# MODELLING LOGISTICS BEHAVIOUR IN THE FMCG INDUSTRY

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## ABSTRACT

The state-of-practice in commercial vehicle modelling often neglects the sophisticated behaviour found between stakeholders in a supply chain and the impact thereof on the ultimate vehicle flow. The state-of-the-art in commercial vehicle modelling needs to capture this behaviour to accurately predict the influence of changes in the supply chain. In this paper, we discuss how changes in the behaviour of the receiver influence the behaviour of the shipper and carrier, while focussing on a supply chain in the Fast Moving Consumer Goods (FMCG) industry. Retailers in the FMCG industry typically order in large quantities with high stock turnover rates. Utilising an order policy, they place orders with suppliers, either replenishing stock to a predetermined level every certain number of days or once a certain re-order point is reached. The supplier (the shipper and carrier) utilises route optimisation and scheduling of deliveries to cater for the demand of its customers. We show how the behaviour of these stakeholders can be captured in an agent-based modelling environment and how the behaviour of the shipper and carrier is sensitive for changes in the order policies of its customers.

## 1 INTRODUCTION

Transport planning models play a vital role in evaluating the effect of transport infrastructure decision-making. Multi-billion rand investment decisions in transport infrastructure development and maintenance are based on models that are not representative of commercial vehicle behaviour.

Transport models in practice often cater for commercial vehicles by inflating private vehicles or are based on aggregate commodity flows. Furthermore, many transport models do not integrate private and commercial vehicle populations. It is imperative to model and simulate both these populations since their behaviour and reason for conducting activities differ. In this paper we focus on commercial vehicle transport models.

Joubert et al. (2013) attempt to bridge the gap between two main schools of thought in commercial vehicle modelling: commodity-based and activity-based models. Many commercial vehicle models are based on aggregate commodity flows and neglect explicit vehicle movements. Other models in turn focus on vehicle movements but neglect the commodities carried.

Supply chains have various stakeholders from the suppliers to the end customers. The more stakeholders that are involved, the more complex the interactions become. For this reason, commercial vehicle models should incorporate the stakeholders in a supply chain and allow the stakeholders to make decisions and interact with one another. These interactions ultimately cause vehicle flow.

Anand et al. (2012) review trends in city logistics modelling techniques and notice that commercial vehicle transport modelling attempts have gradually started to incorporate the elements found in supply chains. It is widely acknowledged that proper commercial vehicle modelling attempts should incorporate stakeholder behaviour and therefore modelling trends tend to move in such a direction.

Various approaches on behaviour-based freight transport models that incorporate supply chain stakeholders have recently been considered in the literature. Roorda et al. (2010) explain that the different stakeholders in a freight transport system should be understood and represented accordingly. They also argue that both the interactions between these stakeholders and the changes in their actions over time should be included when modelled. They further show how one could model the various functions and interactions between business establishments, firms, and logistical facilities.

Ruan et al. (2012) argue that decisions of the stakeholders in a system results in commercial vehicle deliveries. They classify the stakeholders in the system as: the Shipper, the Carrier, and the Receiver.

Similarly, Schröder et al. (2012) provide a freight framework in the Multi Agent Transport Simulation (MATSim) Toolkit to more realistically model freight agent behaviour. These agents include Shippers, Transport Service Providers, and Carriers. Shippers are those entities that wish to move goods. Transport Service Providers compete for the contracts of the Shippers and ultimately employ Carriers to execute the actual transport legs. Carriers then do vehicle routing and scheduling and deliver the products using their available fleet of vehicles.

Joubert et al. (2013) describe how logistical functions in the supply chain can be modelled using the freight framework developed by Schröder et al. (2012). We build on the paper of Joubert et al. (2013) in this paper by implementing a behavioural model using real data, by focussing on a supply chain in the FMCG industry. We show how to model carrier-receiver interaction and touch on what data sources are required to model at such a level. We evaluate two scenarios: the influence of traffic congestion and the customer's order policy on the Carrier's choice of vehicle utilisation and fleet composition.

