MULTI-AGENT MODELING FOR CITY LOGISTICS POLICY ANALYSIS: POTENTIALS AND CHALLENGES

Nilesh Anand, Technical University of Delft
Ron van Duin, Technical University of Delft
Lori Tavasszy, Technical University of Delft

Abstract
Heterogeneous stakeholders with diverse interests and distributed decision making process add complexity and unpredictability in the large city logistics domain. This complexity demands well designed approach for policy analysis which cannot be achieved by traditional modeling techniques due to their restrictive hypothesis. Multi-agent modeling for city logistics policy analysis focuses on understanding urban freight movement not based either on buying-selling and supply-demand of commodities or aggregate totals of demand, but on importance of under what structures these forces play out, and how to measure these effects in order to determine effective policy measures for city logistics. Multi-agent system provides potential to meticulously replicate the urban freight movement by mapping complexity of domain, time and discipline simultaneously. Describing the domain naturally & flexibly and capturing its emergent behavior are other benefits of multi-agent modeling. Along with these potentials, some of the important challenges associated with developing multi-agent system for city logistics policy analysis such as describing different stakeholder roles, restricting the scale of the model, designing environment with all affecting factors, developing interaction mechanism and defining scope for the model are discussed.

Introduction
Regardless of its importance in city life, city logistics always got less concern in policy making (Van Duin and Quak 2007) (EU-Report) Frequent delivery, inefficient use of trucks, poor routing, improper/unauthorized (un)loading, high emission vehicles are primary reasons for poor accessibility, congestion, air and noise pollution in cities. Vehicle access restriction (size, time and

emission), urban freight village, consolidation centers are some of the most tried policy measures and initiatives to solve these problems (Muñuzuri, Larrañeta et al. 2005). Although, there exist policy measures for city logistics process, field of city logistics policy making is still in its immature stage. This immaturity is directly connected with its methods used for policy making. The most widely used traditional modeling techniques are differential equations and statistical modeling. However, their uses are restrictive in many problems because of unrealistic assumptions they carry like linearity, homogeneity, normality, and stationarity etc. (Bankes 2002) Heterogeneity of stakeholders, coupled with changing level of information, decision factors and scenarios, creates dynamic and complex city logistics processes. For successful city logistics policy analysis there is a need for a tool that can deal with such deep uncertainly and provide insights about urban freight movements not easily captured with traditional domains. Multi-agent modeling for city logistics policy analysis focuses on understanding city logistics processes at meso-scale that describes the urban freight movement not based either on the micro scale of buying -selling and supply-demand nor on the macro scale of aggregate totals of demand, but on the importance of under what structures these forces play out, and how to measure these effects in order to determine effective policy measures for city logistics.

Literature review

City logistics associated problems have stirred research interest among government, researchers, companies and environmentalists equally for acquiring better knowledge about city logistics to aid policy analysis process. The survey of urban freight modeling by BESTUFS (Browne, Piotrowska et al.) shows that countries like Italy, Spain, UK, Belgium, Netherlands, Germany and France actively use some kind of modeling for policy analysis in city logistics domain. These models are used primarily to understand qualitative and quantitative pattern of urban freight related problems, to understand the policy impacts and to study other city freight related situations. A variety of methodical approaches are identified for the similar challenges because of different level of importance (i.e. congestion, pollution, safety etc) apropos to different country, however, no model covers dynamic of city logistics. Instead, these models consider the static movements of goods and aggregate them in one equation to find the solution. Additionally, these modeling efforts mostly focus on infrastructure optimization and traffic improvement without considering the goods movement, which make them poor predictors of city logistics scenarios. Conclusively, city logistics policy mostly follows “Learning by doing” approach with very limited or no use of modeling or scientific approach.

