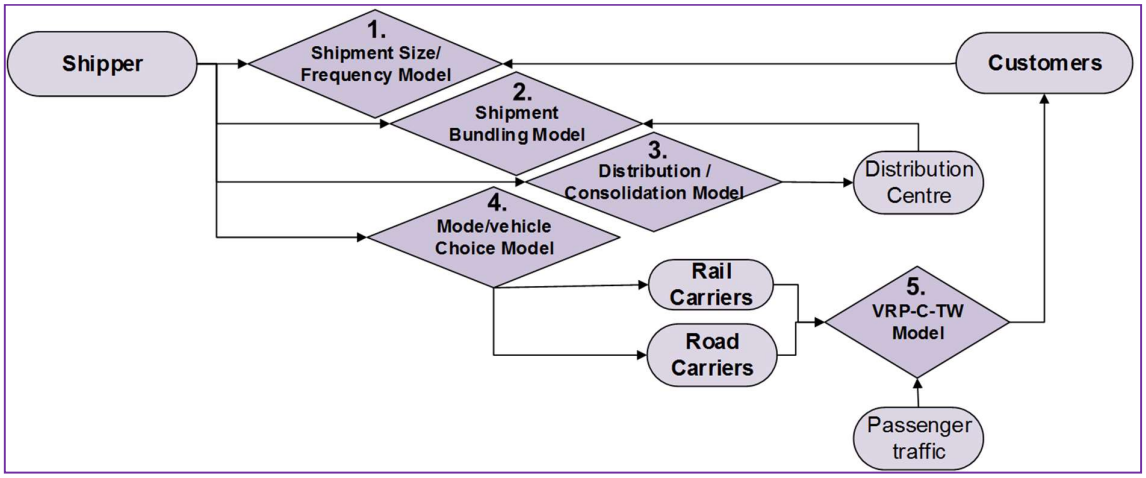
Key Words: Behavioral freight modelling, agent-based modelling, choice modelling, urban freight distribution system

1. Introduction

The objective of this research is to propose a framework to simulate the interaction of key actors involved in the inland distribution system of Port of Brisbane as a case study. The research questions to be answered in this framework are: (1) how do actors in the market make decisions in terms of shipment size, mode, vehicle and route? And, (2) how would different policies, such as creation of new distribution centres, affect the actors' decisions and freight movement patterns?

This research investigates five major decisions regarding inland container movements from the Port of Brisbane, as described in Figure 1. This research is still in progress; however, as a preliminary analysis, carriers' decision to use a distribution centre has been tested using a Q-learning algorithm.

Figure 1: Proposed framework



Through the first model, the size and frequency of the shipments are modelled based on minimizing the total logistics cost to the shipper. In the second model, shippers' decisions to bundle the shipments are captured by modelling the optimum combination of shipments to transport together, considering the rate at which shippers may accept storage costs until the next shipment arrives and more bundling can occur.

Moreover, while the freight task in Australia is expected to grow to around 1,700 million tonnes in the next 20 years, new distribution systems are needed to improve logistical performance and to counteract the negative externalities of freight shipments. Elimination of additional trips, decreasing the movement of empty vehicles, efficient scheduling, and matching the timetables of various actors, are considered an essential step towards more sustainable freight movement. As one example, establishing a new logistics hub is an important scenario in Southeast Queensland to develop a premier inland port and intermodal distribution centre. Thus, in the third model, the shipper's choice of using a distribution centre/terminal is modelled. This model determines the rate at which shippers are willing to utilize a consolidation/distribution centre for specific time slots and for particular products or commodities.

On the other hand, assessing the impacts of regulations and investments in infrastructure requires an accurate forecasting tool. Expanding the use of rail freight has been determined as the first priority of Queensland Transport and Main Roads (TMR) in its 2013 Moving Freight Strategy (TMR, 2013). Therefore, the fourth model simulates the degree of intermodal competition between rail and road carriers and determines the shippers' behaviours in mode and vehicle type choice. The questions to be answered by this model are: (1) What are the effective factors and attributes in mode and vehicle type choice? (2) What is the probability of using each transport mode or vehicle type for a given shipment? The factors that will be examined are transport cost, type, size and price of the commodity, time windows for delivery, reliability, distance, and the geographic origin and destination of the shipment.