## 2 SUPPLY CHAIN INSIGHTS FROM DISTRIBUTION DATA

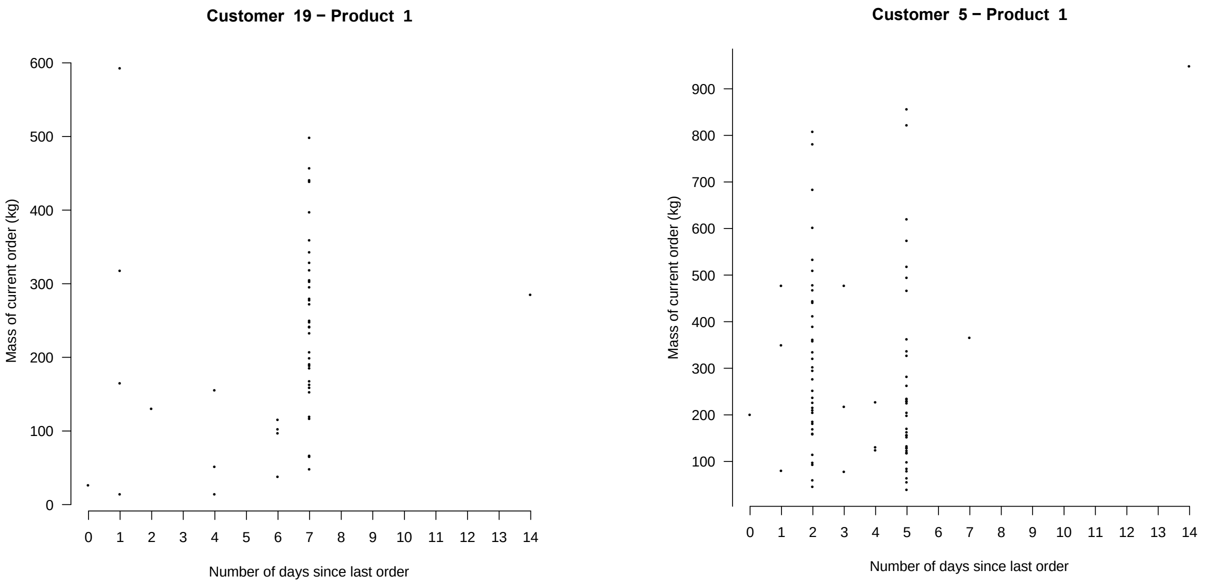
The Carrier in our model is an organisation in the FMCG industry, situated in the Nelson Mandela Bay Metropole (NMBM). The Receivers are the customers of this organisation, which operate retail outlets that cater for the end consumer's demand. The FMCG industry is characterised by the quick cycle times of selling and replenishing perishable products. Also, this industry is a typical case of moving high volumes with low margins.

The datafile used in this paper consisted of the exact deliveries made by the organisation over a ten month period. It includes details relating to the customer, the product delivered, the mass of the shipment, and the month and day on which the delivery took place.

Retailers typically utilise an order policy when doing their Material Requirements Planning (MRP). They place orders with suppliers, either replenishing stock to a predetermined level every certain number of days or once a certain re-order point (RoP) is reached. The supplier (the Shipper and Carrier) utilises route optimisation and scheduling of deliveries to cater for the demand of the customers.

From the data, we analysed the frequency of orders that customers placed. Figure 1 depicts, for two of the customers, the number of days since a customer last ordered a certain product and the mass of the orders.

