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Transportation Research Procedia 00 (2018) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2019 Mumbai 26-31 May 2019

The incremental development path of an empirical agent-based simulation system for urban goods transport (MASS-GT)

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Abstract

Urban planners face a few challenges in making urban freight transport more sustainable: reduce urban congestion, provide reliable delivery windows, decrease logistic costs, reduce emissions, improve safety. New data may provide a key in tackling these issues. This paper presents an agent-based urban freight modeling framework: MASS-GT. Objective of the project is to develop a comprehensive simulation framework that describes logistic decision making in the context of urban transport planning. Empirical basis is provided by a large dataset with observed freight transport data for The Netherlands. Part of the data has been collected using an automated procedure to report complete freight trip patterns from the transport management system. This provides more dense and complete data compared to conventional internet surveys. The paper describes the design principles for agents, markets and logistic decisions. Furthermore we elaborate on the incremental development path of building a comprehensive agent-based simulation system. We describe the first baseline prototype of the agent based modeling framework that simulates all urban freight transport patterns for an urban area, in the case the agglomeration of Rotterdam. This baseline model applies a data driven simulation approach. Next, we present the intermediate estimation results of the first logistic choice models that will be implemented in the second version of the agent based modeling framework: a model for simultaneous shipment size and vehicle type choice, and a tour formation model. Future work will consists of further extending the framework with the step-wise integration of more advanced discrete choice models for logistic decisions.

Peer-review under responsibility of WORLD CONFERENCE ON TRANSPORT RESEARCH SOCIETY.

Keywords: Agent based simulation; urban freight; big freight transport data; agile model development; The Netherlands; Vehicle type choice; Tourformation

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1. Introduction

Simulation models are sometimes used as tools for strategic evaluation of freight transport policies, but most operational models do not have sufficient behavioral detail to simulate the impacts of developments in logistic services, policy measures, or planning scenarios in a representative and satisfying manner. However, simulation models are becoming increasingly disaggregate: microsimulation or a combination of aggregate and disaggregate models are finding its way in a growing number of logistic or freight transport models (Davidsson et al. 2005; Tavasszy, 2006; De Jong and Ben Akiva, 2007; Wisetjindawat et al, 2007; Liedtke, 2009; Roorda et al., 2010). The dimensions and simulated choices that are simulated vary between these examples: usually it is the outcome of data availability or the scope of the model. Approaches can be trip based (e.g. Hunt and Stefan, 2007) or commodity based where shipments are simulated explicitly (Holguín-Veras, 2013; Wisetjindawat et al, 2007; Liedtke, 2009; Roorda et al., 2010; Samimi et al, 2010). Shipments are a fundamental dimension in an agent based model, because many transport and distribution related decisions take place at the level of shipments. Simulations also vary in agent representation. Agent behavior is sometimes lacking or often simplified: shippers and carriers are sometimes distinguished explicitly (e.g. Holguín-Veras and Sánchez-Díaz, 2016), but the characteristics of shippers are often neglected. An important element is the distinction between shippers that organize their transport themselves (own account carriers) and shippers that outsource their transport to external carriers, third part logistic service providers (3PL's). This outsourcing decision is simulated in some more advanced agent based models (Boerkamps et al., 2000; Cavalcante and Roorda, 2013). 3PL's have much more consolidation possibilities of shipments between different sender/receiver combinations, which affects greatly the transport- and distribution related choices downstream of a logistic chain.

In a recent review of empirical studies on logistic decisions in freight transportation modeling efforts from the perspective of supply chain management (SCM), we distinguished a framework of logistic decisions across six strongly interdependent functional areas: sales, production planning, sourcing, distribution structures, warehousing and transportation (Tavasszy, de Bok, Rezaei, Alimoradi, 2018 forthcoming). From the review two important aspects came out that are relevant for building descriptive models of logistic decisions in freight transport demand. First of all, decisions take place in different functional areas with different agents and choice behavior. Secondly strong interdependencies exist between choices that are up- or downstream of the supply chain. Integration of these choices in a simulation framework is crucial in describing logistic choices in SCM. Agent based models seem to be the way forward for improving logistic choice behavior: it allows the simulation of agent specific behavior, taking into account the variation of decision makers.

It is challenging to develop empirical agent based models because of the data requirements. Most agent based models described in literature are developed with elaborate conceptual models, such as TAPAS (Davidsson et al., 2005), INTERLOG (Liedtke, 2009), FAME (Samimi et al. 2010) or FREMIS (Roorda et al., 2010), but finding sufficient empirical data behind the models remains challenging, in particular behavioral freight transport data.

