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Computationally Simulating Intermodal Terminal Attractiveness and Demand

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Abstract: The use of open data to analyse and model freight movements has been minimal to date. Primarily this is due to the shortage of open data focusing on freight movements across cities, regions or countries. Here we leverage openly available government data to enrich and further analyse commercial data to develop a flexible and dynamic tool enabling intermodal terminal operators to model demand, set prices and in turn maximise their profitability.

Keywords: modelling transport networks, whole-city computational model.

Introduction

Inter-modal terminals (IMTs) reduce road congestion and exploit economies of scale by pooling demand from surrounding areas and using rail to transport containers to and from ports. The alternative to using IMTs is using trucks[1] to transport containers directly to port. Trucks increase road congestion but rail requires additional handling of containers (lift on and lift off). The attractiveness of truck versus rail is dependent on a number of variables such as cost, total travel time, frequency of services, risk etc. Currently operators and policy makers model the attractiveness of IMTs by using coarse-grained information. We aim to build a dynamical tool that leverages open and commercial data to enable various stakeholders including IMT operators, port authorities, and government policy makers to make more informed decisions initially about pricing and then about scheduling, internal operations etc.

We simulate the operations of IMTs and their resulting container throughput given the underlying demand for container imports and exports in the greater Sydney region. Our objectives are to improve the efficiency and profitability of IMTs. This is performed through modelling to predict profit based on different asset mixes (such as number of trains and wagons, number of forklifts etc.) and pricing structures. We develop a value-driven modelling framework that incorporates: (i) a detailed IMT operational model capturing costs, capacities and service times for different asset mixes; (ii) demand forecast model (in progress); (iii) competition from other offerings; e.g., direct truck transport or other IMTs (in progress). The model components are calibrated to internal operational data and publicly available (open) geospatial data. The model allows *what-if* scenarios to be conducted to quantitatively predict the outcome of different investment and operational decisions: this in turn allows us to optimise the profitability of the IMT. In the future we will extend the tool to also consider the return on investment.

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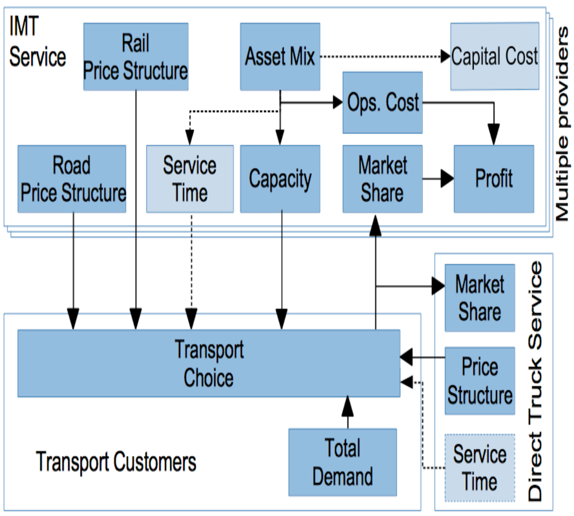
[1] Barges are also an alternative but not applicable in Australia

Model Description

Our model is composed of the following components (Fig. 1, left panel):

- **IMT Service Provider**: The operation of the IMT is modelled by an **asset mix**. This includes the rail assets (wagons/locomotives) and container handling assets (forklifts) and captures the total throughput **capacity** of the terminal, the **operational costs**, and the **service time**[*] to deliver containers to the port. The total retail price paid by a customer includes the **road price** to deliver the container to the IMT via truck and the **rail price** to transport it to the port. The **capital costs**[*] represent the investment costs to change the asset mix. The **profit** generated by the IMT is determined by the revenue captured by the **market share** and the **operational costs**.
- **Direct Truck Service:** This represents the existing market players and has a fixed **price structure** based on a zone-based commercial model (implicitly accounts for travel distance). **Service time**[*] includes travel time and the time to load/unload the container at the port.
- **Transport Customers:** Aggregate **total demand** for container transport is modelled at the suburb level. Customers within each suburb determine their **transport choice** by selecting the service provider that best satisfies their price and service time[*] requirements.



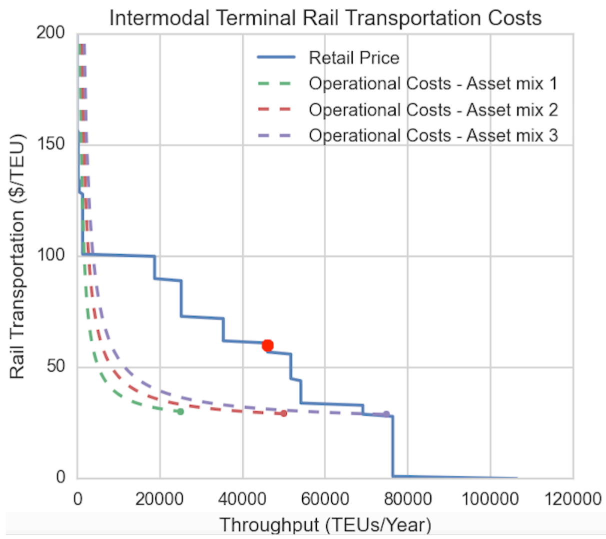


Figure 1. (Left panel) Schematic of the model. (Right panel) Plot of retail rail price (blue) and operational costs incurred by IMTs (dotted lines) vs. container throughput via the IMT. The red dot marks the optimal retail rail price for Asset mix 2 that maximizes the profit of the IMT.