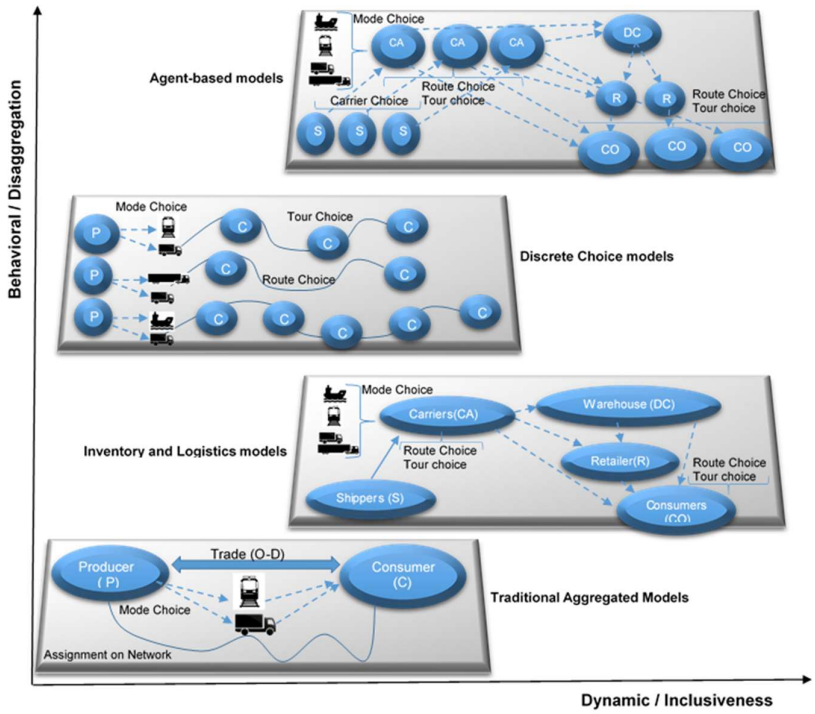
Furthermore, providing and promoting the road freight network is the second priority of TMR. So, the last model simulates the routing behaviours of road carriers. This model determines the optimal delivery routes for a fleet of vehicles in the specified time-windows, for each commodity type. The main parameters to be considered in route selection are time-window specifications, roadway capacity, transport cost per unit time and distance, maximum order counts, and the maximum allowed total time and distance of driving based on the driver regulations. Through this last model, we can anticipate the high demand routes in the road network and how the truck traffic may change with increased freight demand or changes in

infrastructure. For example, we can explore the effects of various toll and pricing policies such as peak-hour tolls or a cordon toll for trucks.

2. Literature review

The literature in freight transportation modelling has been increasing since the 1980s. However, during recent years the trend is changing from the typical aggregate four-step model framework to more disaggregate behavioural models. The lack of detailed data to calibrate and validate models, the simplicity of aggregate models, and confidentiality issues in understanding the complex and unknown decision factors of various agents, are the main reasons that aggregate models were the state of the practice until recently. However, disaggregate freight models are gaining more favour for their policy sensitivity and ability to capture the complexities of the freight transport system. All models in the field of freight transportation can be categorized into four major types, which are classified in the way they incorporate the behavioural and dynamic elements as well as their inclusiveness of different actors, as shown in Figure 2.

Figure 2: Four major categories of freight modelling studies



The category of inventory and logistics models is defined as studies which use aggregate commodity flow rates based on the observed data and are mostly based on the four-step approach, but also include microsimulation components such as vehicle routing or inventory optimization. Illustrative models in this category include those by Gonzalez-Feliu and Routhier (2012), Ambrosini et al. (2010), Wisetjindawat et al. (2007), Wisetjindawat et al. (2012), De Jong and Ben-Akiva (2007), Donnelly (2002), and Donnelly (2007).

The econometric approach of discrete choice analysis has been applied in freight transportation studies to simulate the choice behaviours related to mode, tour construction, route and shipment size. The most common choice models in use are the multinomial logit (MNL), nested logit (NL), and mixed logit (ML). These models provide probability estimates for each alternative based on its utility. In this modelling approach, decision makers choose among a set of alternatives to maximise their utility. Examples of this approach include studies done by Holguin-Veras (2002), Holguin-Veras and Patil (2005), Holguin-Veras et al.

(2006), Hunt and Stefan (2007), Wang and Holguín-Veras (2008), and Ruan et al. (2012). In some cases, this methodology also has been extended by transferring the choice structure from another region in the same country (e.g. Outwater et al. (2013), Ferguson et al. (2012)).

Agent-based modelling is a relatively new method for freight systems. Rather than assuming a certain decision-making structure, we may instead have insight into how the system's objects behave. If this is the case, we can start by identifying the objects (agents) and by defining their behaviours. Interestingly, the number of papers devoted to agent-based modelling has grown enormously in the last decade. Davidsson et al. (2005) provided a review of agent-based models in traffic and transportation and categorized them based on the domain, mode, time horizon, model structure, agent type, and type of evaluation (quantitative or qualitative). They noted that agent-based modelling seems very suitable for freight transport. Other studies applying an agent-based approach in freight transportation include Boerkamps et al. (2000), Van Duin et al. (2007), Liedtke (2009), Taniguchi et al. (2007), Tamagawa et al. (2010), Baindur and Viegas (2011), Holmgren et al. (2012), Roorda et al. (2010), Cavalcante and Roorda (2013), and Teo et al. (2015).

To conclude, agent-based approaches appear to be well-suited in the freight realm, given the frequent interaction between the agents and the complexities of the market environment. However, from the literature review, many of the existing agent-based modelling systems remain either as conceptual frameworks or as prototypes with very small examples.