Our aim is to contribute to the development of empirical agent based logistic simulation models for urban freight transport by using a large dataset with observed freight transport data for The Netherlands. We build the design of our simulation model around three main principles: a commodity based approach, representing agent based decision making explicitly, and by implementing empirically tested choice model. As agents we distinguish different types of agents in the simulation framework: producing firms, consuming firms, shippers, own account carriers and third-party logistics (carriers). Also, our objective is to simulate representative urban freight transport patterns and the underlying logistic decision making, using big data on freight transport as an empirical basis.

This paper describes the design principles for agents, markets and logistic decisions. Furthermore we elaborate the development path of building a comprehensive framework, in which we apply an incremental development path. First, we describe the baseline prototype of the agent based modeling framework that simulates all urban freight transport patterns for an urban area, in the case the agglomeration of Rotterdam. Second, we present the intermediate estimation results of the first logistic choice models that will be implemented in the second version of the agent based modeling framework.

2. Agent based model for urban goods transport

2.1. Conceptual model

The aim of the MASS-GT research project is to develop an agent based simulation model for urban goods distribution. The scope of this model covers parts of the Transportation and Distribution system, as described in Tavasszy et al. (2018). We apply a commodity based approach and distinguish different types of agent and their behavior, and different types of markets. Mosty advanced agent based models for freight transport distinguish different markets explicitly: e.g. Calvalcante and Roorda (2013) distinguish commodity and freight market, Boerkamps et al (2000) distinguish the commodity, transport services, traffic services, and infrastructure markets.

In the MASS-GT framework we distinguish four markets. The commodity market is where interaction takes place between the producers (senders) and consumers of goods (receivers): the *sourcing* process. Figure 1 illustrates the markets, agents and logistic choices that take place at these markets.

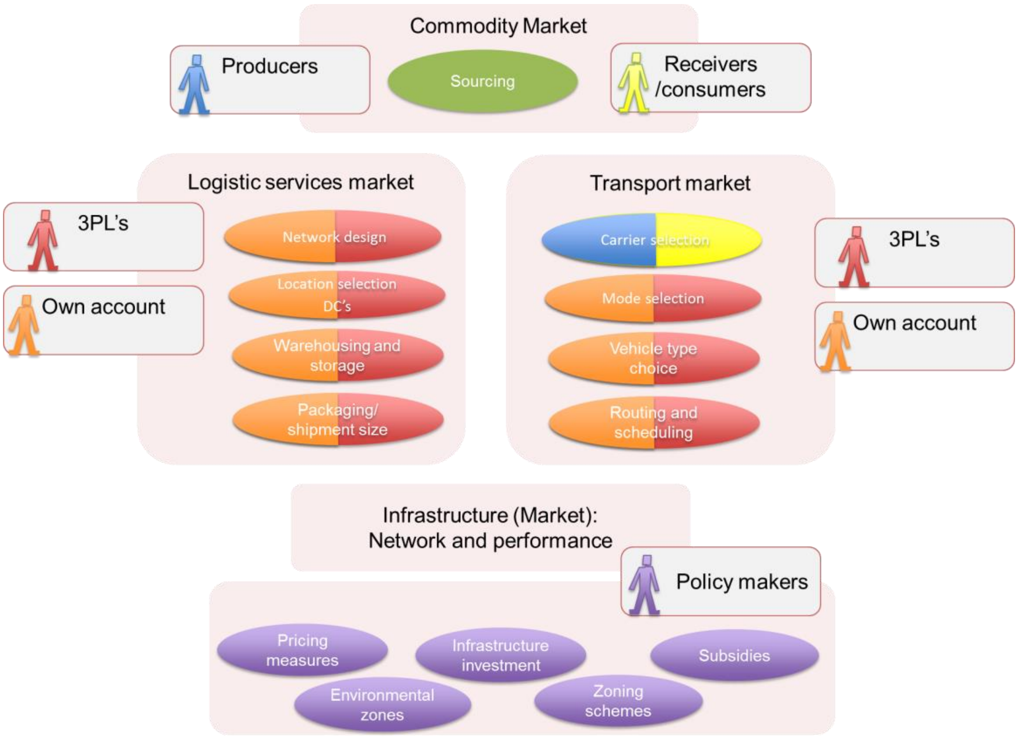

Figure 1: Agents, markets and logistic choices in the conceptual model for MASS-GT.

At the logistic services market, the organization of *distribution structures* and *warehousing* takes place. This market is typically served by specialized third party logistics but may as well be served by own account carriers (typically large companies). Logistic decisions that take place at this market are network design, the location and selection of DC's, warehousing and storage, and packaging/shipment size.

At the transport market the *transportation* of goods is organized. This market is both served by specialized third party logistics as well as own account carriers. Logistic decisions that take place at this market include carrier selection, mode selection (road, rail, inland waterway, maritime, air), vehicle type choice and routing and scheduling choices.

