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Procedia Computer Science 170 (2020) 771–778

Procedia Computer Science

www.elsevier.com/locate/procedia

The 9th International Workshop on Agent-based Mobility, Traffic and Transportation Models, Methodologies and Applications (ABMTRANS)
April 6-9, 2020, Warsaw, Poland

# A large-scale, agent-based simulation of metropolitan freight movements with passenger and freight market interactions

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**Abstract**

This study summarizes the first stage in the implementation of an agent-based freight modeling system that has a global representation of agents and detailed modeling of a large-scale transportation network. The model is used to evaluate the transportation and energy impacts of goods movement across urban and national scales. The framework is implemented within POLARIS, a C++-based Planning and Operations Language for Agent-based Regional Integrated Simulation, which consists of an activity-based modeling (ABM) and dynamic traffic assignment (DTA) system that has robust features for passenger travel. This platform provides a tool to model interactions among consumers, producers, and the transportation system. The main objective of this initial implementation is to implement a freight model within POLARIS following an agent-based paradigm with behavioral and simulation methods. This paper presents the initial framework and illustrates the application of the model. Building upon earlier works, a parcel location assignment algorithm for business establishments in the population is documented, along with a method for estimating establishment production and consumption volumes. In addition to population generation, other features of the model include push-pull supply chains, multimodal path choice, choice of transportation logistics node, and dynamic traffic assignment. A module with e-commerce supply and demand was also developed to analyze the effects of e-commerce delivery on last-mile energy use and congestion.



*Keywords:* Agent-based freight; POLARIS; e-commerce; push-pull; supply chain; logistics; parcel location

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10.1016/j.procs.2020.03.157

## 1. Introduction and background

Transportation demand models are powerful tools for evaluating current and future demands on transportation system. They feature prominently in energy and emissions analysis due to transportation's effects in these areas. Including freight modes in transportation models is critical for accurate assessment of the transportation impacts.

**Nomenclature**

| | |
|---|---|
| ABM | agent-based model |
| DTA | dynamic traffic assignment |
| VMT | vehicle-miles travelled |

For instance, freight trucks comprise about 10 percent of VMT in the US and consume about 30 percent of transportation energy [1]. If freight is left out of transportation demand models, then a large part of VMT, energy and emissions cannot be sufficiently accounted for.

However, modeling freight transportation has many challenges, which are mainly due to the large variety of agents that are involved with freight production, consumption, or carriage, as well as the wide array of options that are available to these businesses in forging business partnerships, choosing modes of transport, and other decisions. Further, they operate in a global environment, which complicates the decision-making process and expands the number and nature of agents that are relevant to local agents.

Aggregate models, which are designed mainly for estimating total flows or trips ([2], [3]) at the zonal level, often focus on major decision factors such as distance while ignoring more nuanced factors. For instance, early models generally did not consider logistics activities, such as transloading, that often occur on the shipment journey. Subsequently, models such as [4], [5] and [6] began to include logistics in shipment paths but still had some limitations due to the use of aggregate techniques.

To address these complexities in the freight environment, the authors proposed a detailed freight demand forecasting framework [7] that utilizes an existing integrated ABM with DTA platform [8]. In the full framework, variety among businesses is handled by using individual agents. Interactions are handled by modeling behavioral and economic preferences of agents. Agent response to potential partnerships and their environments can be handled by modeling their behavioral preferences – in this model, strategic choices are explicitly made, which have major impact on transportation externalities [9]. Responses to traffic conditions are evaluated using DTA. Design features to address major gaps in extant agent-based freight models, which focus on both trucks as agents [10] and on businesses as agents (examples include [11], [12], [13], [14], [15], [16]), were planned in detail. These earlier efforts are limited in the way they handle agent interactions, especially shipper-carrier relationships and firm partnerships. Further, the full proposed model introduces several important key features, including modeling of strategic decisions, the operationalizing of the push-pull boundary, and key emerging trends. Other frameworks are relevant but have not been fully implemented: ([17], [18]) elaborate on agent decisions and interactions, such as contractual relationships, and to some extent covers sensitivities to emerging trends in policy, business and technology.

Due to the number of features to be modeled, it is not possible to develop all features immediately. Therefore, an incremental development approach is used wherein major elements from each stage of the model are implemented, in some cases with placeholder model formulations and parameters, in order to operationalize the model. This document, then, describes the initial implementation of the model. The initial implementation is centered on the Chicago metropolitan region in the Midwestern US. Thus, the model contains the most detail for this region while also including agents and transportation network features that are external to the region.

