COMPLEXITIES IN MOVING FROM COMMODITY TO VEHICULAR FLOWS

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Abstract:

Two main schools of thought exist in the modelling of commercial vehicle movement. Firstly, the top down commodity flow models start at an aggregate level using metrics such as Gross Domestic Product (GDP) to derive the origin-destination flows of different commodities. The vehicle flows are then inferred using, amongst other things, traffic counts. The downside is that vehicle chains are disregarded, and load factors are overly simplified. Secondly, disaggregate activity-based models considers the more detailed movement of the logistic vehicles, but often disregard the commodities being carried. Although disaggregate models are much more accurate for predicting the influence of commercial vehicles on traffic patterns, they offer little help in evaluating the more aggregate economic impact challenges. In this paper we take a valuable step to bridge the gap between the two seemingly divergent schools of thought. Using recent agent-based developments in transport modelling, we demonstrate how different agents can be added to the transport model's commuter population. *Shipper* agents are those wanting to convey goods (commodity perspective), and assign the shipments in a market-environment to logistic service providers and, ultimately, *Carriers*. The latter is injected into the agent-based model as individual commercial vehicles executing the pickups and deliveries that result from typical route-optimisation initiatives within companies (activity-based perspective).

1 INTRODUCTION

The development of proper commercial vehicle and freight models has lagged behind that of private vehicle models. This has detrimental implications for transport planning models that assist with the evaluation of transport infrastructure decision. Freight vehicles are often relegated in transport models as a minority road user group, even though their impact on emissions and pavement damage is disproportionately large. Consequently, decisions to fund multi-billion rands' infrastructure projects are frequently based on outdated or suboptimal models. As a result, many unexpected expenses arise due to overlooked risks caused by the limitations of the modelling techniques.
In this paper we attempt to bridge the gap between two main schools of thought that exist in modelling commercial vehicle movement – commodity flow models and activity-based models.

Commodity flow models are normally based on Gross Domestic Product (GDP) or aggregate economic sectors from where origin-destination flows for different commodities are derived, for example Tan et al. (2004). Commodity movement cannot accurately predict vehicle movement since the explicit activity chain characteristics are unknown. Also, vehicle loads and load factors are often neglected, simplified or unknown. Liedtke and Schepperle (2004) argue that a system's decision makers should be analysed and understood and their behaviour not merely inferred from commodity flows.

Accordingly, various studies have been conducted on activity-based freight models, taking into account the detailed movement of commercial vehicles, such as De Jong and Ben-Akiva (2007) who consider frequency of activity chains and distribution centre use. Joubert and Axhausen (2011) infer activity chains from GPS logs and consider the temporal and spatial characteristics of the activity chains. Following this approach, Joubert et al. (2010) develops a commercial vehicle population consisting of intra-provincial traffic and simulates it in the Multi-Agent Transportation Simulation (MATSim) toolkit. From very accurate time-dependent results, they show the potential that agent-based commercial vehicle models have. Even though activity-based models are more accurate to predict the impact on traffic conditions, they often disregard the commodities being transported.

Although some of the models are promising, there are still various assumptions to be challenged. Many of the models lack behavioural aspects and assume that commercial vehicle behavior is similar to that of private vehicles. Hensher and Figliozzi (2007) and Samimi et al. (2009) highlight the need to understand the behavior of freight vehicles to enable us to capitalize on the decision-making benefits in disaggregate freight models. Chow et al. (2010) also reiterates that good freight demand models should contain a strong behavioural foundation. The commercial vehicle flow that we observe on the roads is actually the result of a much more complex set of interactions between different stakeholders in supply chains.

The behavior of different logistics stakeholders within a supply chain is rather complex. Logistic managers are faced with various decisions such as, among others, fleet sizing and composition, warehouse locations or relocations, shipment sizes and whether or not to outsource some of the logistic functions. Also, various strategies such as Collaborative Planning, Forecasting, and Replenishing (CPFR), Just-In-Time (JIT) and economies of scale, all influence the frequency of vehicle trips and load sizes of shipments.