We can also identify the infrastructure market: infrastructure networks make up the supply side of the transport market. The network and traffic conditions on the network determine the transport performance, and may affect route choices for vehicles. It also determines other transport performance indictors such as reliability, or parking facilities at loading/unloading locations. The development and management of the infrastructure market is not so much the domain of the agents that are responsible for the freight transport demand or execution of goods transport, but lies in the public domain. Therefore we define policy makers as the last category of agents. Their decision making set the conditions for freight transport: pricing measures, infrastructure investments, environmental zones, subsidies, zoning schemes. Their behavior is not simulated explicitly in the framework but is contained in the urban freight input scenario. A simulation model for urban freight transport is typically designed to test the impact of public planning measures, or other developments, on the freight transport demand and infrastructure performance (accessibility, reliability).

There are different types of ‘agents’ that are active in one or more of the freight transport markets: producers, receivers/consumers, shippers, carriers, own account carriers, third party logistics (3PL’s). When we look closer, in many cases ‘agents’ are often one and the same person, so maybe it is better to speak of ‘agent roles’. An agent is a firm, and this agent may fulfil one or more different roles. Advanced agent based simulation models usually distinguish between shippers and carriers. But typical to freight transport is that the shippers can be the producers of the goods, but instead the shipper may just as well be the consumer of the goods. The same bipolarity applies to carriers: the transport may take place by own account or by a 3PL’s carriers. It is important to distinguish these different types of roles, and translate them correctly to agent behavior. The challenge in developing an agent based urban freight model lies in the correct representation of the different roles in the logistic choice models. We will operationalize this in the MASS-GT framework by simulating agent specific behavior, including the roles the agent has (sender/receiver and/or shipper/carrier).

2.2. Development strategy

The development of an agent-based simulation model for urban goods transport is complex due to the choices simulated, their interaction, and the heterogeneity in agent behavior. The presented project is data-driven and has a focus on empirical choice modeling and microsimulation. To manage complexity, development takes place following an incremental development path, starting with a baseline model with as little choice modeling as possible. We use Python as development platform. As a first step we developed a quick prototype based on the data that is available. This prototype contains the agents (producing and consuming firms), synthetic shipments, and a baseline tour formation procedure. In increments to follow we will extend this framework with choice behavior for the respective agents. The first prototype covers the transport market, and is completely based on observed distribution functions from the observed microdata. This baseline model is presented in this paper. In this paper, in addition, we present the first results of two logistic choice models that are being developed: the joint shipment and vehicle type choice, and a tour formation choice model. These models will be implemented in the next version of the agent-based simulation model.

The objective of this step-wise development strategy is to manage simulation complexity during the development of the model. Two advantages of this approach are first of all potential useful results from the intermediate prototypes: a synthetic projection of commodity- and truck type specific freight trip patterns. Second, the experience resulting from the prototypes helps in optimizing the simulation structure of the agent-based framework during the model development.

3. Data

In our project we aim to contribute to the development of empirical agent based urban freight models. For this purpose we have access to the microdata in an extensive road transport database with transported shipments, that is being collected by the Central Bureau of Statistics Netherlands (CBS). This database offers a rich source for the formalization and calibration of simulation models of logistic choice behavior. The database has a high data density for two reasons. First of all, the survey is mandatory: transport companies are obliged to report the vehicle use of each truck that was randomly drawn by the CBS from the population of all registered license plates of trucks. On top of that large part of the data collection takes place using an innovative and efficient data collection method: transport companies can use an XML-interface to deliver their inputs automatically from their transport management system. As a result a database with 30 thousand surveys is constructed with an extremely high data density. The data that is collected through this XML-interface contains trip patterns at coordinate level. In addition to the transport database we use data on the firm population from the CBS. The table below gives an overview of all the data sources that we are using to develop the modeling system.

Table 1: Sources of data for baseline prototype of MASS-GT

Data	Statistic	Source:
Shipments	Shipment size: descriptive statistics	Commodity flow database: 'Basisbestand goederenvervoer' (CBS)
Tours	Observed vehicle type use, Observed tourcomposition (1,2,3,4+ stops)	Commodity flow database: 'Basisbestand goederenvervoer' (CBS)
Trip patterns	Detailed statistics on departure time, stop time, stoplocation	XML-data collection in commodity flow database (CBS)
Firm population	Location, size and sector of firms	Algemeen Bedrijven Register (ABR) (CBS)
Commodity Matrix	Flow of goods between region/zones	Aggregation of commodity flow database or Commodity forecast from strategic freight model Basgoed

4. Prototype

4.1. Introduction

The agent based simulation system is based on three main assumptions: commodity based, agent based and data-driven. As a first step in the development path of a complex agent-based simulation model we develop a simple quick prototype using the available data to simulate representative truck patterns for an average working day for an urban agglomeration in The Netherlands, applying the commodity- and agent based framework. Main idea is that we use observed commodity- tour and trip statistics and Monte Carlo simulation (MCS) to determine shipment- and tour characteristics.