**Figure 1 - The order size and frequency of two customers**

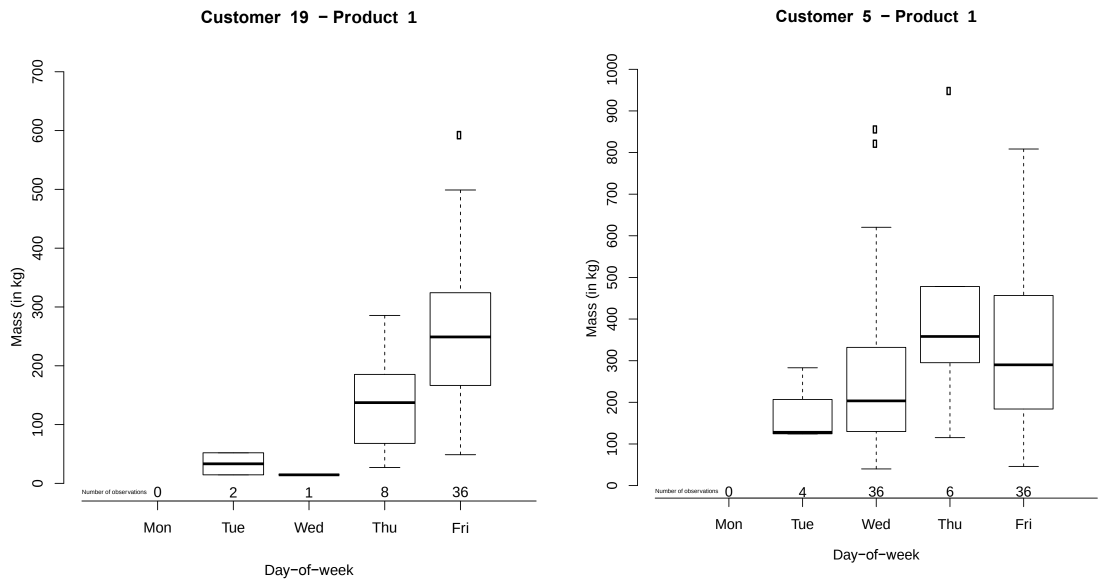


From Figure 1, it is evident that different customers utilise different order policies for the same product. Customer 19 orders mostly once per week (every seven days), whereas customer 5 orders twice per week (every two or five days). Orders on the other days are typically rush orders or orders on abnormal days caused by, for instance, public holidays.

We then further analysed on which day of the week deliveries were made to customers. Figure 2 depicts the mass distributions of delivery size as well as the number of deliveries that took place on a given day in the 10-month period. Here again it can be noted that Customer 19 utilises a once-per-week order policy with most of the deliveries taking place on a Friday. Customer 5 had most deliveries on a Wednesday and a Friday, confirming the twice-per-week policy shown previously.

These analyses provide valuable insights into understanding the receivers' behaviour. It reiterates that receivers' behaviour should be understood and modelled to enable the interactions between the receiver and the carrier to be more accurately captured.

**Figure 2 - Mass distribution of orders on different days of the week**

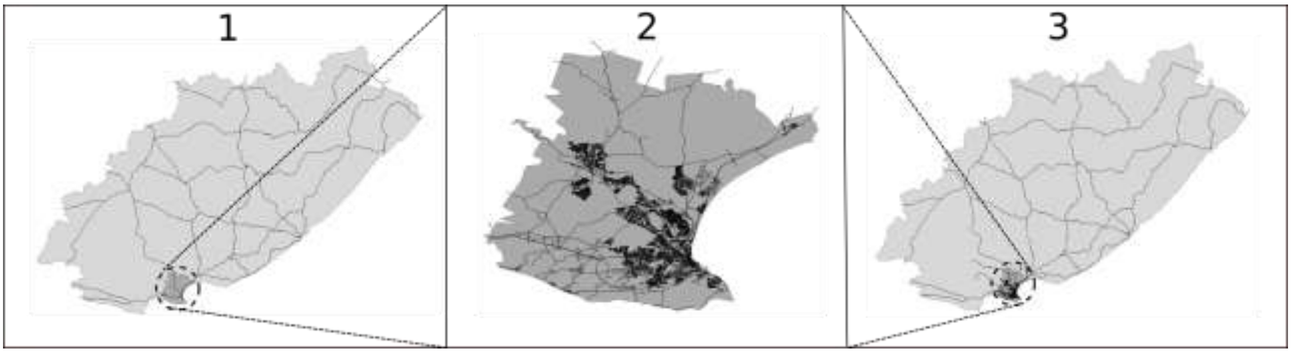


## MODELLING OF THE RECEIVER AND CARRIER

The road network for the NMBM region was generated from *OpenStreetMap* (OpenStreetMap contributors, 2013). In this paper we generated an extended road network. The first step was to extract only the major roads in the Eastern Cape Province. Next, we generated a detailed road network for the NMBM area. Finally, we merged these two networks to obtain a road network that extended into the greater Eastern Cape.

These three steps are depicted in Figure

**Figure 3 - Generation of the road network**




The Receivers were modelled to generate demand. This demand was generated from the distribution data by using one particular day's actual deliveries (day 2 in the file). Thus each customer placed an order consisting of different products and the mass per product. All customers were modelled to have a time window of 06:00 – 21:00 for deliveries. The duration of drop-off activities was set to be 300 seconds (5 minutes) since actual durations were unknown. For visualisation purposes, the demand of all products was aggregated per customer and is depicted in Figure 4. This Figure depicts that some customers are situated quite far away in the Eastern Cape Province and also have quite high demand for products on this given day. The total mass of all orders for this given day was 55.8 tonne.

