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A multi-scale agent-based modelling framework for urban freight distribution

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Abstract

Comprehensive modelling of urban freight operations remains a challenge in transportation research. This is partly due to the diversity of commodities transported, shipment units, vehicle types used, stakeholders' objectives (e.g. suppliers, carriers, receivers), and to the limited availability of data. Thus, existing modelling efforts require several assumptions yet have limited behavioral foundations and minimal interaction between agents. This paper proposes a new agent-based modelling framework, which considers the heterogeneity of urban freight agents and their interactions. Agents include establishments (suppliers, carriers, and receivers) and freight vehicle drivers. Agents' decisions are structured in three temporal resolutions: strategic, tactical, and operational. A single set of agents is represented throughout all modelling levels ensuring a consistent and sequential flow of information. At the strategic level, establishments' characteristics and strategic decisions are modelled. These include location choices, fleet constitution, annual production/consumption of commodities, and establishment-to-establishment commodity flows. At the tactical level, shipments are assigned to carriers, who in turn plan their operations in terms of vehicle-driver-route assignments. Finally, at the operational level, the interactions between daily operational demands and transportation network supply are simulated. The supply representation has two different resolution levels (micro or meso) allowing for either detailed or computational efficient simulation. The simulation platform is distinct from previous works, as it explicitly considers planning horizons, replicates agent decision makings/interactions and involves a structure that allows for the propagation of influences bottom-up (e.g., prior simulation travel times on future route choice). The paper describes the simulation platform, constituent models, and illustrates its capabilities using an application of the modelling framework to the city of Singapore.

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Keywords: freight transport, city logistics; commodity flow; freight tours; simulation; ABM

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1. Introduction

Growing interest from urban planning agencies in freight-sensitive policy interventions has brought to light the importance of simulation platforms to analyze the impacts of such policies. Developing these platforms has been a challenge for researchers. The diversity of commodities transported, shipment units parceled, vehicle types used, and stakeholders' objectives make urban freight transport system highly heterogeneous, with different stakeholders responding differently to policies. In addition, data on freight are often unavailable or not widely accessible, which leads to limited behavioral foundations for the existing modelling approaches (Teo et al., 2015).

In this paper, we present the framework and application of a multi-scale agent-based simulation platform for urban freight, representing the system's heterogeneity, agents' behavior and their interactions. Its usefulness is justified in testing freight-influencing policy scenarios. For example, how land-use policies impact establishment relocation, which in turn influences receiver-supplier relationships and, lastly, freight traffic flows. Its development is timely as large-scale freight data collection efforts such as in Cheah et al. (2016) potentiate the estimation of the underlying behavioral models. This platform has been developed and implemented as an additional set of models in SimMobility, an open-source mobility simulation platform (Adnan et al., 2016).

SimMobility represents agents such as households/individuals and their behaviors in multiscale time levels ranging from seconds to years, using the activity-based modelling paradigm. SimMobility provides an ideal simulation environment for the proposed freight models. First, freight modelling is commonly performed top-down in the supply chain (e.g., from commodities flows to vehicle flows), disregarding the influence of lower-level decisions and outcomes in higher-level decision making processes. The structure of SimMobility allows for such feedback loops. Second, a considerable part of freight research is devoted to reveal freight impacts, such as contribution of freight movements to total traffic performance and emissions (Kladeftiras and Antoniou, 2013), or of freight infrastructure needs in urban freight operations (Aiura and Taniguchi, 2005, Alho, 2017). The parallel and integrated architecture of SimMobility platform is inherently suitable for modelling freight movements in direct competition for infrastructure with passenger movements. Next, we provide a brief literature review. Following, we detail the modelling framework and models' formulation. Then, the paper elaborates on the framework application to a case study in Singapore and presents the preliminary results of the model implementation. Finally, we conclude the paper with conclusions and a future research section.