The prototype simulates all urban freight transport taken place to/from and within the city of Rotterdam, for ten commodity types (NSTR chapters). The prototype has a modular structure: it comprises of a **Shipment synthesizer**, and a **Tourformation** model. The first step of the prototype is the simulation of the formation of (synthetic) shipments. The second step is the routing and scheduling of deliveries (tourformation). The output, freight tour patterns, can be assigned to the urban network to derive network performance indicators.

4.2. Shipment synthesizer

Objective of the shipment synthesizer is to build a dataset of individual firm-to-firm shipments from an aggregate commodity flow matrix, and disaggregate firm data. In microsimulation models, commodity generation typically takes place by a bottom-up approach applying firm level regression models estimating production and consumption based on firm level attributes (Wisetjindawat et al, 2007; Abed et al, 2015). In our approach we use an aggregate freight transport demand matrix, derived from a strategic freight transport demand model as input, to simulate shipments between producing and consuming firms. Aggregate commodity flows are broken down to shipments using the observed shipment size distribution, and next each shipment is allocated to individual firms, based on the firm's characteristics (size, industry type, location) and the make/use probability of the industry sector for the respective commodity type. Output is a dataset with firm-to-firm shipments, containing the commodity type of shipments, and the attributes of sending and receiving firms (location, firm size, industry). The flowchart describes the synthesizing procedure.

The size of shipment is drawn from an observed standard distribution:

$$f(x|\mu,\sigma^2) \quad (1)$$

The probability of firm f belonging to sector s, being the **sender** of shipment with commodity type gt depends on the 'make' probability for the sector, $P_{s;gt}^{make}$, the firm size, E, and other firms in the origin zone:

$$P_{f;gt}^{sender} = \frac{E_{f;s} * P_{s;gt}^{make}}{\sum_{i \in orig}\left[E_{i;s} * P_{s;gt}^{make}\right]} \tag{2}$$

The probability of firm f belonging to sector s, being the **receiver** of shipment with commodity type gt depends on the 'use' probability for the sector, $P_{s;gt}^{use}$, firm size, E, and other firms in the destination zone:

$$P_{f;gt}^{receiv} = \frac{E_{f;s} * P_{s;gt}^{use}}{\sum_{i \in dest}\left[E_{i;s} * P_{s;gt}^{use}\right]} \tag{3}$$

Table 2: Shipment size from Commodity flow database (CBS).

		Shipment size	
	NST/R	Average	StdDev
0	Agricultural products and live animals	15.3	9.5
1	Foodstuffs and animal fodder	13.7	9.9
2	Solid mineral fuels	25.6	4.2
3	Petroleum products	25.4	11.5
4	Ores and metal waste	16.8	7.9
5	Metal products	14.8	10.1
6	Building materials, minerals	22.2	9.9
7	Fertilizers	16.7	11.4
8	Chemicals	15.8	10.3
9	Machinery, transp. eq., manuf. articles and miscell. articles	7.7	8