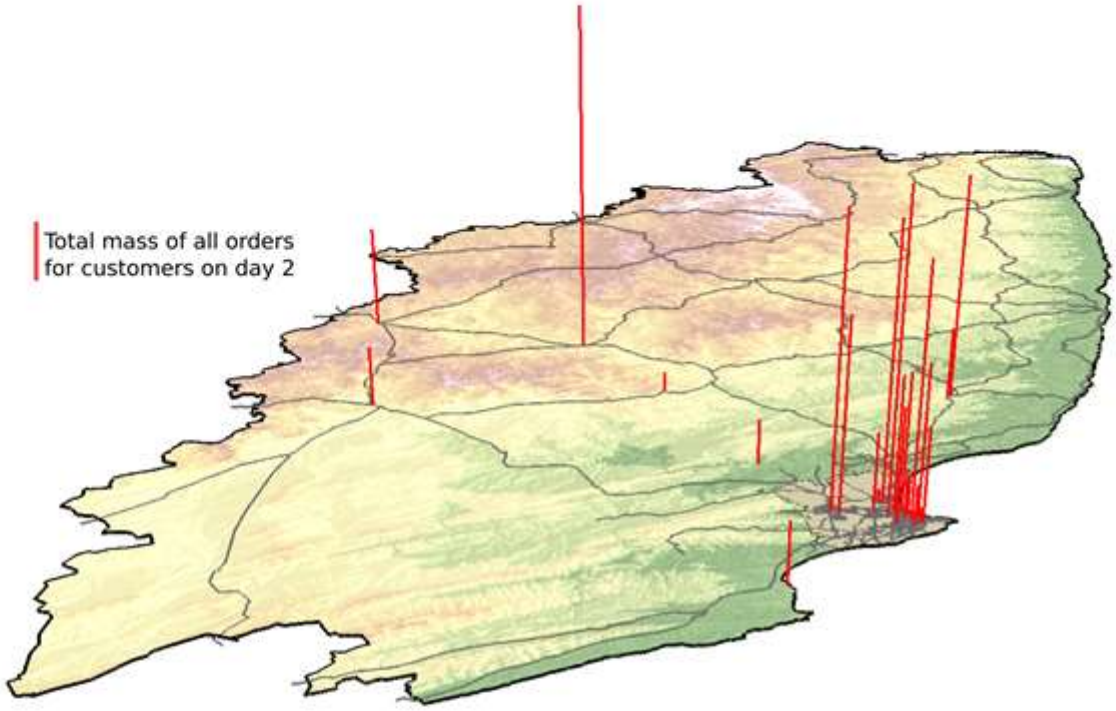


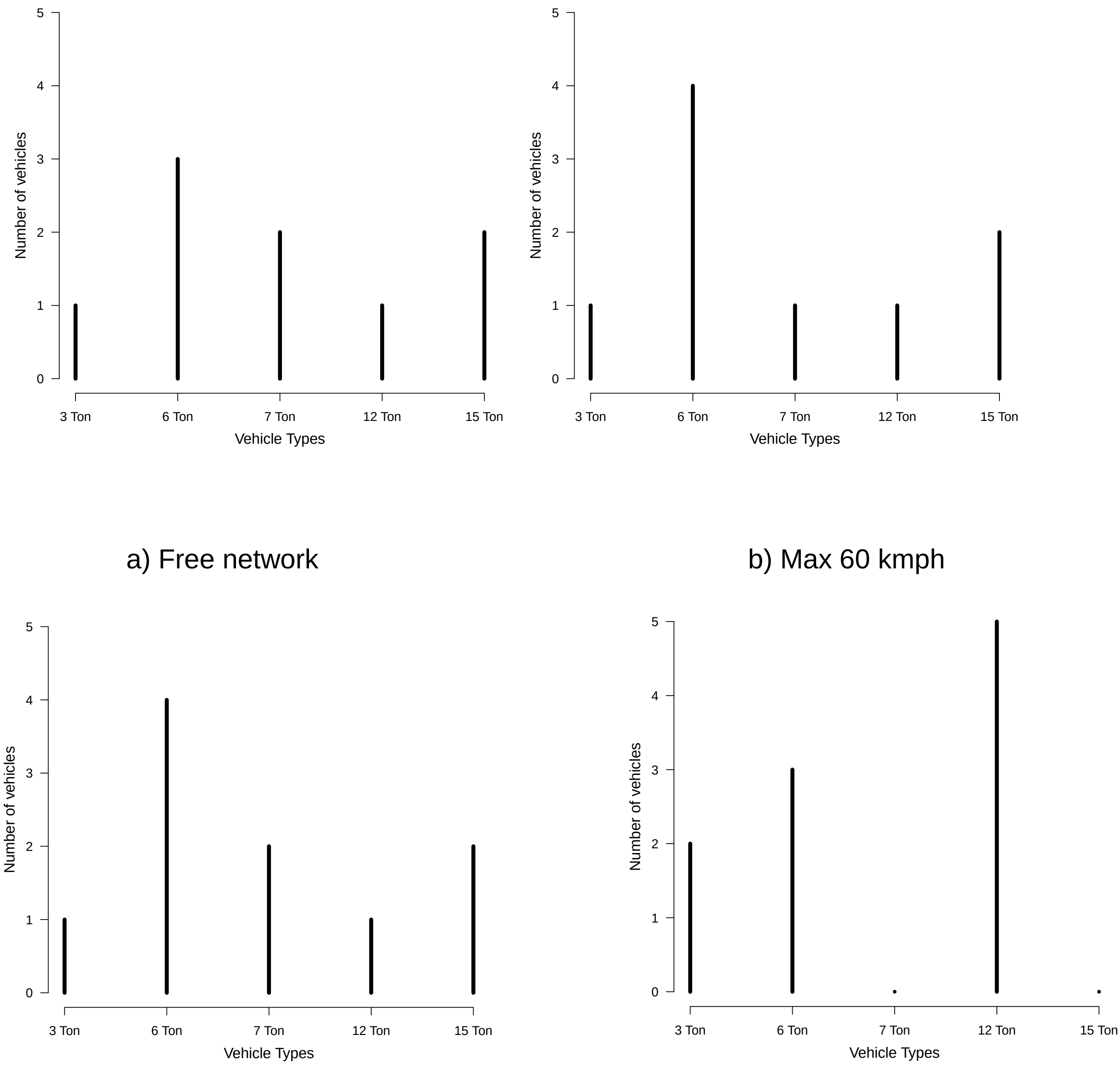

Figure 1 - Total demand per customer on day 2

The Carrier was modelled to have a vehicle fleet that represents that of the actual organisation: 10 vehicles consisting of five different vehicle types. These types are modelled in MATSim as what is known as *Carrier Capabilities*. The five vehicle types are: one 3-Tonne, four 6-Tonne, two 7-Tonne, one 12-Tonne, and two 15-Tonne commercial vehicles. Operating costs were determined from the Road Freight Association's vehicle cost schedule (The Road Freight Association, 2012). These costs included a per-kilometer value for both variable and fixed costs and the nearest equivalent vehicles in the cost schedule to the actual vehicles were used. The time window during which the carrier operates was set to 06:00 – 21:00.

## 3 THE EFFECT OF TRAFFIC CONGESTION

There are two methods with which to evaluate the effect of traffic congestion in MATSim. The first is to model synthetic populations and simulate them on the road network and observe and evaluate the effects. Secondly, one can emulate congestion by reducing the maximum freespeed on the network for a certain time window during the day. We utilised this method of emulating congestion by reducing the maximum freespeed on the network between typical peak times of 07:00 – 09:00 and 16:00 – 18:00 in three separate scenarios. We reduced the maximum freespeed to 60 kmph, 20 kmph, and 15 kmph respectively and compare it to a free-flowing network, which is only limited by the legal speed limitations.