The aim of this paper is to bridge the gap between the seemingly divergent schools of thought of commodity flow models versus activity-based models, by utilising recent agent-based developments in transport modeling. We demonstrate how different agents can be added to the transport model's commuter population. *Shipper* agents are those wanting to convey goods (commodity perspective), and assign the shipments in a market-environment to logistic service providers and, ultimately, *Carriers*. The latter is injected into the agent-based model as individual commercial vehicles executing the pickups and deliveries that result from typical route-optimisation initiatives within companies (activity-based perspective).

So instead of injecting activity chains into the model that are based on past observations (Joubert et al, 2010), the activity chains are the result of a series of actor interaction, starting at commodity movement at the highest level. The paper is structured as follows. In Section 2 we give an overview of agent-based modelling using the MATSim toolkit as well as the freight modelling framework in MATSim. In Section 3 we show an example of how one can model the different freight agents and the different logistical decisions one can make utilizing this modelling technique, where after we conclude in section 4.

2 AGENT-BASED FREIGHT MODELLING

Disaggregate modeling often provide richer, time-dependent results that improve decision-making capability. More accurate commercial vehicle models should result in improved travel time predictions. Both Gao et al. (2009) and Fourie (2010) show how agent-based modeling delivers more accurate travel time predictions using MATSim as opposed to an EMME/2 model, which is often still used in practice.

2.1 The Multi-Agent Transportation Simulation (MATSim) Toolkit

MATSim is a simulation toolkit that provides the ability to simulate large-scale transport models. Figure 1 depicts the simulation process in MATSim, also known as the MATSim controller. It starts with an initial demand, which typically consists of a synthetic population of agents, where each agent represents one person in the real world. There are various attributes associated with each agent such as, among others, household income, gender, and age.

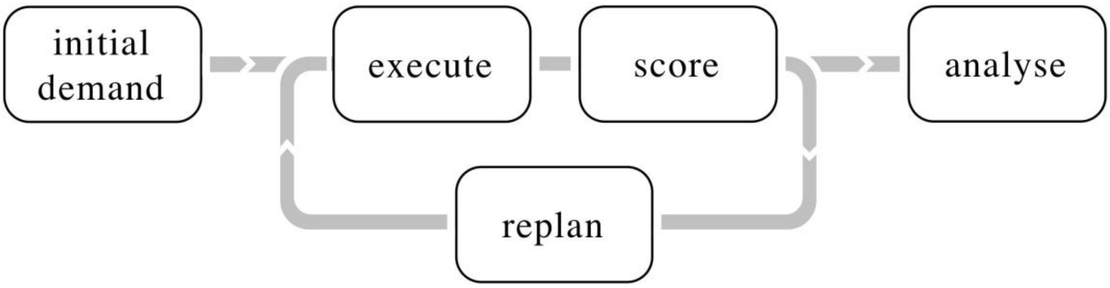

Figure 1 - The MATSim Controller

Each agent has a *plan*; a description of a sequence of activities and their timing and locations, alternated by transportation legs. An agent can choose a specific transport mode for each transport leg and these choices are also captured in the plan.

Agents are provided with a road network, which represents the real road network consisting of links with the vehicular capacity for each link. Each agent then picks a plan from memory and all agents execute their plans simultaneously sharing the road network. Due to limited capacity, congestion occurs. One iteration in the model typically represents one day in reality as we tend to model 24-hour horizons. At the end of the day, after executing all activities, agents score their plans: positive utility is accumulated when agents participate in activities and negative utility is accumulated when travelling or arriving late for activities.

Once scored, the score of the executed plan in the agents' memory is updated, and each agent picks a plan for the next iteration. The majority of agents pick an existing plan from memory. Typically the better the perceived value (utility) of a plan, the higher the probability of being chosen. A portion of agents is also allowed to adapt their plans, a process called *replanning*. Some strategies allow agents to change the timing of an activity, for example leaving earlier from an activity to attempt arriving earlier at a following activity or reroute so as to avoid possible congestion. Also, agents can reroute between a pair of activities. Once each agent has a plan for the next iteration, the process is repeated. Each agent tries to maximize its own utility; with the simulation ending once a steady state has been reached.

The agents' movements within the simulation are captured in what is known as *events*. Every activity start, activity end, entering a link, leaving a link, is captured. Once the simulation is completed, the events can be analyzed without having to rerun the simulation.