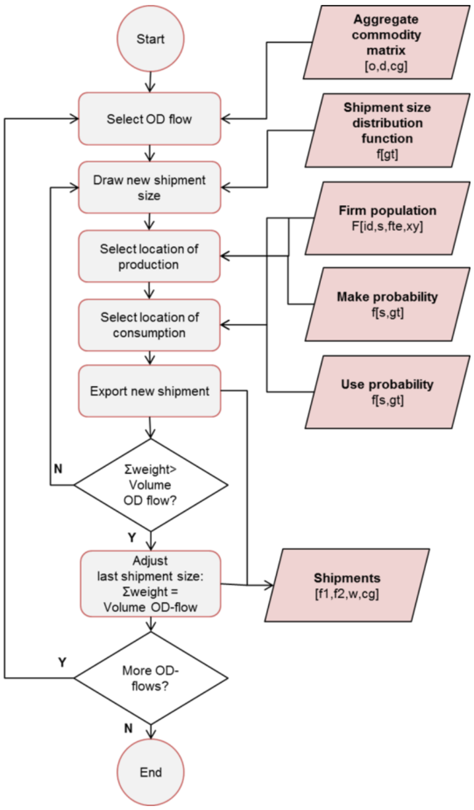

Figure 2: Shipment synthesizer procedure

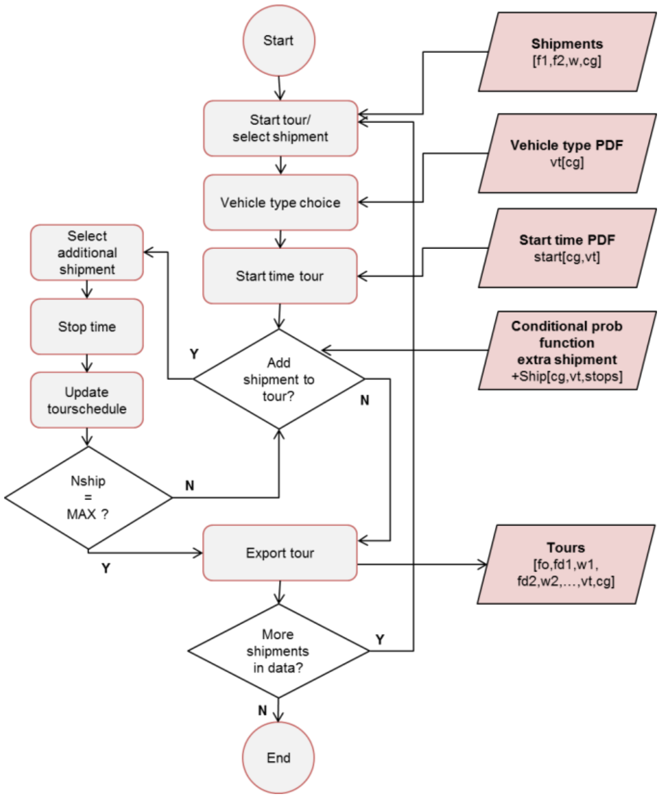

Figure 3: Tourformation procedure

4.3. Tourformation

The second module in the prototype simulates tour formation: it builds tour patterns from the synthetic shipments. There are a number of existing examples of simulation approaches to simulate the formation of trip chains or roundtours, such as Hunt and Stefan (2007), Wisetjindawat et al. (2007), Wang (2008) or Nuzzolo et al. (2012). Our first module does not apply a logistic choice model yet; instead it uses monte carlo simulation to replicate observed tour statistics. Output is a dataset with urban freight tours, containing the commodity type of shipments, a number of discrete shipments to be delivered, and the location and industry sector of sending and receiving firms for each shipment.

Submodels are based on observed commodity statistics; where relevant these steps will be improved by applying logistic choice model for the corresponding agent. First of all the probability density function of the vehicle type, chosen for each commodity type is used to allocate a vehicle type for a tour. This probability density function is shown in Table 3. The next step is the simulation of tour start time: again, this is allocated by using the observed start time of tours by vehicle type and commodity, available from the data. The detailed time schedule of truck patterns is not available in the standard survey, but only for the registrations collected from the automated trip registration procedure.

Table 3: Probability density function for vehicle type from ‘deelrittenbestand’

	NST/R	2: Lorry	3: Trailer truck	4: Special Vehicles
0	Agricultural products and live animals	20%	80%	0%
1	Foodstuffs and animal fodder	10%	90%	0%
2	Solid mineral fuels	10%	90%	0%
3	Petroleum products	39%	60%	0%
4	Ores and metal waste	61%	38%	1%
5	Metal products	19%	81%	0%
6	building materials, minerals	46%	54%	0%
7	Fertilizers	19%	77%	3%
8	Chemicals	36%	57%	6%
9	Machinery, transp. eq., manuf. articles and miscell. articles	19%	78%	3%

Table 4: Stop probability: conditional probability function additional tour: P(n+1|n) from ‘deelrittenbestand’

	Conditional probability function additional tour: P(n+1|n)				
	2	3	4	5	Round
NST/R 0: Agricultural products and live animals					
2: Lorry	43%	82%	85%	85%	3%
3: Trailer truck	45%	81%	82%	83%	1%
4: Special Vehicles	0%	0%	0%	0%	0%
NST/R 1: Foodstuffs					
2: Lorry	83%	94%	92%	92%	0%
3: Trailer truck	64%	80%	80%	82%	2%
4: Special Vehicles	94%	97%	85%	94%	2%
NST/R 2: Solid mineral fuels					
2: Lorry	25%	100%	100%	45%	0%
3: Trailer truck	3%	100%	100%	76%	0%
4: Special Vehicles	0%	0%	0%	0%	0%
…..					