The rest of the paper focuses on this initial implementation. First, an overview of the model architecture is presented and its key conceptual and operational features are summarized. Second, each component of the initial model is presented in more detail. Test results are shown for various components in order to demonstrate the application. Finally, a summary and listing of next steps is presented.

## 2. Approach: model overview

Three tiers serve as a schematic guide for the full framework (Fig. 1, left pane) [19] in order to frame an understanding of agents, decisions, and the operational structure of the model for implementation in a computational framework. In the strategic layer, model agents make long-term (3 mo.-1 yr.) decisions regarding business-to-business collaborations, trade more generally, and transportation and logistics capacity. They form strategies that guide their long-term as well as short-term activities. Our model focuses on sourcing, sales, and transport strategies since these types of strategies have a major impact on origin-destination patterns and transport decisions, which are both pivotal to simulating freight transportation. In the medium-term (1 day-3 mo.) tactical layer, agents engage with their collaborators to arrange specific trade activities—in particular, the virtual exchange of shipments and planning of associated transportation and distribution activities. Practical plans such as driver schedules emerge here. The operational layer simulates the resulting physical flows of vehicular traffic. It also models short term (<1 day) decisions of agents such as route changes, parking decisions and fulfillment of express (1-2 hour or same-day) delivery demand. An e-commerce delivery module, which is coupled with a household-level e-commerce module from the POLARIS passenger component, currently feeds into the DTA also. The right pane of Fig. 1 demonstrates the structure of the initial implementation and illustrates which features are used in the initial version.

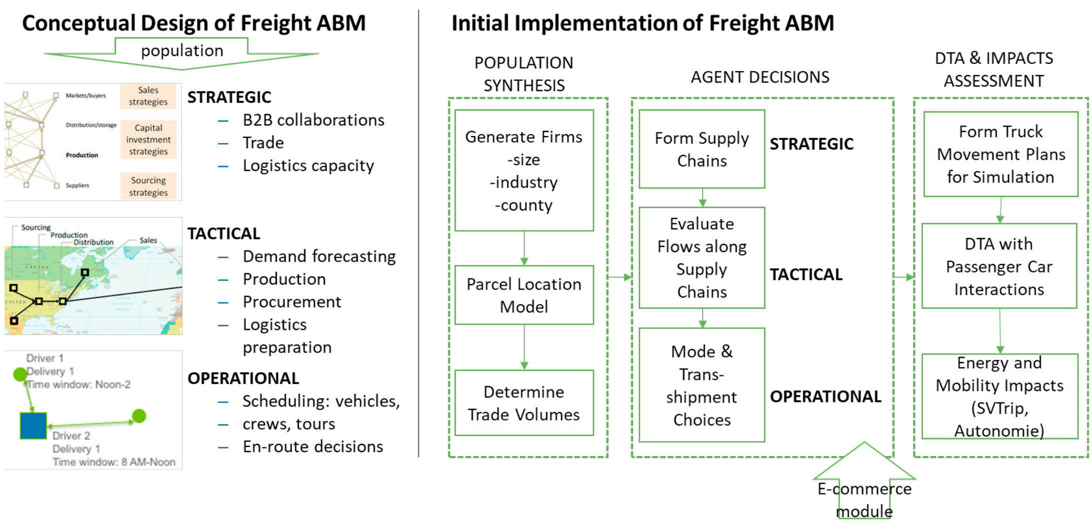


Fig. 1. (a) Conceptual features of model; (b) Flowchart of initial model implementation.

The level of geographic detail and network resolution in each layer differs as shown in Table 1 below. Locations of establishments outside of the region are currently at a coarse geographic resolution between US counties and regions of the world. Thus, the framework incorporates the ability to model a wide span of geographies. The initial e-commerce module includes last-mile delivery trips, i.e., trips from depots to homes and businesses.

Table 1. Geographic level of detail for each layer of the model.

| Layer | Establishment location in Chicago Region | Network |
|---|---|---|
| **Strategic** | County | Sketch representation of major links and nodes |
| **Tactical** | Parcel | Sketch representation of major links and nodes |
| **Operational** | Parcel | All links and nodes |

## 3. Implementation, data and results

This section presents the implementation of the model, with data requirements and initial results discussed for each stage. Data from POLARIS' passenger transportation modules are also used, including: transportation network and land use data from the Chicago Metropolitan Agency for Planning; population data from the US Census Bureau; and, for validation, traffic count data from the Illinois Department of Transportation.