The Carrier responded to the demand and did vehicle routing and scheduling based on the expected travel time on the road network. *Jsprit* is an open-source Java toolkit that can solve multiple versions of the Travelling Salesman and Vehicle Routing Problems and is also incorporated in the MATSim freight framework. Utilising the Jsprit libraries, a solution to the Vehicle Routing Problem is generated and saved as a *Carrier Plan*. The Carrier Plan contains details of all tours to be undertaken, the routes that will be travelled as well as the expected travel time. Figures 5a through 5d depict the vehicle utilisation in each of the traffic congestion scenarios. As congestion increased, more vehicles were utilised since all deliveries could not be made in time. For a maximum speed of 15 kmph, no feasible solution could be generated. We then supplied the Carrier with an infinite fleet to choose from, but limited to the five vehicle types available. The Carrier chose two 3-Tonne, three 6-Tonne, and five 12-Tonne trucks to transport the goods. This capability of the model could allow organisations to do fleet composition planning.




a) Free network

b) Max 60 kmph

c) Max 20 kmph

d) Max 15 kmph

**Figure 4 - Vehicle utilisation under different levels of congestion**

Furthermore, we analysed the total distance travelled by all vehicles as well as the total travel time of all vehicles, as can be seen in Figures 6 and 7. While the distance travelled did not differ much as congestion increased, the total travel time did increase considerably. Coupling this with the vehicle utilisation provides the organisation with a tool to predict travel time given different traffic conditions.