The next step is to simulate the decision to make an extra stop during the tour. The available data consists of observed truck tour patterns and provide information on the occurrence of multi stop tours (1,2,3,4,5 or more shipments per tour). From this observed statistic a conditional probability function is derived that describes the probability to make an additional tour during the tour formation procedure. This probability depends on the type of good, and the vehicle type that was used. This statistic is illustrated in Table 4 for the first three commodity types. If an extra stop is made, the selection of additional shipment is conditional on commodity type. The baseline model selects the first shipment of the same commodity type that is available. In addition observed statistics on waiting times for loading and unloading shipments will be used to construct a complete timing for the tourschedule. The decision to carry- and selection of additional shipments for a round tour will be one of the first simulation steps that will be replaced by a choice model that is based on logistic choice behavior.

4.4. First results

The prototype produces a database with individual shipments from the shipment synthesizer and a database with tour patterns, describing the distribution sequence of the individual shipments, with all relevant attributes such as starting point, number of shipments, total weight carried, total transport time and vehicle type used. The results are also available as shapefiles for quick visualization.

Figure 4 illustrates the micro results. The map shows the distribution pattern of all truck trips within Rotterdam for commodity type NST/R 6 (Crude and manufactured minerals, building materials). One of the tours is highlighted on the map and in the attributes table of the tour shapefile. As can be seen, the highlighted tour illustrates the tour pattern for the delivery of two shipments for NST/R 6.

This paper introduces the agent based framework and we only want to illustrate the output level at which the model simulates urban truck patterns. The model is completely based on observed statistics and monte carlo simulation and does not contain any explicit logistic choice models yet. However, it does illustrate the first use of the rich dataset that is available in the study. The presented approach is a baseline prototype that is a simulated representation of the observed freight transport demand database that is being used for further developing the agent based modeling framework.

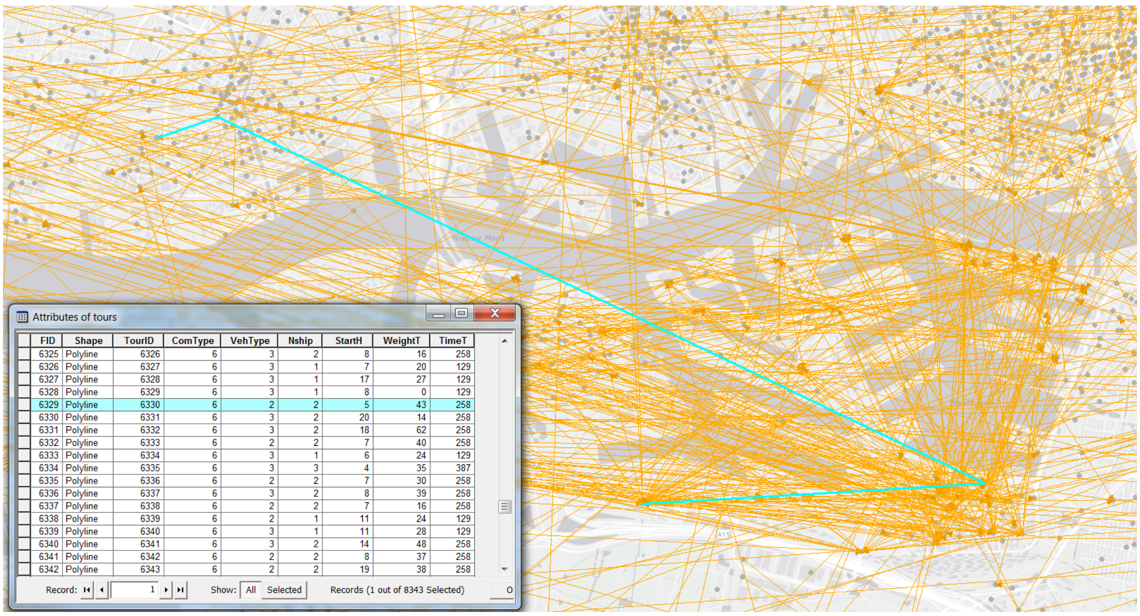

Figure 4: distribution pattern of truck trips within Rotterdam for commodity type NST/R 6 (Building materials, minerals)

5. First logistic choice models

The next step in the development strategy is to develop a simultaneous vehicle and shipment size choice model, and a tourformation choice model. We present a sneak preview of this next step by presenting the first basic specifications for these two logistic choice model. We will elaborate these models in the coming months.

5.1. Simultaneous vehicle and shipment size model

The vehicle and shipment size model simulates the vehicle type and shipmentsize choice simultaneously. Because these decision are very much interrelated (Hall, 1985) we choose to simulate the decision simultaneously. The empirical literature on simultaneous shipment- and vehicle type choice is rather scarce: Holguín-Veras (2002), Holguín-Veras et al. (2011), Abate and De Jong (2014) are the only examples known to the authors. We distinguish 14 vehicle types, categorized by 7 vehicle types (truck 0 – 10T/ truck 10 – 25 T/ truck > 25 T / truck+trailer < 15 T/ truck+trailer > 15T/ tractor+trailer/ special vehicle) and two emission classes (low/high). Six shipment size categories are distinguished: <3T/3-6T/6-10T/10-20T/20-30T/>30T. This results in a total of 84 alternatives, unique vehicle type and shipment size combinations, in the MNL choice model for simultaneous vehicle and shipment size choice.