### *3.1. Population synthesis*

Currently, model agents include business establishments that engage in trading goods. They may produce goods, consume goods, or both. The agent population is generated by enumerating the number of establishments in each US county based on industry category and size (number of employees). The input data for this is the US Census Bureau County Business Patterns (CBP) data. Fig. 2 shows how the input data are transformed into a set of model agents.

| NAICS code | County | 1-5 employees | 6-10 employees | 11-20 employees | |
|---|---|---|---|---|---|
| … | | | | | |
| 313110 (Fiber, yarn and thread mills) | DuPage | 2 | 0 | 1 | … |
| … | | | | | |

| NAICS code | County | Employees |
|---|---|---|
| … | | |
| 313110 (Fiber, yarn and thread mills) | DuPage | 1 to 5 |
| 313110 (Fiber, yarn and thread mills) | DuPage | 1 to 5 |
| 313110 (Fiber, yarn and thread mills) | DuPage | 11 to 20 |
| … | | |

Fig. 2. (a) Input data: marginal population totals; (b) Output data: synthetic population.

Next, each agent is assigned to a specific location for simulation purposes. This is needed because counties are quite large (on the order of one hundred square miles). Let *i* denote an index for the set of industries *I*, *z* denote an index for the set of zones *Z*, $p_z$ denote an index for the set of parcels in zone *Z*, and *e* denote an index for the set of establishments *E.* The parcel location algorithm quasi-code is as follows:

For every *i* in *I*:
    For every *z* in *Z*:
        Compute $S_{iz}$ = Sum($\text{Employment}_{i,z}$)
        Determine ranking $R_z$ (order from highest to lowest) based on $S_{iz}$
    For every *e* in *E*:
        Form set of candidate zones, $Z_c$ as follows:
            For firms with 5,000+ employees, $Z_c$ = zones with highest $R_z$
            …
            For firms with 5 employees, $Z_c$ = all zones
        Use Monte Carlo draws to assign a *z* to *e*

Finally, after assigning each establishment to a zone, its exact parcel location within the zone is simulated using a Monte Carlo draw from the set of all parcels with a commercial land use in that zone. Fig. 3 shows the synthetic agents in the Chicago region at their simulated locations.

Trade volumes, or production and consumption volumes, are then assessed for each establishment. To do so, first a set of rates is computed for each industry. The input data for the rates are the CBP data and the US Department of Transportation Federal Highway Administration Freight Analysis Framework (FAF) data, which has the dollar value of freight flows that are produced and consumed in various areas of the country. The FAF data are in terms of commodity flows, therefore assumptions were used to create a crosswalk between commodity type and industry type that produces or consumes each type of commodity. First, total employment by industry is summarized using the CBP data. Next, total production and attraction values are divided by employment in each industry to estimate the value produced and consumed by each employee in each industry for a given commodity type. Finally, using these rates, production and consumption volumes are simulated for each model agent based on industry type and number of employees.

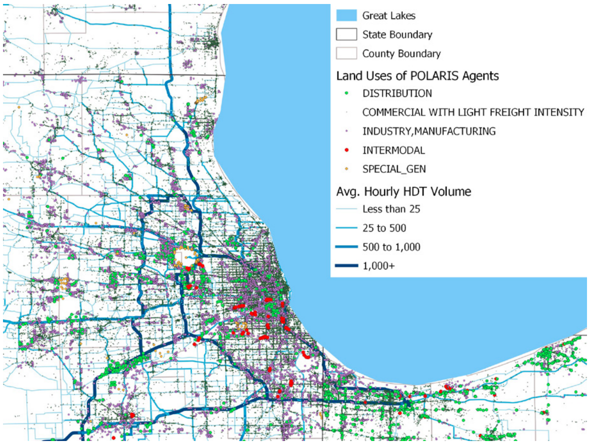


Fig. 3. Synthetic population with parcel locations in the Chicago metropolitan region.

## 3.2. Supply chain formation and flow evaluation along supply chain

Ultimately, a relatively elaborate scheme of collaborations among business is planned for implementation. For now, a supplier selection model is used wherein each buyer selects a supplier to supply an input commodity. First, a candidate set of suppliers is formed by randomly drawing ten potential suppliers based on the suppliers' production industry and simulated production volume. Second, the well-known Multinomial Logit model [20] is used to select a supplier based on its characteristics as well as a stochastic element. The utility formula is a placeholder as data for specifying a model and estimating its parameters are currently being collected. The utility of supplier $s$ for the initial model is $U_s = \boldsymbol{\beta}'\boldsymbol{X_s} + \varepsilon_s$ where $\boldsymbol{\beta}$ is a vector of parameters to be estimated, $\boldsymbol{X}$ is a vector of supplier attributes that includes its size, location (foreign vs. in-region vs. other US-not in region), and distance to the buyer; and $\varepsilon_s$ is an error term. Fig. 4 illustrates this process.