2. Literature review

Comprehensive freight models are not new and several models go beyond one-dimensional classifications such as truck-based, commodity-based, or delivery based (Nuzzolo and Comi, 2012). Boerkamps (2000) presents a conceptual framework of the freight distribution system as the foundation of the GoodTrip model. This model starts as commodity-based but achieves a tour-based representation of freight vehicle movements. It has been used to study freight policies in the Netherlands. Wisetjindawat (2007) proposes an improved version of the four-step approach by considering agents individually. The model, applied to the Tokyo Metropolitan Area, Japan, has four stages: (a) commodity production/consumption, (b) commodity distribution, (c) conversion of commodity flows to truck flows, and (d) traffic assignment using vehicle OD matrices. Nuzzolo and Comi (2014) rely on a 3-step modelling process to achieve quantity OD matrices, delivery OD matrices, and finally vehicle OD matrices. This model system was applied to the inner-city area of Rome, Italy. To the best of our knowledge, none of these models clearly delimited the agents' decision-making process to time-scales. Crainic and Laporte (1997) explore time-scale definitions from a supply chain perspective; whereas Comi et al. (2012) present a similar perspective of city logistics policies/measures implementation. Their definitions of the time-scales are described below with additions that reflect the definitions used in this paper.

- *Strategic*, or *long-term planning* can be related to capital investments over an extensive time horizon. This could be facilities' location and resource acquisition decisions, e.g. commodities or fleet (Crainic and Laporte, 1997), or policy implementations such as Urban Distribution Centers (Comi et al., 2012).
- *Tactic(al)*, or *medium-term planning* decisions refer to those aiming to ensure an efficient and rational allocation of existing resources including freight terminal work allocation, and design of service networks (e.g., route

choice and repositioning of empty vehicles) (Crainic and Laporte, 1997) or, policy-wise, shipment sizes/load requirements or emissions restrictions (Comi et al., 2012).

- *Operative/Operational*, or *short-term planning*, pertains choices where time is an essential element in the decision-making process and can somewhat overlap with the medium-term planning. These include scheduling, routing and dispatching decisions (Crainic and Laporte, 1997). Comi et al. (2012) list policies such as time-windows and weight constraints or road/parking pricing decisions.

The definitions of the time scales in this work are in line with those of Crainic and Laporte (1997) and Comi et al. (2012). However, we suggest that long-term contracts between agents, commodities volumes traded, and shipment sizes might also be considered strategic decisions. Furthermore, carrier selection and load factor goals by carriers are medium-term decisions, although the selection of carriers can also be a long-term decision depending on the dynamics of the market. En-route route choice, parking location choice or re-ordering of planned delivery/pickup stops can also be considered operational decisions.

3. SimMobility Freight

We propose a core set of models to represent a set of relevant freight agents' interactions leading to freight movements. The model represents: (a) the main agents engaged in the process of producing, consuming and distributing commodities; (b) the interactions between these agents; and (c) the changes in time associated with system evolution. This paper presents the strategic (Long-term) and tactical (Mid-term) models of the comprehensive simulation platform that is being developed.

3.1. Framework

The proposed structure follows and builds on the existing SimMobility Passenger implementation (Adnan et al., 2016), as can be seen in Figure 1. Strategic and Tactical models run respectively in the 'Long-term' and 'Mid-term' demand simulation modules. The operational models run in the 'Mid-term' and 'Short-term' supply simulation modules. With respect to simulation's spatial and temporal granularity the Mid-term supply simulator is mesoscopic in nature and the short-term supply simulator is microscopic. Some models – for instance, the model that predicts establishment population (Le et al., 2016) – are shared from the SimMobility Passenger structure. From a passenger movement modelling perspective, this model is relevant to predict work/shopping trips for individuals. On the other hand, from a freight movement modelling perspective, establishments (suppliers/receivers/carriers) are agents with an active role in the supply chain. Models can also be shared across time-scales, and used for different purposes. For example, freight route choice models for carriers in Mid-term can also be used to re-assess route options considering additional information (such as unexpected congestion and new pickup/delivery orders) in Short-term.