2.2 Freight modelling framework

Currently, commercial vehicles' activity chains are the result of observed activity chains (Joubert et al., 2010). Recent developments in MATSim have seen the development of a freight-modeling framework by Schroeder et al. (2012) that allows for more realistic modeling of freight agent behavior. They present a computational framework to model logistical freight transport decisions and activities.

Shipper agents are introduced as entities wishing to fulfill a business commitment by delivering certain products to consumers. For example, a mine wants to ship X amount of ore from the pit (sender) to a smelter (receiver). Or a beverage company wants to ship its product from the bottling plant (sender) to a set of retail outlets (receiver). At an aggregate level, commodity flows can be described in the form of an origin-destination matrix, similar to what is found in a commodity flow perspective. The type of commodity and the quantity are noted. This is broken down into specific shipment sizes. A trade-off is made between inventory levels and the frequency of required shipments, typically by the Economic Order Quantity (EOQ) method of production planning. Consequently, frequency and scheduling is done to deliver the whole commodity flow. Scheduling includes the pickup and delivery time windows. The *Shipper* chooses a Transport Service Provider (*TSP*) to carry out the transportation, which could be an outsourced company or the *Shipper* entity itself.

The *TSP* agent has the responsibility to fulfill the business contract, set between the *Shipper* and *TSP,* to deliver goods from the sender to the recipient. The *Shipper* pays a fee for the use of the *TSP*'s service. *TSP*s have certain capabilities such as transshipment and intermodal centres and knowledge on carrier offers/rates. Based on this knowledge, *TSP*s create tours to fulfill all contracts and choose *Carriers* to perform the actual movement of the goods.

Carriers in turn fulfill contracts with *TSP*s. A *Carrier* is assigned specific shipments to transport. Attributes pertaining to these shipments include: type of commodity, quantity, origin, destination, and time windows for pickups and deliveries. The *Carriers* have a mode choice and do their own route optimisation and scheduling based on their available vehicle fleet. This is where the commodity movement is translated into actual vehicle movement. The result is *Carrier plans*, similar to the *plans* of private commuters, which describe the start time, route to be driven, pickup and delivery locations and times as well as the end time.

These carriers can then be injected into the simulation model in conjunction with the private vehicle commuters before the simulation starts (execution step of the MATSim simulation process).

3 IMPLEMENTATION

The freight-modeling framework provided by Schroeder et al. (2012) includes a proof of concept implementation consisting of various scenarios that are modelled and simulated on a basic 8x8 road network square grid. We opted to implement the framework on a real-world network to capture the decision making under more realistic conditions. Although this implementation is based on real-world entities, it still remains a proof of concept aimed to show the potential of this modelling technique.

3.1 Road network

We chose the Nelson Mandela Bay Metropole (NMBM) as the study area. We extracted the road network of NMBM from *OpenStreetMap* (OSM) and converted it to a MATSim road network consisting of a set of links and the capacity of agents it can handle. Figure 2 depicts the NMBM area with the road network as well as the locations of different freight agents.