3. Methodology

In the proposed framework, five main models are considered:

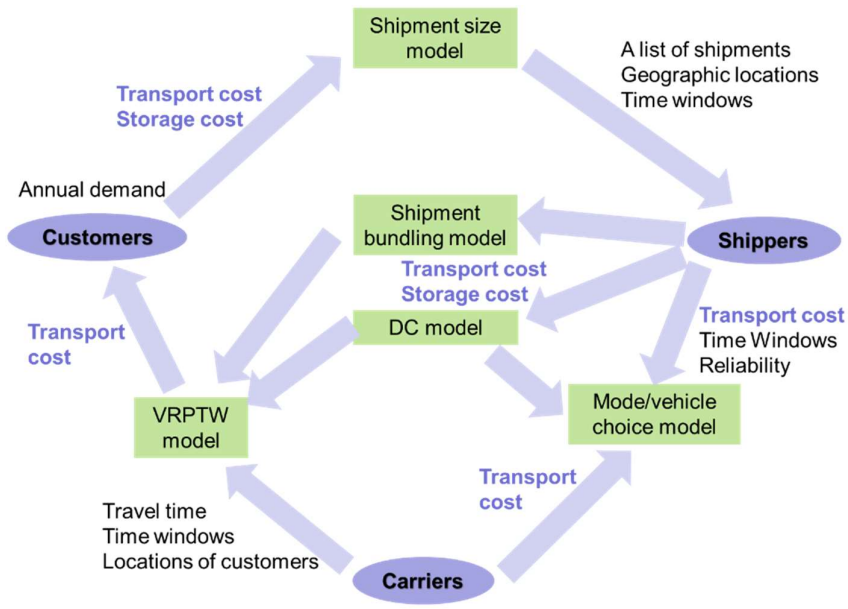
- Shipment size/frequency model
- Shipment bundling model
- Consolidation/Distribution model
- Mode choice/vehicle choice model
- Vehicle routing problem with time windows (VRPTW) model

The following algorithm describes the proposed framework, as shown in Figure 3:

1. Customers have an annual demand for each commodity, and they choose the frequency and size of shipments they receive, based on their logistics cost in receiving shipments. The prices for these shipments are determined by shippers and carriers, as a result of the shipment size model in which shipment size is a function of the transport and logistics cost. Customers estimate their logistics cost based on their experience in previous periods.
2. Based on the customers' demands, shippers receive a list of shipment requests, geographic locations and delivery time windows.
3. Shippers make decisions on shipment bundling and the use of any distribution/consolidation centres. the shippers evaluate and update their associated shipment cost in each scenario, which is based on their costs experienced in previous periods. Decisions on both shipment bundling and use of centres are made based on the characteristics of the market, and should be evaluated using an agent-based approach.
4. Carriers are categorized into rail and road operators, which both have resources (vehicles) and constraints regarding time, vehicle size, and commodity type. For a specific shipment (contract), they propose a price to deliver, which is based on a perceptions of costs from their experience in previous periods.

5. Shippers then decide the shipment mode and/or vehicle type based on the transport price and time window constraints on the delivery. This is addressed in the mode/vehicle choice model.
6. The shipment (contract) is delivered to the customers by a carrier, solving the VRPTW model, and the transport cost is updated and saved. A carrier chooses a vehicle routing plan based on the minimum travel time, based on the experience in previous periods. From the VRPTW model, individual truck routes are created and added to the network. The assigned truck flow results in new travel times on each link in the network, and new transport costs, which are used in the next period.
7. Customers update the total logistics cost in the new period.
8. This process continues until the system reaches an equilibrium in transport and logistics costs.

Figure 3: Proposed algorithm



3.1. Shipment size model

Generally, as the shipment size increases, the transport cost per unit shipped decreases. The Economic Order Quantity (EOQ) model is a deterministic method to identify the order quantity. This model only applies when demand for a product is uniform and known over time. Also, it assumes the item cost, ordering and holding cost is fixed. In this model, the optimal shipment size is found by minimizing the sum of total logistics cost, defined as a function of ordering, handling, transport and storage costs.

$$\mathrm{TLC} = \mathrm{C}_O^P\left(\frac{\mathrm{Q_P}}{\mathrm{q_P}}\right) + ((\mathrm{S}_{od}^P + \mathrm{T}_{rq}^P) \times \mathrm{q_P}) + (C_H^P \times \mathrm{q_P}) + (C_S^n \times \mathrm{q_P} \times \mathrm{t}_n^P) \qquad \text{Equation 1}$$

Where:

$\mathrm{C_O^P}$: Order cost for product P (cost per order)

$\mathrm{Q_P}$: The annual demand (tonnes per year) for product P

$\mathrm{q_P}$: The average shipment size (tonnes) for product P

$\mathrm{T_{rq}^P}$: Transport cost per unit for shipment size q, route r, for product P

S_{od}^{P}: Shipping cost per unit for shipment size q, from origin o to destination d, for product P including handling, insurance and all other related costs

C_{H}^{P}: Handling cost per unit for product P (loading, unloading cost)

C_{S}^{n}: Storage cost at node n (consolidation/distribution centre, or terminal) per day including picking and packing

t_{n}^{P}: Expected storage time at node n

Thus, the optimal shipment size is a decision variable, with the objective to minimize the total logistics cost. It is then calculated as:.

$$q_P = \sqrt{\frac{C_O^P \times Q_P}{C_H^P + T_{rq}^P + (C_S^n \times t_n^P)}} \qquad \text{Equation 2}$$

However, the decision about shipment size and frequency in reality is much more complex than the standard EOQ model. Our ongoing research is investigating a model to better match with the real-world situation.