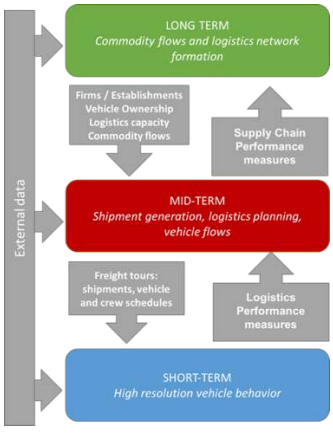

Fig.1 - SimMobility Freight Conceptual Framework.

3.2. Long-term (strategic) models

Long-term models simulate the strategic decisions that the agents make for a given year. These decisions are simulated on a synthetic population of establishments, where each individual establishment is generated along with its relevant attributes. The establishment-synthesis was performed with data and inputs from several sources, using a multi-step method as described in Le et al. (2016). The outputs of this step are the establishments' locations, industry type, employment size, and occupied floor area. In addition to these attributes, each establishments' fleet (i.e. freight-vehicle-ownership by vehicle-type) is synthesized, using a disaggregation approach keeping the regional vehicle-registry as the control.

Estimating annual production and consumption of commodities is commonly done at establishment-level (Muñuzuri et al., 2010) and by land-use attributes (Lawson et al. 2012, Sanchez-Diaz et al., 2013). In the specific application that will be presented later in this paper, we assume production and consumption to be primarily dependent on the employment and combination of industry type and supply chain function.

To disaggregate the annual flows into different commodity types, the relevant types and their respective shares in an industry can be inferred from regional economic data. For example, "supply and use" tables reflect the commodities produced and consumed by establishments from an aggregated perspective of each industry. This allows creating industry-specific distributions of commodities produced and consumed, and assigning a bundle of inbound and outbound commodities to each establishment.

Subsequently, the supplier-selection model matches suppliers to receivers, by sequentially running two sets of discrete choice models. The first set of choice models assume the receivers to perceive the attractiveness of each zone based on: (a) the zonal quantity of the commodity produced, (b) the zonal number of potential supplier-establishments, and (c) the distance between the centroids of the supplier's zone and the receiver's zone. Coefficients to the above parameters are considered specific to commodity-type and the receiver's position in the supply-chain. Secondly, the utilities of all suppliers in each zone are computed based on the non-allotted quantity as the simulation progress.

Note that the process is dependent on the sequence of receivers taken in simulation. This sequence can be decided exogenously. In the application detailed in this paper, we prioritize receivers based on their age. The computed utilities are employed to generate the conditional probabilities of selecting a supplier, given a zone. The probabilities of a receiver selecting a shipper for a commodity are clustered using an x-means algorithm to arrive at a cluster of most probable suppliers. Finally, the quantity of this commodity consumed by the receiver is proportionately assigned to these suppliers. This model outputs the commodity-wise annual flow between each supplier-receiver pair.

Following supplier-selection, the shipment-size cum frequency model specifies typical size of a shipment and the distribution of shipments throughout the year. Typical size of a shipment is dependent on attributes of the supplier, carrier, receiver and the commodity-type. For instance, an analysis of the shipment microdata from the 2012 US commodity flow survey led to the identification of commodity type, supplier industry, and carrier type (own/hired) as influential factors to the shipment-size distributions. The frequency of shipments, and subsequently the probability of a shipment being moved on a specific day, can be arrived at using these distributions. Thus, these variables are used to narrow down the set records from which a random frequency value is drawn. The set of models in the Long-term output the shipment-size (in weight) and frequency for shipments of a given commodity expected to be moved between the supplier and receiver locations.

3.3. Mid-term models

Mid-term models simulate the tactical decisions that the agents take on a typical day. Given that Long-term models output shipment information for a given year, a set of shipments relevant to a representative day is to be selected. This is done in the day-selection model, where a random draw considering the probability of shipping in each day results in a set of shipment movements to be simulated. This selected set of shipments is then input to the carrier-selection and carriers' operations planning models. These models consist of a sequence of heuristics that assign vehicles to shipments in a two-step process. First, supplier-establishments assign as many of their own shipments as possible to their own vehicles, based on their fleet capacity. Secondly, unassigned shipments are

pooled to be potentially outsourced to carrier-establishments. A procedure iterates over this list of shipments, triggering a series of subroutines up to exhaustion of available vehicle-capacity or shipments.