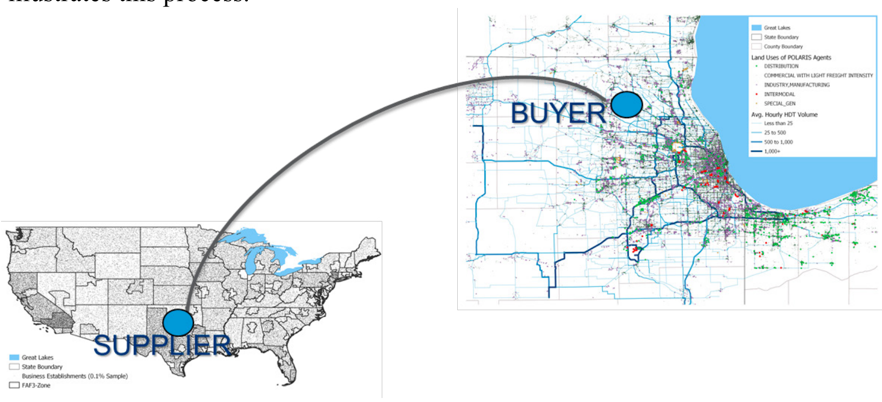


Fig. 4. Supplier selection (supply chain formation).

At this time, the amount of flow is assumed to be the consumption volume that is needed by the buyer. In the future, the methodology will be revised to account for the production capacity of the seller.

In the remaining downstream areas of the model, the buyer-supplier pair are treated as a single decision maker, as from this point they are effectively working together to furnish the needs of the buyer.

### *3.3. Mode and transshipment (path) choices; and DTA*

In this step, mode and transhipment path options are chosen for each shipment. The model is multimodal and includes the following modal options: rail carload, rail-truck intermodal, full truckload (FTL), less-than-truckload (LTL), parcel, and air. Transshipment locations are included as part of the multimodal path option. These options include:

- Choice of airport (O'Hare, Rockford, Midway, etc.)
- Choice of trucking terminal / crossdock location (for LTL / FTL shipments)
- Choice of rail terminal (e.g., BNSF Global-I)

The methodology used for path selection is as follows ([21], [22]). For supplier-buyer pair and each candidate path, the optimal shipment size and frequency is determined based on commodity characteristics, which is consistent with inventory theory. The first characteristic is discount rate, which covers the cost of physically storing goods (e.g., warehousing leasing rates) as well as perishability factors. The second characteristic is the value of the good, which is normalized as the value density in dollars per pound. Goods are distinguished as Bulk, Intermediate, and Finished goods, with discount rate and value density varying by these distinctions. The optimal shipment size $Q^*_p$ for path $p$ is calculated as:

$$Q_p^* = \sqrt{\frac{2DC_{order}}{C_{holding}}}$$

where $D$ is annual demand, $C_{order}$ and $C_{holding}$ are the order and holding costs, respectively. Order cost is computed as the value density divided by the square of path transportation cost per unity weight while holding cost is the value density multiplied by the discount rate.

Total relevant path cost, $TRC_p$, using path $p$ is then computed as the sum of total transportation cost, total order cost, total holding cost, and total pipeline inventory cost over the annual demand time horizon, which is one year. Transport cost is the unit cost multiplied by distance and $D$. Order cost is the unit order cost multiplied by $D$ and divided by $Q^*_p$. Holding cost is the unit holding cost multiplied by $Q^*_p$ and divided by two. Pipeline inventory cost is unit holding cost multiplied by $D$ and the transit time.

Finally, path selection is performed as follows. First, the inverse square root of $TRC_p$ is computed for each path $p$. Second, the sum of these inverses is computed, and the proportion of the sum is computed for each $p$. Third, Monte Carlo draws are used to select a path based on these proportions. Although this process is somewhat ad hoc and serves as a placeholder for a more carefully specified, data driven model and parameters, it is effective in guiding agents toward selecting modes and transhipment locations that are relatively low cost yet account for tradeoffs in inventory and transport costs.