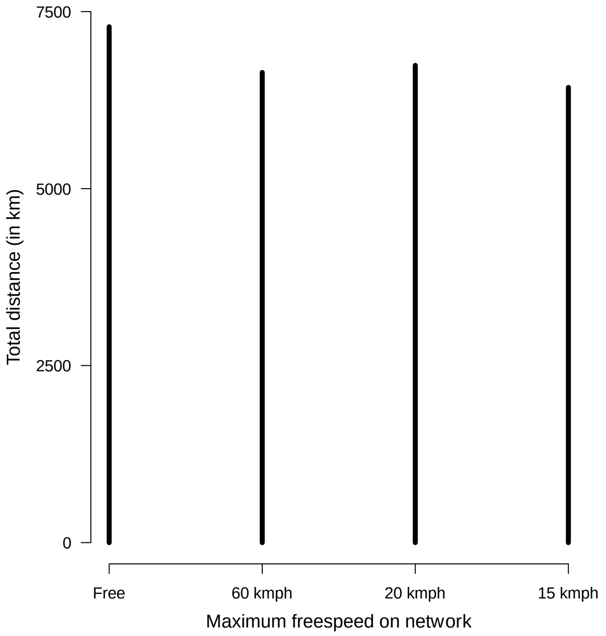



**Figure 5 - Total distance travelled under different levels of congestion**

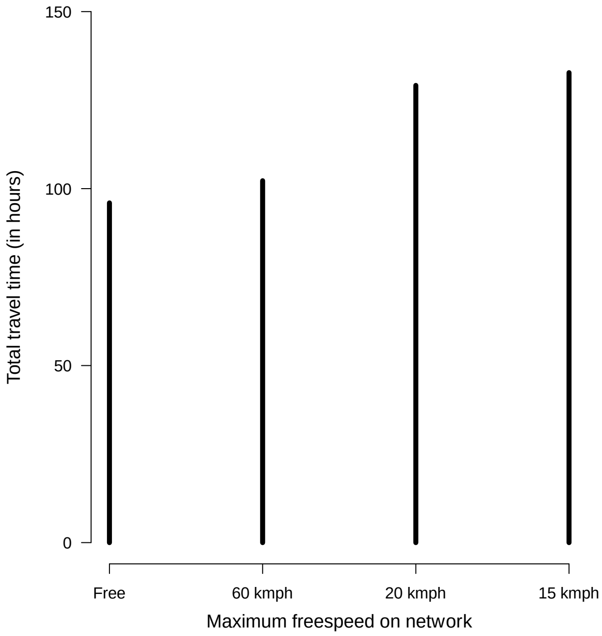



**Figure 7 - Total travel time under different levels of congestion**

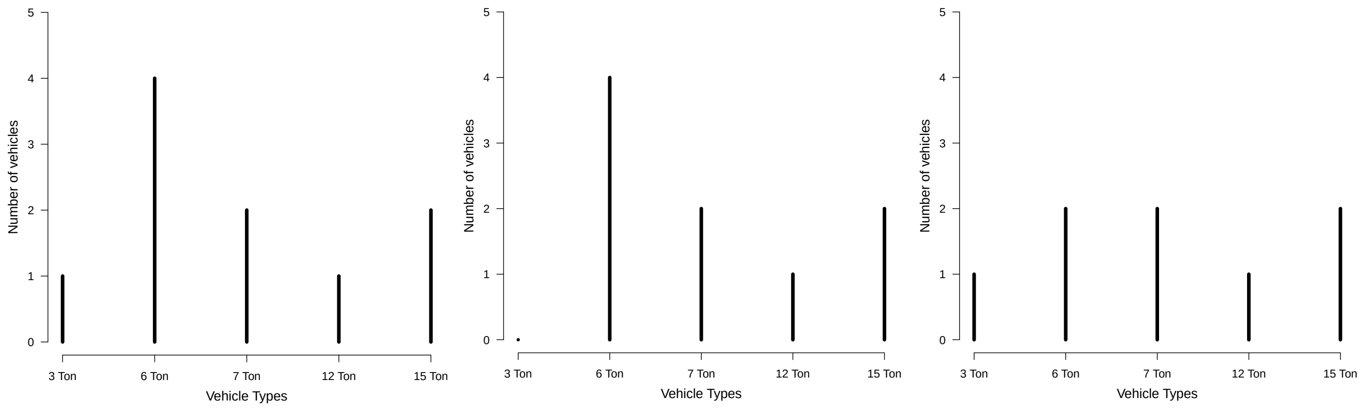
## 4 THE EFFECT OF THE CUSTOMER'S ORDER POLICY

Next we evaluated the effect of the customer's order policy on the Carrier's behaviour. This was achieved by adjusting the order frequency of certain customers. We firstly calculated the average weekly demand as well as the average weekly order frequency per customer per product.

To model whether a customer orders a particular product on a given day or not, a probability was calculated: the average order frequency was divided by the number of days available per week (which is 5 in this case since the organisation only delivers during weekdays). A random number was generated and if this number exceeded the probability, an order was placed for that customer. The order size was subsequently calculated by multiplying the average weekly demand by the probability of an order being placed. This served as the base demand to work from.

We then chose 5 customers and adjusted the order frequency of their orders and recalculating the size of orders. Firstly, the average order frequency was decreased by 0.8, which resulted in a higher weekly demand and subsequently higher order sizes. Then the average order frequency was increased by 0.8, which resulted in lower weekly demand and ultimately lower order sizes for these customers. These demands formed the basis of three scenarios.

For each of the three scenarios, the Carrier again generated Carrier Plans, which we analysed. Figure 8 depicts the vehicle usage in the three scenarios. For the average demand, 9 out of the 10 available vehicles were used. When the average order frequency was lowered by 0.8, the Carrier adapted by utilising all 10 available vehicles. The demand increased by almost 3 ton, justifying the use of the available 3-Tonne truck, which wasn't used in the average scenario. When the average order frequency was increased by 0.8, the Carrier responded by selecting the 3-Tonne truck again, but using only two 6-Tonne trucks. Here it is clear that the order policy of the customers has an influence on the vehicle utilisation of the Carrier and that the model is sensitive to changes in the order policy.




a) Average - 0.8　　b) Average frequency　　c) Average + 0.8

**Figure 8 - Vehicle utilisation for different order frequencies**

## 5 CONCLUSION

In this paper we implemented an agent-based commercial vehicle transport model that is sensitive to changes in the system. The effect of traffic congestion and the customer's order policy on the behaviour of the Carrier were evaluated. Furthermore, it was shown that the Carrier's choice of vehicle utilisation, the total distance travelled, and total travel time are influenced by changes in the system. The benefits of these capabilities are twofold: organisations can do fleet sizing and composition analyses and could also consider the benefits of owning different sized vehicles.

In this model, we only considered a cost per distance travelled. The model can be enhanced by adding cost for time spent during loading and unloading activities or adding the value of products carried. Having a comprehensive set of costs in the model will allow organisations to evaluate the effect of changes in the system on their total logistics cost.

From government's perspective, there is potential to assist in decision-making on road infrastructure spending with such a model since the influence on the private sector can be more accurately modelled. For instance, if government considers upgrading a corridor for increased freight movement, they can model and evaluate three scenarios. The first would be the as-is state. The second would be a scenario where a section of road network's capacity is reduced, to see what effect it will have on traffic congestion. Finally, the upgraded road network with increased capacity can be modelled and the changes in distance travelled and total travel time could be evaluated.

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