The subroutines include models such as: (a) vehicle-selection model, (b) shipment-clustering and vehicle loading model, (c) stop-sequencing model, and (d) stop-time model. The vehicle-selection model takes into account the vehicle capacity and time availability considering prior utilization of each vehicle. Upon confirmation of capacity and availability this model assigns a shipment to the vehicle from the list of unassigned shipments. Treating this as a primary shipment, the shipment-clustering model identifies a subset of other unassigned shipments based on origin and destination proximity as well as shipment type compatibility. Remaining shipments from this cluster are added to the vehicle until: (a) any additional shipments would exceed vehicle capacity, or (b) the vehicle's delivery count exceeds a threshold number of deliveries per tour. The stop-sequencing model then generates a sequence of delivery locations for each vehicle, constrained on thresholds on total tour-time. Upon violation of this constraint, shipments for a given receiver are dropped. These shipments are then considered in the next iteration of the shipment-clustering and vehicle loading model. For stop-sequencing, a 'closest-node-next' heuristic is integrated in the simulation platform. A more computationally burdensome TSP optimization algorithm that generates stop-sequences based on carrier-level priorities (time or distance savings) is implemented as an add-on.

Lastly, the tour details (vehicle, driver, shipments/stops, departure time) are passed to the supply simulator which is capable of outputting, among others, the following traffic performance indicators: (a) vehicle flow on links per vehicle type and time period, (b) average speed and associated travel time index, (c) tour duration and delay against planned tour, and (d) route choices.

4. Model application

We present an application of SimMobility Freight to simulate freight movements in Singapore. This section is intended to better illustrate the process flow in this simulation platform, and also to throw some light on the various inputs/outputs configurable in it. The synthesized population of establishments represents Singapore as of December 2012. It is generated as described in Le et al. (2016), and then extended to include additional establishment attributes, such as foundation year and fleet ownership.

Singapore being an island city-state, the national economic data is an accrual of activities exactly within the area to be simulated. The commodity flow is, in the first stages, handled in dollar values. Therefore, the per-employee production and consumption is estimated such that the industry-level production and consumption matches the total production and consumption in Input-Output tables for Singapore (Singapore Department of Statistics, 2017). The Singapore Supply & Use table (Singapore Department of Statistics, 2017) is used to predict commodity types and quantities. In the process, the symmetric Supply & Use table with 71 commodities and industry-types is transformed into a version of 12 commodities and 45 industry-types. Commodity types that are produced and attracted are identified for each industry-type, and commodity-wise productions and attractions are computed.

The Supplier Selection model then pairs the supplier-receiver establishments. In the absence of local data, we use the coefficients estimated by Wisetjindawat et al. (2006) as seed values. To define shipment size, we use the U.S. C.F.S. 2012 Microdata, drawing a random record from a subset of the data (intra-urban shipments), subject to whether a supplier uses own-vehicle, supplier's industry type, and type of product. Commodity flows are converted to weight before the application of the shipment size model using the coefficients from the summary table of the 2015 Japan commodity flow survey (Ministry of Land, Infrastructure, Transport and Tourism, 2015).

An establishment that owns at least one freight vehicle is considered an own-account carrier. The following data is used in the application of the Mid-term demand simulation models, specifically, the Carrier Selection and Operations Planning model: (a) total stops per tour and vehicle type (Olszewski et al., 2003); (b) delivery stop durations from Lisbon (Alho and de Abreu e Silva, 2014) and Singapore (Dalla Chiara, 2017); and (c) vehicle payload usage (% of capacity in weight) from the U.S. Vehicle Inventory and Survey data (United States Census Bureau, 2002). All mentioned datasets are to be fully replaced with local data from (Cheah et al., 2016) in a near future. Vehicle payload usage and maximum stops in a tour are drawn as a cumulative distribution function (CDF) of deliveries per tour per vehicle type. Three vehicle types are considered according to their Maximum Laden Weight: Light Commodities Vehicle (LGV), Heavy Commodities Vehicle (HGV) (3.5-16 tons), and Very Heavy

Commodities Vehicle (VHGV) (> 16 Tons). Stop durations, also from a CDF, are added to each pickup/delivery. The maximum tour duration is currently set for 8 hours.