To illustrate the output, mode shares for agriculture, hunting, fishing and forestry products, which are bulk goods, as estimated by this process are shown in the left pane of Fig. 5 below. The right pane of the figure is a bandwidth plot of heavy duty truck (HDT) traffic volumes into, out of and near the Chicago O'Hare International Airport, which illustrates results of the transhipment location selection aspect of the path decision.

For the DTA, each shipment is assigned to one vehicle trip. Fleet selection for each establishment as well as routing algorithms are in progress and will provide a significant enhancement to the current process. For now, Monte Carlo draws are used to simulate the use of truck type and powertrain features. For purposes of brevity, this process is not described in detail here.

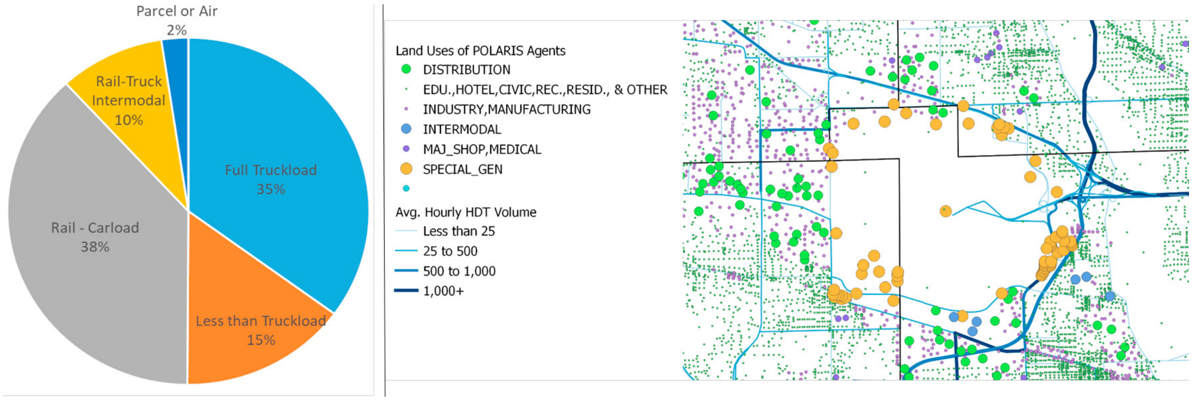


Fig. 5. (a) Mode shares of bulk goods; (b) Truck volumes near O’Hare Airport.

### 3.4. E-commerce module

The e-commerce module is fully documented in [23]. Briefly, its workings can be summarized as follows. Demand for e-commerce deliveries is generated for each household in the metropolitan region. The demand estimates are provided to an external procedure that uses Python scripting and Geographic Information Systems (GIS) to generate delivery routes for the demand based on observed depot locations and the traveling salesman algorithm. The resulting parcel delivery truck tours are fed into POLARIS. In this way, the demand and supply features of e-commerce behaviour interact. This process is targeted to be fully integrated within POLARIS in the future. Example output from this process is shown below in Fig. 6, which illustrates the individual and combined VMT by medium-duty delivery trucks (MDT) and light-duty shopping vehicles (LDV) in the baseline (one delivery per household per week), short-term A scenarios (three deliveries per week) and long-term B/C scenarios (five deliveries per week) with other varying conditions such as high levels of autonomous vehicle penetration in the C scenarios. Full details on the scenario results are available in [23].


Fig. 6. Estimated VMT associated with last-mile retail activity.

## 4. Summary and next steps

This paper presented the initial development of a freight ABM with DTA. The model structure includes population synthesis as well as agent decision making in the strategic, tactical and operational spheres, and ultimately truck movements that are assigned along with passenger vehicles in a transportation network. Demonstration results for population synthesis, the parcel location algorithm, mode choice, and transhipment location choice have been provided along with an e-commerce application with VMT impacts. Future steps include developing the remainder of the framework according to the proposed outline presented in [7].

## Acknowledgements

The submission has been created by UChicago Argonne, LLC, Operator of Argonne National Laboratory ("Argonne"). Argonne, a U.S. Department of Energy Office of Science laboratory, is operated under Contract No. DE-AC02-06CH11357. The U.S. Government retains for itself, and others acting on its behalf, a paid-up, nonexclusive, irrevocable worldwide license in said article to reproduce, prepare derivative works, distribute copies to the public, and perform publicly and display publicly, by or on behalf of the Government. Argonne National Laboratory's work was supported by the U.S. Department of Energy, Office of Vehicle Technologies, under contract DE-AC02-06CH11357.

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