3.2. Shipment bundling model

Since economies of scale and scope exist in freight markets, shippers are likely to combine diverse shipments in the same contract, which reduces the total contract costs. Generally, when both trips in the tour are full truckload (from origin to the destination and from the destination to the origin), shipments are usually combined. In long-haul shipments, shippers may be willing to accept storage cost until the next shipment arrives, before shipments are bundled.

$$r_{(S_n,S_m)} = \propto \left(T_{S_n}^{t_n} + T_{S_m}^{t_m} - T_{(S_n,S_m)}^{t_n} \right) + \beta(C_{S_n}^{t_n} + C_{S_m}^{t_m} - C_{(S_n,S_m)}^{t_n}) \qquad \text{Equation 3}$$

Where:

$r_{(S_n,S_m)}$: The rate at which shipper is willing to accept the bundling of shipments m and n

$T_{(S_n,S_m)}^{t_n}$: Transport cost of bundled shipments n and m in time window t_n

$T_{S_n}^{t_n}, T_{S_m}^{t_m}$: Transport cost of shipment n in time window t_n and transport cost of shipment m in time window t_m when they are not bundled.

$C_{(S_n,S_m)}^{t_n}$: Storage cost of bundled shipments n and m in time window t_n

$C_{S_n}^{t_n}, C_{S_m}^{t_m}$: Storage cost of shipment n in time window t_n and storage cost of shipment m in time window t_m when they are not bundled.

α, β: Weighting parameters which can be obtained from calibration

3.3. Consolidation / Distribution Model

The rate (r_c^t) at which a shipper is willing to use a consolidation/distribution centre for time t and product P is defined as a function of transport, handling, and storage costs, and also the costs associated with damage or loss which occurs as a result of storage:

$$r_{DC}^t = \gamma[T_0^P - T_{DC}^P] + \mu[(C_H^P \times q_P) + (C_S^n \times q_P \times t_n^P)] - \tau[d^P \times j \times q_P] \qquad \text{Equation 4}$$

Where:

T_0^P, T_{DC}^P: Transport cost for product P without and with use of a distribution or consolidation centre, respectively

C_L^P: Loading/unloading cost per unit for product P at the consolidation/distribution centre

C_S^n: Storage cost at node n (consolidation/distribution centre, or terminal) per day

t_n^P: Expected storage time at node n

q_P: The optimum shipment size

d^P: Damage cost per unit for product P

j: The fraction of the shipment that is lost or damaged due to storage

γ, μ, τ: Weighting parameters which can be obtained from calibration

3.4. Mode Choice/Vehicle Choice Model

There is a general consensus in the literature that mode choice decisions are not made by a single party but typically involves both the shipper and the customer. Shippers may contract third party logistics (3PL) or freight forwarders to arrange the logistics contracts. The options for the shipper and freight forwarder relationship are varied; some examples include: close partnership with the decisions being made jointly; shippers indicating a desired mode and the freight forwarders preparing the business case, selecting and ultimately choosing the carrier; or freight forwarders advising on possible mode choices. In this research, the focus is the mode choice decisions and determining the factors influencing these decisions, whether these decisions are made by shippers or by other logistics service providers such as freight forwarders. The main factors in mode/vehicle choice decisions could include type and size of the commodity, time windows for delivery, service reliability, distance, and origin and destination. As it is commonly modelled, such mode and vehicle choices can be captured in a discrete choice modelling approach.

3.5. Vehicle Routing Problem Model

The vehicle routing problem (VRP) is a combinatorial optimization and integer programming problem which asks, what is the optimal set of routes for a fleet of vehicles to traverse in order to deliver all shipments to a given set of customers? In a VRP, a set of orders needs to be assigned to a set of routes or vehicles such that the overall transport cost is minimized. The solution also needs to consider real-world constraints including vehicle capacities, delivery time windows, driver constraints and work rules, and network constraints for some vehicle types.

Considering the logistics costs as well as time window and vehicle capacity constraints, the focus of this research is on the capacitated vehicle routing problem with time windows (CVRPTW). This problem considers that the delivery locations have time windows within which the deliveries (or visits) must be made, and also that the vehicles have limited capacity for the commodities that must be delivered.

Because of the high level of complexity, various software tools have been built to solve this problem. In this research, ArcGIS has been used. ArcGIS is a geographic information system software, providing geo-referenced spatial analysis in collaboration with combinatorial optimization techniques. The main parameters used in this module include time-window specifications, vehicle capacities, estimated transport costs per unit time and distance, a maximum number of orders, and a maximum total time and distance for each vehicle.