Model calibration is performed independently for Long-term and Mid-term models. The scope of the Long-term calibration is as follows: (a) 90 parameters for production and consumption models (2 parameters × 45 industries); (b) 1,080 proportions of commodity-wise productions and consumptions (12 commodities × 45 industries × 2 (production or consumption)); and (c) 108 parameters of the commodity-cum-supply-chain-specific supplier-selection models (12 commodities × 3 supply-chain tiers for receivers × 3 model parameters). The simulation results are compared with the industry-to-industry flow matrix (Singapore Department of Statistics, 2017). The first two sets of parameters (a) and (b) are calibrated against the commodity and industry specific productions and consumptions of the matrix, using a standard optimization algorithm. Calibration of the third set of parameters in the Long-term models – those of Supplier-selection models – and those of Mid-term models is currently being performed employing a Weighted Simultaneous Perturbation Stochastic Approximation (W-SPSA) algorithm (Lu et al., 2015). For the Mid-term, the parameters being calibrated are: (a) the share of vehicles that are not working on a given day; (b) the CDF parameters for vehicle payload usage (per vehicle type), number of stops per tour (per vehicle type), and stop duration; (c) the conversion factors from commodity value to weight. Mid-term calibration is performed against a set of LGV and HGV counts obtained in 2012 from 408 sensors at various locations in Singapore, with a resolution of 15 minutes.

5. Results

This section focuses on the results of the Long-term model. The calibration of the Mid-term model is currently ongoing. The Long-term model operates on an establishment population of 172,075 agents and a vehicle population of 135,134 freight vehicles. In the given year, the total combined production and consumption of the establishments is around 180 billion Singapore-Dollar (SGD) worth of commodities. The aggregated outputs from the supplier selection model are presented in Figure 2. The image is a screenshot from an interactive application that visualizes suppliers of a commodity type to any selected receiver and vice-versa. Another output from the Long-term models is given in Figure 3. The results allow for a comparison of total commodity flow simulated at receiver and supplier ends with those obtained from the industry-to-industry flow records.

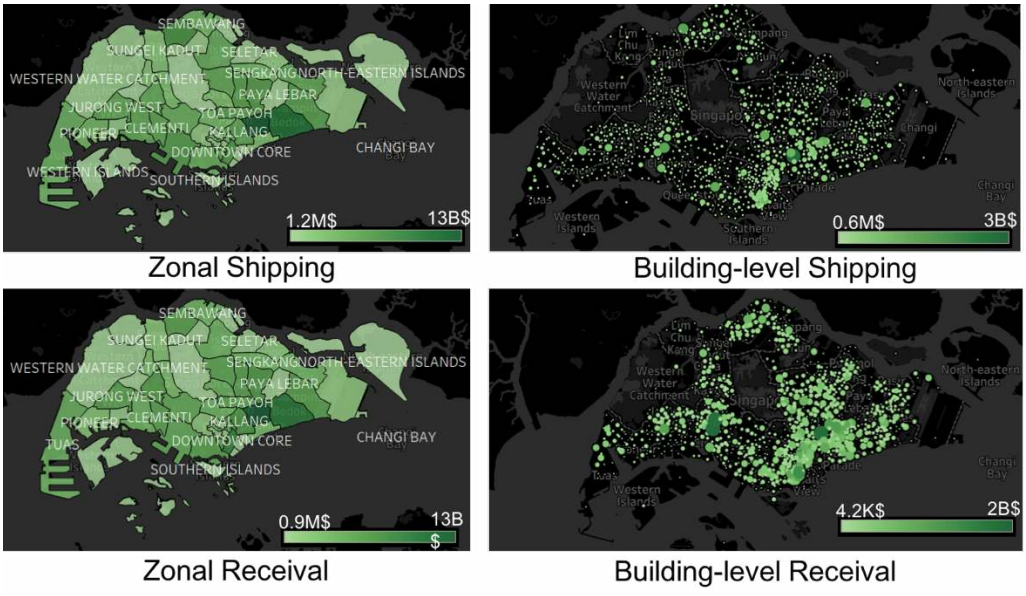

Fig. 2 – Geographic spread of commodities shipped and received in Singapore.