The cost function is specific for each vehicle type m, shipment size q and emission class e. It is based on time- and distance costs, with vehicle type specific unit prices, $cd_{m,e}$ and $ct_{m,e}$. The number of vehicles required is calculated based on the ratio of shipment size and carrying weight of the vehicle, CW_m, rounded up to nearest integer:

$$C_{m;q;e} = (cd_{m,e} \cdot d_{ij} + ct_{m,e} \cdot t_{ij}) \cdot \left\lceil \frac{S_q}{CW_m} \right\rceil \tag{4}$$

In this paper we present a basic MNL specification in which we estimated a choice model based on transport costs, alterative specific constants for each vehicle and shipment size category, and interaction dummies between urban density and vehicle type. These results can be found in Table 5.

Table 5: Estimate results for commodity group 1 and 2 (significance codes * = 0.05, ** = 0.01)

			Commodity group 1 General cargo	Commodity group 2 Bulk
Number of observations			9178	6094
Log-likelihood (C)			-19382	-17185
Final Log-likelihood			-19131	-16341
ρ^2 (C)			0.013	0.049
Costs			-0,0021**	-0,020**
Vehicle type:				
Truck	< 10 ton (ref)		0	0
	10 - 25 ton		-1,370**	1,93**
	> 25 ton		-2,425**	1,59**
Truck + Trailer	< 15 ton		-0,115	-0,74**
	> 15 ton	all	1,311**	-1,52**
		urbandensity orig	-1,18**	
		urbandensity dest	-1,72**	
Tractor + trailer	all	all	2,921**	3,01**
		urbandensity orig	-1,18**	3,19**
		urbandensity dest	-1,72**	-2,75**
Special vehicle	all		-3,647**	
Shipment size:				
Ship. < 3 ton (ref)			0	0
Ship. 3 - 6 ton			-2,14**	-1,47**
Ship. 6 - 10 ton			-3,10**	-1,42**
Ship. 10 - 20 ton			-2,94**	-0,06**
Ship. 20 - 30 ton			-1,21**	1,43**
Ship. 30 - 50 ton			-2,32**	0,78**
Emission class:				
High Emission class			0	0
Low Emission class			3,00**	1,81**

The estimations show that vehicle and shipment sizes can be explained by transport costs: the estimated parameter for transport costs has the expected sign and is significant. Furthermore, commodity group 2 (bulk) are more cost sensitive compared to commodity group 1 (general cargo) which is a plausible result.

If the urban density is high, the probability to use tractor + trailer and truck + trailer in highest carrying capacity decreases, which is evidence that these larger vehicle types are much less used for delivery or pick-ups in the city centers. This evidence was found for the first commodity group, general cargo. For bulk we found a negative parameter, lower probability, for using tractor + trailer for urban deliveries. For pick-ups, the parameter is positive: this was first unexpected but can be explained by a large number of truck trips that start from a port terminal, generally also with a high urban density.

Currently, more elaborate specifications are being tested, where we include more information on the commodity's (NSTR chapter) and more specific location attributes about the loading and unloading locations, such as logistical node (multimodal terminal or DC).

5.2. Tourformation model

In order to include logistic choice behavior behind the tourformation model, we are using the observed truck tour patterns to estimate discrete choice models. We are applying an incremental logit model to simulate tour formation based on shipments. Similar examples have been applied in literature, most of which are trip-based (Hunt and Stefan, 2007; Wang, 2008; Kim and Park, 2017), and few are commodity or shipment-based (Nuzzolo et al., 2012; Outwater et al., 2013). In our approach we distinguish two sequential models: first the decision to add a shipment to the tour, and second, to select a shipment to be added to the tour.

The 'end tour' model is a binary choice model where the outcome is 0, continue adding a shipment to the tour, and 1, end tour. From the descriptive statistics we know that the probability of ending the tour after the first shipment is structurally higher, than ending tour with multiple shipments, so we estimate two separate end tour models: one for the first shipment, and one for later shipments. The probability of ending a tour will be explained using different attributes of the shipment, vehicle type and loading/unloading locations. Table 6 presents the first models that were estimated for the first- and later shipments. The basic models show significant and plausible parameters. When the vehicle capacity is utilized more, the probability to end the tour is higher, both for the first as later shipments. The probability to end the first tour is higher when the tour duration is lower: this result is also found in Nuzzolo et al. (2010), and the result is interpreted as evidence that there is a desire to construct simple tours for short distance transports. It was also found that if the distance to the nearest shipment is shorter, the probability of adding a shipment is higher.