4. Case study

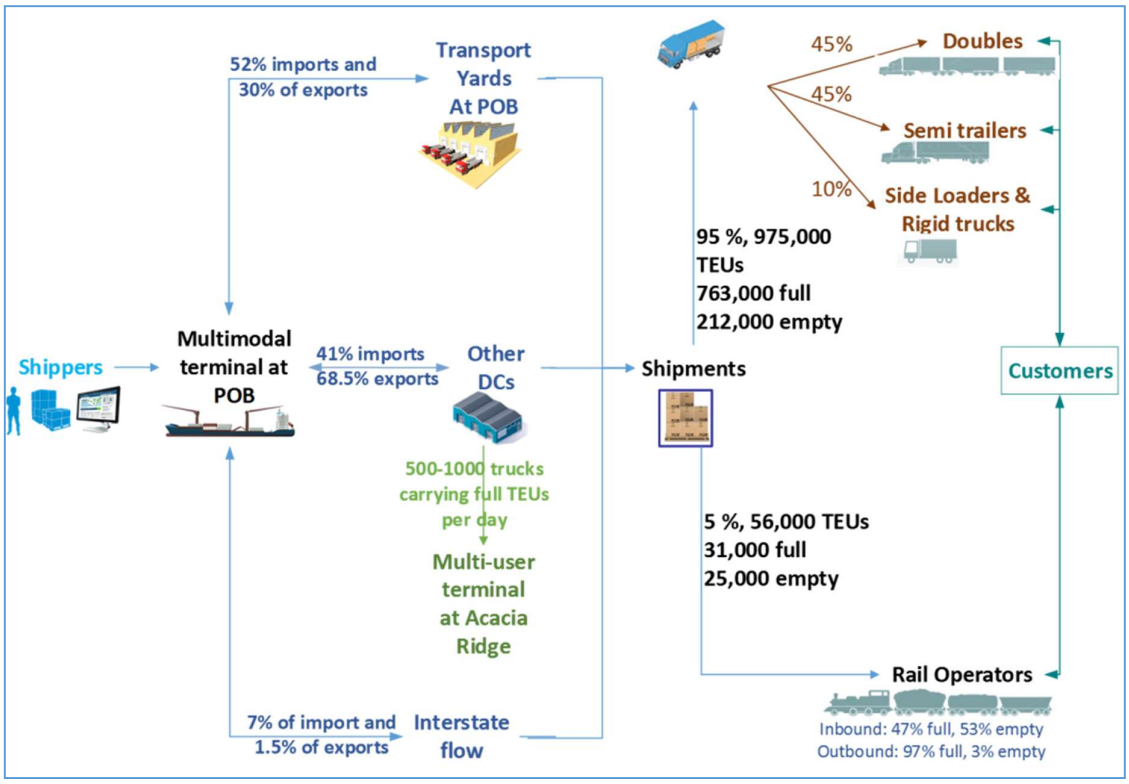
To this point we explained the suggested methodology and how the models interact with each other. We posit here that the supply chain is a combination of nodal and modal activities. Modal activity includes the preferred mode for each commodity type based on the shipment size. Nodal activity identifies the locations of key functions, including points of

origins, destinations, and intermediate locations like distribution, consolidation and storage. The mismatch between the modal, nodal and transport network in the supply chain causes long waiting time, congestion, double handling, imbalance of empty vehicle movements, and higher logistics cost, which directly affects the economy.

The activity nodes in the Port of Brisbane's supply chain include the intermodal terminal and transport yards inside the port and other distribution/consolidation centres across Southeast Queensland. One of the high demand terminals in Brisbane is the multi-user intermodal terminal at Acacia Ridge on the south side of Brisbane. The daily movement through this terminal is commonly 500– 1000 trucks carrying full containers, connecting to major north-south corridors in the rail network.

The involved transport modes in this chain are road carriers with 95% share and rail operators which carry bulk commodities, mainly coal and mining products. **Error! Reference source not found.** shows the interactions between various actors in this freight system.

Figure 4: Main nodal and modal activities for the Port of Brisbane



A preliminary analysis has been performed to examine the potential use of a distribution centre. In this analysis, we have used reinforcement learning to model the dynamic behaviours of carriers. A reinforcement algorithm is a computational method in which a learner (agent) is trained to take the optimal action through interaction with its environment. Through a learning process, the agent finds out the set of optimal actions that affect its environment, where the environment is defined as the set of feasible states that the agent may consider. The aim of learning is finding the optimal action for the agent when it is in each feasible state.

There are two kinds of learning methods, on-policy and off-policy, based on the level of exploitation versus exploration. Exploitation means repeating the action (policy) which has been rewarded in the past, while exploration means trying other possibilities that may produce a better reward. Without balancing these two activities, the agent will not learn successfully. Off-policy methods promote sufficient exploration by updating the estimated

value functions using hypothetical actions, meaning those which have not been tried. Conversely, on-policy algorithms just update the agent's value function based strictly on the agent's experience.