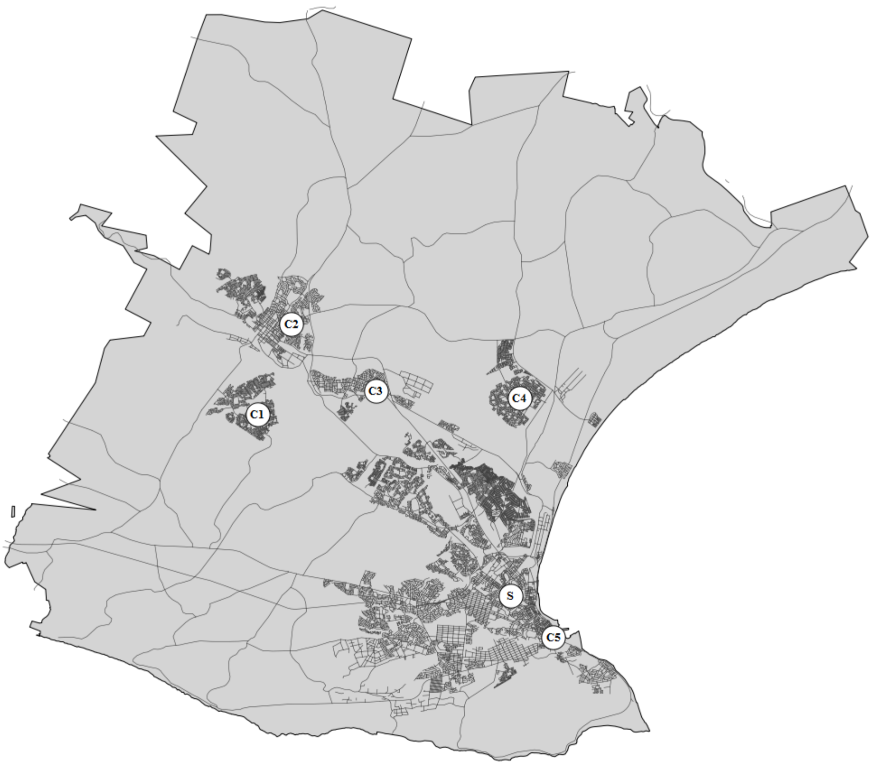

Figure 2 - The Shipper and Customers on the Nelson Mandela Bay Metropole road network

3.2 Freight agent generation

The freight population consists of three agent-types: a *Shipper*, a *Transport Service Provider*, and a *Carrier*. In this instance, we chose to model the business as having its own in-house fleet; hence all three agents are in fact the same business. The interactions between the different agent types, however, remain, and will be explained.

The *Shipper*, depicted in Figure 2 with an “S”, was modeled as a business located near the port, which has five customers. The five customers were created at random positions in different suburbs within NMBM. The business wants to ship a single commodity type to the five customers. Random shipment sizes were assigned to the customers with latest delivery possible to any of the customers being 16:00. The business only opens at 06:00 for the day’s business activities, thus the earliest time for a pickup is 06:00. Given the pickup and delivery time windows, the *Carrier* agent needs to decide at which time to do the pickup followed by the transportation leg to ensure on-time delivery. Table 1 contains a summary of the initial setup.

Table 1 - Summary of shipments

Location[1]	Suburb/Region	Shipment Size	Earliest Pickup	Latest Delivery
C1	Kwa-Nobuhle	30	06:00	16:00
C2	Uitenhage	40	06:00	16:00
C3	Despatch	30	06:00	16:00
C4	Motherwell	10	06:00	16:00
C5	Harbour	50	06:00	16:00

[1] See Figure 2

Our implementation of the *TSP* agent was in the form of a *Logistics Department* within our modelled business. The role of the logistics department is to ensure the movement and delivery of the goods for which the business is responsible. This agent could also have been modelled as a 3PL provider, for instance *Value Truck Rental*, where the transportation function would then have been outsourced.

We only modelled one *Carrier*, assuming here that the business has a homogeneous in-house fleet of 5 vehicles with capacity of 100 units each. The operating hours of the vehicles were set to be between 06:00 – 24:00. A least-cost path calculator was used in a ruin-and-recreate optimization algorithm to solve the Vehicle Routing Problem (VRP) of delivering the five shipments utilizing the vehicle fleet. The algorithm takes the road network and vehicle fleet as input and based on the expected travel time between the business and the customers, calculates the best combination in which to use the vehicles and the order in which to do the deliveries.

The result is a *Carrier Plan* that consists of the detailed trip information of each vehicle: the start time of all vehicles, the pickup time of all shipments, the transportation durations of all legs, the exact routes that will be driven, the delivery times as well as the end times of all vehicles once they arrive at the depot again. Table 2 summarises the information in the *Carrier* plan and figure 3 shows the sequence in which deliveries will take place.

Table 2 - Summary of pickups and deliveries in base case

Vehicle	Shipment Picked Up	Shipment Size	Pickup Time	Shipment Dropped	Delivery Time
2	5	50	06:00:00		
				5	06:07:32
4	3	30	06:00:00		
	2	40	06:00:00		
	1	30	06:00:00		
				3	06:17:50
				1	06:36:21
				2	06:50:10
5	4	10	06:00:00		
				4	06:21:38

The *Carrier* plan shows that only three vehicles were chosen by the *Carrier* agent to deliver all shipments. The latest delivery took place at 06:50 and the vehicles were all back at the depot at 07:10. We are interested in the time that a vehicle returns to a depot as that determines its availability for consequent scheduled deliveries. Accordingly, knowing when your vehicles will return to your depot will assist in determining your business' flexibility and adaptability to new contracts. Unfortunately, many commercial vehicle models often neglect the return leg of the vehicles to the depot.