Table 6: First estimation results of the end tour choice model.

	First shipment	Later shipments
Number of observations	23206	20308
$R^2_{Nagelkerke}$	0.778	0.172
-2 LL	11848	18531
Explanatory variables	Beta (S.E.)	Beta (S.E.)
Constant		-3.211 (0.065)
Tour duration [h]	-2.012 (0.109)	0.149 (0.009)
Transported weight / vehicle capacity	4.889 (0.067)	0.902 (0.023)
Distance nearest shipment [km]	0.003 (0.001)	0.006 (0.000)
Number of stop locations [ref: 1-2]		
Number of stop locations [3]		2.368 (0.093)
Number of stop locations [4]		1.270 (0.069)
Number of stop locations [5]		0.792 (0.090)
Number of stop locations [6-10]		0.634 (0.074)
Number of stop locations [>10]		0.731 (0.056)

The 'select shipment' model is a multinomial logit model where a shipment is selected from a choice set with a discrete number of shipments. A choice set composes of the observed additional shipment, and a randomly sampled number of shipment alternatives that are drawn from the universal choice set. This universal choice set comprises of all the shipments that a carriers is transporting on the specific date. In the first model estimation we constructed choice sets of 6 alternatives: the chosen shipment plus five sampled alternatives from the universal choice set. Table 7 presents the first model that was estimated for the select shipment model.

Table 7: First estimation results of the select shipment choice model.

Number of observations	15062
$R^2_{McFadden}$	0.487
LL	-13835
Explanatory variables	Beta (S.E.)
Additional generalized cost [€]	-0.049 (0.004)
Additional number of stops [ref. 0]	
Additional number of stops [1]	-1.008 (0.029)
Additional number of stops [2]	-6.525 (0.129)

As can be seen, the additional transport costs of the next shipment is significant: so carriers will try to minimize additional transport costs in constructing freight tours. Depending if the additional shipment has a shared origin or destination with a previous shipment, it will lead to 0, 1 or two additional stop locations for loading and unloading. Shipments that have more shared loading- or unloading locations. The negative and significant parameters for 1 or 2 additional stops confirm that shipments that don't have shared loading- or unloading points with the shipments in the tour, have lower probability of being selected. Currently, more elaborate specifications are being tested, where we include more attributes into the tour formation choice models such as the commodity type of the goods, location attributes of the loading and unloading points, such as logistical node (multimodal terminal or DC), or urban density.

6. Discussion and further research

We present a data driven simulation model for urban freight transport patterns. The prototype simulates representative truck patterns for an average working day for an urban agglomeration in The Netherlands: Rotterdam. This prototype is a first step in the incremental development of an urban freight agent based simulation framework. It is still based on monte carlo simulation and observed descriptive statistics and it does not contain choice models for logistic agent behavior yet. We have also presented the first logistic choice models that are being developed to implement in the second protoype. The objective of this step-wise development strategy is to manage simulation complexity during the development of the model. First of all, experience from the prototype development help in optimizing the simulation structure of the agent-based framework. A second advantages is that results from prototypes, such as a synthetic projection of commodity- and truck type specific freight trip patterns, can be useful inputs to other analyses.

The prototype contains the agents (producing and consuming firms), synthetic shipments, and a baseline tour formation procedure. It is the objective of the next research step to extend this framework with choice behavior for the respective agents. The available data is extensive: above 30 thousand observed freight transport observations (from both own account carriers as 3PL's). The individual observations provide a strong basis for empirical analysis and the formalization of empirical choice models for logistic choice behavior. The described example of the first prototype already reveals a bit of the possibilities with the data that is available in this study, and the level of detail and potential for analysis in simulation outcomes.

The tour formation and simultaneous shipment- and vehicle time choice models that are currently being developed, will be implemented into the framework once completed. In this step we will also increase the study area to the province of South Holland (population 3.3 M). The following increments will focus on extending the framework in different directions. One development step is to develop an interface with a network assignment model: first to generate network performance indicators and secondly to simulate route choice behavior. Another step will be the implementation of the distinction between own account carriers and shippers that outsource their transports. The available data provide all statistics to implement this distinction.

Acknowledgements

The work reported in this paper follows from a collaboration project with the Dutch Central Bureau of Statistics. The authors are greatly thankful for the Central Bureau of Statistics for providing access to their transport statistics. Any interpretation or opinion expressed in this paper are those of the authors and do not necessarily reflect the view of the Central Bureau of Statistics.

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