In more detail, temporal difference (TD) learning is a bootstrapping method in which the value function is updated partly using an existing estimate and not by using the final reward. Q-learning is one off-policy learning method which uses TD learning. The algorithm steps are as follows:

1. An agent initializes its Q-values table for each pair of state and action, Q(state, action)
2. The agent observes the current state and chooses an action for that state based on one of the action selection policies (a random policy is common)
3. The agent takes the action and observes the reward as well as the new state
4. The agent updates the Q-value by using the observed reward and the maximum reward possible for the next state according to the following formula:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\,[\gamma \max_a Q(s',a') - Q(s,a)] \qquad \text{Equation 5}$$

   Where:

   α: Learning rate, a value between (0-1)

   γ: The discount factor, a value between (0-1). A factor of 0 represents a short-sighted agent by only considering current rewards

   $\max_a Q(s',a')$: The maximum reward that can be achieved in the following state.

5. The agent sets its state to the new state and repeats the process until a terminal state is reached.

To set up the case study, customers were synthesized based on the type of land use at the Census mesh block level. Commercial mesh blocks were assumed to be the locations of customers, and the demand for a product was generated as a function of the land area. A part of Brisbane was selected as a case study which includes about 60 customers. A shipper was assumed at the Port of Brisbane (POB), and five carriers (vehicles) were assumed to be available for servicing these customers. Each carrier can distribute goods to the customers based on pre-defined time windows and in consideration of vehicle capacity constraints. Travel time was calculated by assuming a fixed speed for all links, and the CVRPTW solution was applied to serving all customers each day. This solution determines a schedule of delivery for each carrier, on the basis of customer demands and travel times between the port and customers and between customers themselves.

In the first scenario, all carriers have to return to the port which produces a closed VRP. In the second scenario, either one or two carriers choose to use the intermodal Acacia Ridge distribution centre. Therefore, they do not return to their depot, and instead, they go the Acacia Ridge Terminal. Figure shows the resulting routes from the VRP algorithm for the two scenarios. In the second scenario, the problem changes to an open VRP. In practice, an open VRP occurs when the vehicle fleet is not owned by the company itself or when the available vehicle fleet is unable to satisfy the demand of its customers, such that (part of) the distribution activities are contracted to a third party logistics (3PL[1]) provider or they use a distribution centre in the middle point of their supply chain. The parameters of the VRP are defined in Table 1.

[1] Third party logistics (3PL)

Table 1: VRP characteristics

Carrier's attributes		**Shipper's attribute**	
Earliest start time	8:00 AM	Start time	8:00 AM
Latest start time	9:00 AM	End time	5:00 PM
Capacity	100	**Customer's attributes**	
Cost per unit time	0.2	Start time	8:00 AM
Cost per unit distance	1.5	End time	5:00 PM
Max order count	10	Demand	Function of land area
Max total time	360 min	Service time	Function of demand
Max total travel time	120 min	**Route characteristics**	
Max total distance	8 km	Travel time	Function of distance

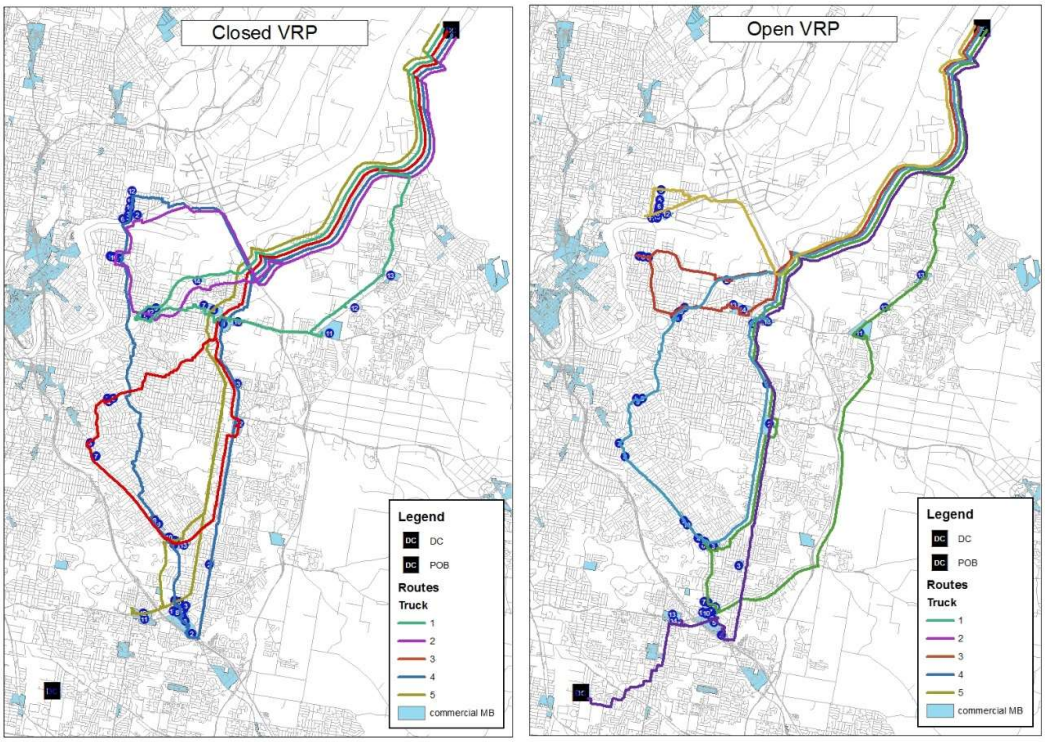
The second scenario is a strategy that optimizes the routing patterns of the existing vehicles by introducing the flexibility that carriers, in this case, do not have to return to their origin (the port). Although this additional depot imposes extra logistics costs, carriers can reduce their total travel cost as well as increase reliability. In this problem, only two of carriers can choose the distribution centre, and the shipper should evaluate this decision with the objective of maximization of profit. For this scenario, carriers are identical, so there is no means of competition between carriers.