Results

Our tool allows IMT operators to perform a "what-if" analysis by choosing a particular retail price and a particular asset mix that captures the operational configuration. It then enables them to predict the overall market share of transport demand served by the IMT and to

[*] To be considered in the future

quantify the profit of the IMT operator. The tool can also calculate the optimal asset mix and retail rail prices to charge customers, enabling the IMT operator to maximize its overall profitability. For the scenario considered in Fig. 1 (right panel), we observe that there is a profitable range of retail rail prices for the IMT (retail price greater than operational costs). The model also enables the prediction of the total price difference between the IMT and direct truck services for different suburbs (Fig. 2).

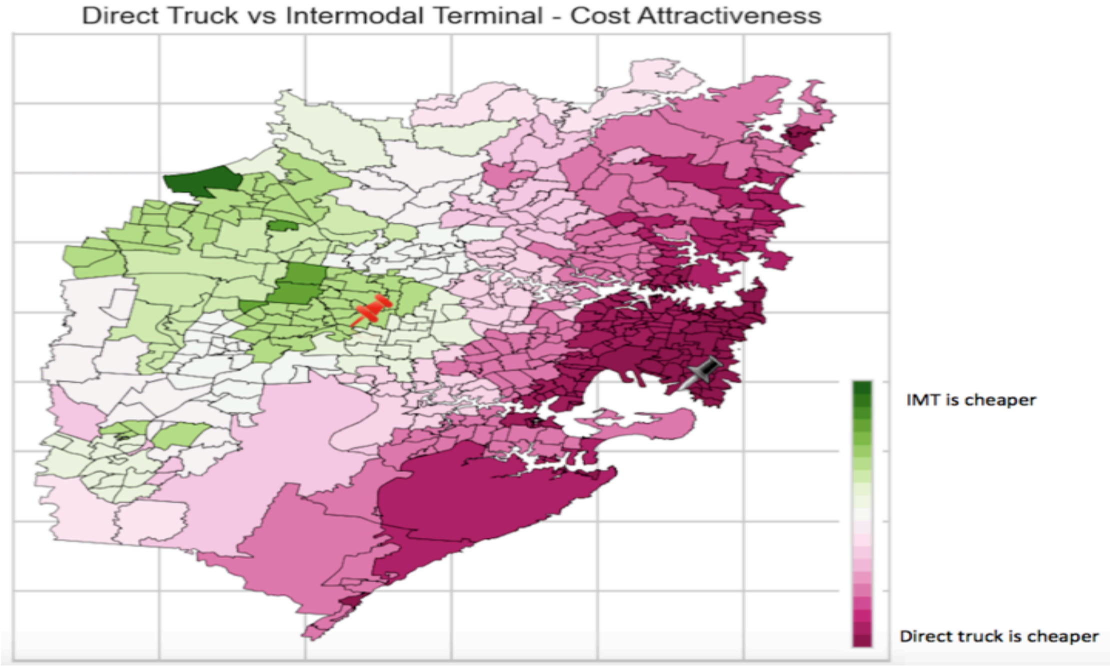


Figure 2. Map of regions coloured by cost difference between using IMT (red pin) vs. direct truck to port Botany (black pin).

Conclusions

We have shown that by leveraging even a small set of openly available government data (such as geospatial data) and combining them with commercial data, we can develop a granular analysis enabling IMT operators to make better decisions across two dimensions: pricing and asset mix. This approach supports the development of a tool, which enables IMT operators to assess their captive market and decide whether they should service a particular customer and under what price. In the future we plan to incorporate additional open data (such as socio-economic, traffic congestion etc.) to increase the fidelity of our tool and include additional variables that affect the selection criteria of end-users (shippers) such as: time to service, risk profiles, price elasticity etc. We expect the tool to be automated (changing as critical parameters such as truck speed and congestion change daily) and dynamic in order to respond to the ever-changing needs of businesses.

Finally, this tool can also be of value to policy makers and local governments since it can be adjusted to a) model the location of IMTs under development and/or b) decide about prices of rail movements, to maximise the overall rail throughput in and out of a port. Ultimately this would result in reduced road congestion and vehicle emissions (by reducing the number of trucks on the roads) and better utilisation of rail infrastructure.