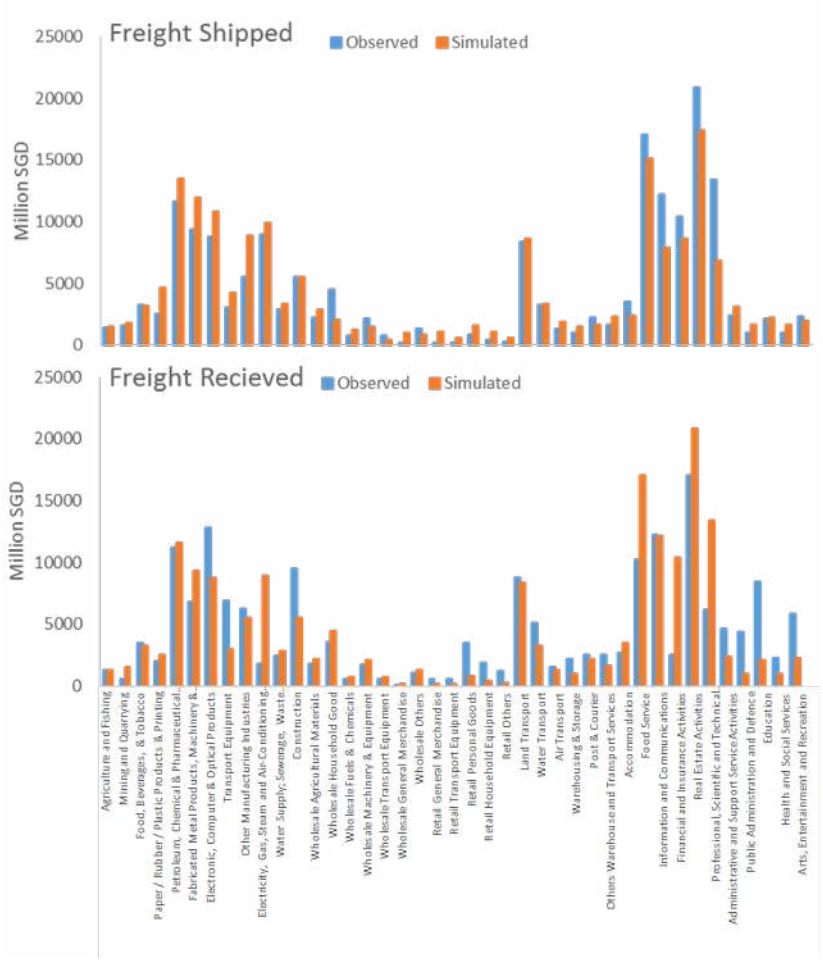

Fig. 3 – Industry level aggregation of freight shipped and received by establishments during simulation vs. those observed in industry-to-industry flow matrix.

6. Discussion and Conclusions

The initial implementation of a novel urban freight simulation platform was presented in this paper. We put forward that it represents core agents' decisions and interactions. Further distinguishing this platform from the existing urban freight models is: (a) the explicit representation of time-scales, and (b) the potential incorporation of the feedback from the lower-level simulation results to the simulation of higher-level decisions. A parallel effort of data collection is underway which, when completed, will be used to improve these constituent models. The platform is currently being improved for use as a decision support system in several policy-related case-studies.

Furthermore, SimMobility Freight is in the process of being expanded with a set of new models, such as dedicated import-export models, alternative formulations of supplier-selection and carrier-selection models. Specifications of a stop-sequencing model with time-windows constraints and an overnight parking model to account explicitly for the first and last legs of the tours are also ongoing.

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