Shippers use the Q-learning method to evaluating their value functions. Benefit in this case is defined as the inverse of the cost function, which is a mixed function of travel time and distance as mentioned in Table 1. Carriers use the optimal routing to service the set of customers, by solving the vehicle routing problem in each state.

1. One policy is determined, e.g. use of the distribution centre (DC) by one of the carriers. Then, the state of the system includes five possible actions, based on choosing a single carrier to use the DC.
2. The shipper observes the current state and chooses an action for that state randomly (e.g., one carrier is chosen randomly to use the DC).
3. The minimum path between customers is obtained which meets the CVRPTW constraints, and then travel cost is determined for each path.
4. Shippers initialize the Q-values table using the inverse of the travel cost obtained from the carriers' best routes for the given state.
5. The shipper observes the total reward. The Q-value for the state is updated by using the observed reward using Equation 5.
6. A new state is chosen, and this process repeats for 365 (simulated) days.

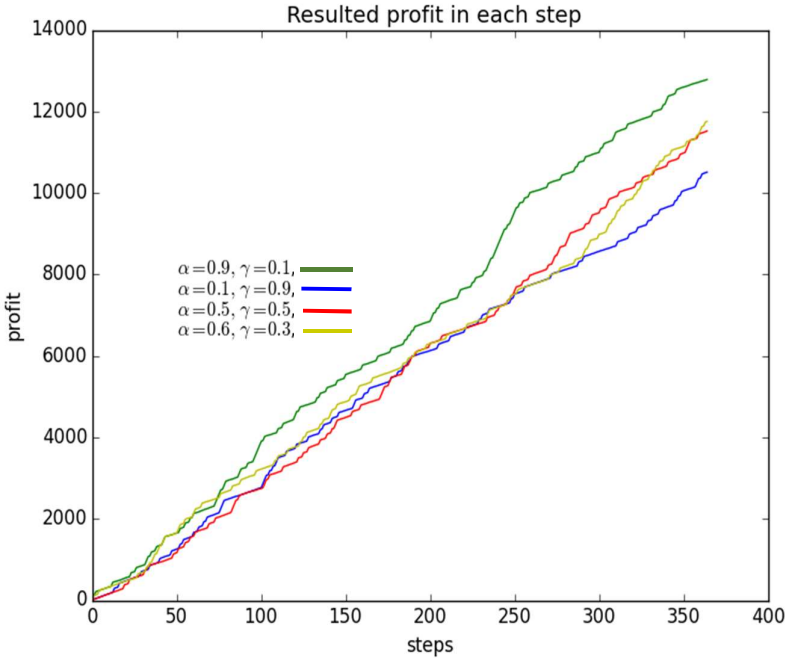
The algorithm has been developed in Python and yielded the optimal policy, which is that replacing the two carriers with a 3PL will result in a lower cost for the shipper. Figure 4 illustrates the two scenarios.

Figure 5: Two scenarios, (a) Not using DC (closed VRP), and (b) Using DC (open VRP)



For this study, the Q-learning algorithm has been applied for various values of the learning and discount rates (α and γ). Figure 6 shows the cumulative Q-values for 365 days. As can be seen, a higher learning rate (α) results in a sharp increase in Q-values. Tables 2 and 3 in the Appendix show the carriers assigned to service customers in each scenario, and the cost for each scenario, respectively.

Figure 6: Cumulative Q values for running in 365 days



Conclusion

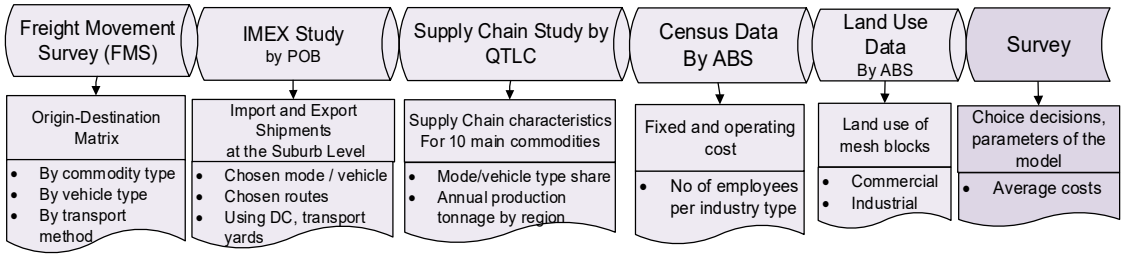
The literature review shows that agent-based models are well suited to simulate the complex freight system. However, while there are several conceptual agent-based models, only a few of them have been applied to simulate real situations, and most have been applied in only small case studies.