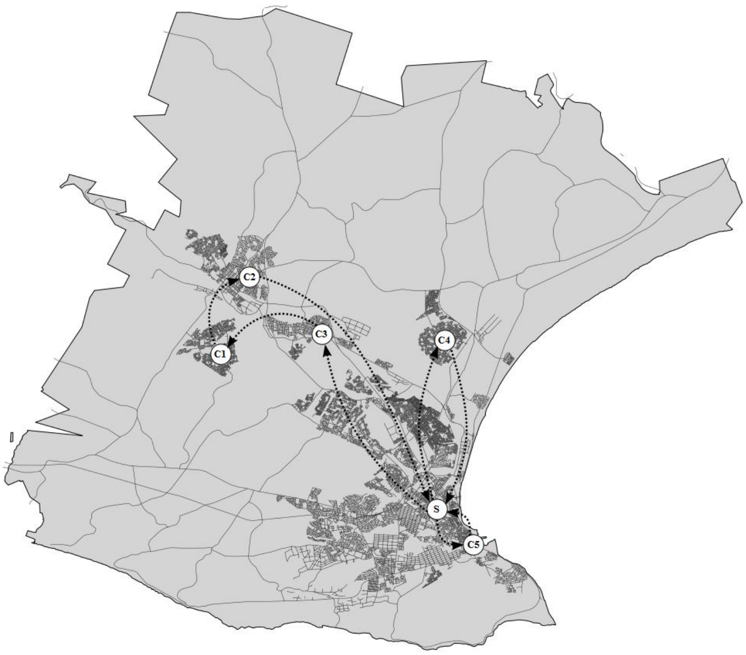

Figure 3 - Sequence of the carrier plans to be executed in the simulation

Next, we considered what the effect would be of a more centrally located *Shipper* agent (see figure 4). We moved the *Shipper* more inland and kept all the other assignments constant. We reran the optimization algorithm and the resulting *Carrier* plan saw only two vehicles being utilized, with the latest delivery being 06:42 and the latest end time being 07:01. We see here that all deliveries were performed in a shorter time and by utilizing fewer vehicles. This is useful when doing warehouse relocation studies since one can measure the impact on expected travel time and vehicle utilisation.

Figure 4 - A more centrally located shipper agent and the resulting tours

Next we evaluated fleet optimization capability. We used the original location of the *Shipper* and only changed the vehicles' capacities to: 10, 20, 30, 40, and 200. The idea here was to see whether the carrier chooses to utilize only the one large truck, or a combination of trucks. The resulting Carrier plans showed that only the large truck was utilized as it could carry all the shipments as well as deliver all shipments within the allowed timeframe. The latest delivery was made at 07:34 and the vehicle returned to the depot at 07:38.

This can be used to evaluate fleet sizing and composition. Companies can evaluate the trade-off of whether to have more trucks of smaller size against having fewer, but larger, trucks in the fleet. The choice of fleet size is also dependent on the logistical decisions such as the frequency and sizes of shipments as well as the inventory levels to keep at warehouses.

CONCLUSION

In this paper we bridged the gap between two schools of thought in commercial vehicle modeling: the commodity-based perspective vs. the activity-based perspective. We showed how one can separate the logistical functions found in complex supply chains and how one can model the interactions between the role players in the supply chain and obtain the resulting vehicle flow in the form of *Carrier* plans. These plans can be injected into an agent-based simulation in conjunction with private vehicles to see evaluate what the effect of congestion would be.

We considered different scenarios to show how this modelling technique allows for evaluation of location choice of warehouses/depots and do fleet optimization. It is also possible to trace commodity types and when the commodities were picked up and dropped off, opening up the possibility for Key Performance Indicators or metrics to be introduced in the modelling technique as well.

To model and simulate a large scale real-world scenario, however, will require intensive knowledge and data of companies. Such models would allow, though, a very useful tool for policy evaluation in companies as well as to measure the impact of government interventions.

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