Considering the scale of the freight task in SEQ, the key actors of inland container movements, and the existing databases as well as the priorities determined by the Queensland Department of Transport and Main Roads, the framework of this research will follow the method outlined in this paper. The methodology to pursue the objective of the research also should be:

- Policy-oriented, which means responsiveness to policy changes
- Output-oriented and understandable
- Calibrated and testable by using less or the same amount of data as would be required to develop any other freight modelling method

This paper also presents a preliminary investigation of only one part of the suggested framework. Figure 7 represents the existing databases and feasibility of derived parameters from a survey that can be applied to complete the full modelling task in this research.

Figure 7: Existing databases



However, the scale of the freight modelling task, as well as the need for model validation, appear as the main challenges of an agent-based modelling approach to the freight transport system. For validation, agent-based models involve behavioural elements. Even sometimes irrational behaviours like random choices can hardly be validated on an empirical basis. However, agent-based models have some advantages over the other methods, such as: providing a reasonable level of heterogeneity for autonomous agents; enabling integration between a variety of behavioural models and constraints through all decision-making phases; providing a basic modelling functionality through a common data collection procedure among agents (individuals) with the same role. Moreover, urban freight markets are not usually in a stable equilibrium (Friesz and Holguín-Veras, 2005). Thus, this agent-based modelling approach can better simulate the dynamics of the market.

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Appendix

Table 2: Assigned carrier to service customers in each scenario

Customer	Not using DC	Using DC by two carriers	Using DC by one carrier	Customer	Not using DC	Using DC by two carriers	Using DC by one carrier
1	Carrier 4	Carrier 4	Carrier 5	31	Carrier 2	Carrier 3	Carrier 3
2	Carrier 4	Carrier 4	Carrier 5	32	Carrier 1	DC	Carrier 4
3	Carrier 4	Carrier 4	Carrier 5	33	Carrier 1	DC	Carrier 3
4	Carrier 2	Carrier 4	Carrier 3	34	Carrier 1	DC	Carrier 3
5	Carrier 2	Carrier 4	Carrier 3	35	Carrier 1	Carrier 3	Carrier 3
6	Carrier 2	DC	Carrier 3	36	Carrier 2	Carrier 3	Carrier 3
7	Carrier 2	DC	Carrier 3	37	Carrier 4	Carrier 5	Carrier 2
8	Carrier 2	Carrier 4	Carrier 3	38	Carrier 4	Carrier 5	Carrier 2
9	Carrier 1	Carrier 3	Carrier 4	39	Carrier 5	Carrier 5	Carrier 2
10	Carrier 1	Carrier 3	Carrier 4	40	Carrier 3	Carrier 5	Carrier 4
11	Carrier 2	DC	Carrier 3	41	Carrier 3	Carrier 5	Carrier 2
12	Carrier 1	Carrier 3	Carrier 3	42	Carrier 3	Carrier 5	Carrier 4
13	Carrier 1	Carrier 3	Carrier 3	43	Carrier 3	DC	Carrier 4
14	Carrier 3	Carrier 5	Carrier 2	44	Carrier 1	Carrier 3	Carrier 2
15	Carrier 3	DC	DC	45	Carrier 1	Carrier 3	Carrier 2
16	Carrier 3	DC	Carrier 4	46	Carrier 4	DC	DC
17	Carrier 3	DC	Carrier 4	47	Carrier 5	Carrier 5	Carrier 2
18	Carrier 3	DC	Carrier 4	48	Carrier 4	DC	DC
19	Carrier 3	DC	Carrier 4	49	Carrier 4	DC	DC
20	Carrier 3	DC	Carrier 4	50	Carrier 4	Carrier 5	Carrier 2
21	Carrier 3	DC	Carrier 4	51	Carrier 4	Carrier 5	Carrier 2
22	Carrier 4	Carrier 4	Carrier 5	52	Carrier 5	DC	DC
23	Carrier 4	Carrier 4	Carrier 5	53	Carrier 5	DC	DC
24	Carrier 2	Carrier 4	Carrier 5	54	Carrier 5	Carrier 5	Carrier 2
25	Carrier 2	Carrier 4	Carrier 5	55	Carrier 5	DC	DC
26	Carrier 2	Carrier 4	Carrier 5	56	Carrier 5	DC	DC
27	Carrier 2	Carrier 4	Carrier 5	57	Carrier 5	DC	DC
28	Carrier 2	Carrier 4	Carrier 5	58	Carrier 5	DC	DC
29	Carrier 5	DC	DC	59	Carrier 5	DC	DC
30	Carrier 5	DC	DC	60	Carrier 1	Carrier 3	Carrier 2

Table 3: State-action value table

		States		
Actions		Not using DC	Using DC by two carriers	Using DC by one of the carriers
	Set 1	62	61	54
	Set 2	62	54	85
	Set 3	79	60	60
	Set 4	95	61	79
	Set 5	84	83	59
Total cost		382	319	337