FRETURB (Routhier and Aubert 1999) is a land use and tour-based model of urban goods transport developed in France. It consists of pick-up and delivery model, town management and purchasing trips model. Although this model takes into account the urban organization of the logistic chains, it does not fit in the operational optimization of routing. WIVER (Meimbresse and Sonntag 2001) is a behavior-oriented simulation model from Germany, which is able to consider explicitly the complexity of urban trip chain pattern focusing on different vehicle classes. The model can compute traffic values for different sectors with respect to logistic activities of sector. It considers purpose of trip, efficiency of tour, distribution of trips over time etc. However, it only models the logistics activity in the urban region without considering the decision making system of city logistics stakeholders. GoodTrip (Boerkamps, van Binsbergen et al. 2000) is urban freight transportation model developed in Netherlands. It links economic, logistic, traffic & transport and environmental data with one another, using a so-called logistic chain of urban freight transport. The model was used to compare alternative urban freight transport concepts in environmental and amenity terms in a qualitative way. According to the author, pick-up and delivery of goods in urban areas can be so diverse and complex that a typology in terms of trips, load factors, delivery frequency cannot be given, especially not in dynamic and quantitative terms. Thus, this model uses static approach that means the space and time (windows) play no role, enabling straightforward modeling.

(Davidsson, Henesey et al. 2005) gives comprehensive review about use of agent technology for transportation and traffic management asserting there are few fielded experiments have been performed and very few deployed systems could be found. Also, evaluation of model is inadequate as comparisons with existing techniques and systems are rare. They conclude agent based transportation modeling and its use for strategic decision-making is still in its juvenile stage. However, some modeling efforts are still noticeable. A microsimulation model for urban freight movement in Tokyo metropolitan area is presented by (Wisetjindawat, Sano et al. 2007) . The model consists of commodity generation, commodity distribution, conversion of commodity flows to truck flows and traffic assignment. The model uses concepts of logistics and operation research to explain the behavior of each freight agent while dealing with freight movement using Monte Carlo Simulation. (van Duin, Tavasszy et al. 2007) describes a model which looks at the feasibility of a hybrid system of contracting freight carrying services by co-operation mechanisms between shippers and carriers. In the model, different carrier-agents negotiate in auction for logistic contract. The model attempts to get insight on the interaction dynamics of bidding behavior among carriers and shippers through distributed intelligence. (Roorda, Cavalcante et al.) proposed a conceptual framework for agent based model of logistic service. The framework describes various roles of different stakeholders and representation of logistics service contracts in mathematical format. Authors assert that the (agent based) framework can represent business decisions ranging from fundamental long term decisions to short term operational decisions and thus provides sensitivity to a variety of technology trends, business trends, and policy scenarios that more conventional approaches cannot do to the same extent.

City logistics policy analysis using multi-agent system

City logistics deals primarily with three different domains, i.e. supply-demand, transportation network and traffic, where urban goods is common entity in all three domains (Van Duin and Quak 2007). Retailer, Suppliers, Logistics providers and administrators (i.e. municipality) are main actors (i.e. stakeholders). The social system created by different stakeholders act under several forces and, often, not only reactive but proactive, goal oriented, conflicting. Mathematical reduction of such a complex urban freight system by conventional modeling would not lead to success, especially when the interactions between the micro level entities are manifold (Haken 1977). Establishing each stakeholder as independent entity can help exploring dynamics of interaction due to distributed decision making. This can be achieved by developing number of functionally specific and nearly modular objects who can solve particular problem aspect. Combination of their interactive movement results into emergent complex system. This modular objects are called "Agent" in the artificial intelligence lingo. A system consist of many different agents is multi-agent system. It can be defined as a loosely coupled network of problem solvers that interact to solve problems that are beyond the individual capabilities or knowledge of each problem solver (Durfee, Lesser et al. 1989)

Each stakeholder in city logistics is an agent in multi-agent system. Each agent has certain goals to achieve and certain rules to follow. Retailer-agent chooses a supplier-agent based on cost of delivery (c_r) size of delivery (s_r), time of delivery (t_r) and cost of goods (g_r). Based on these variables, the objective function of retailer-agent looks like,

$$f_r(x) = f\,(t_r\,,\,c_r\,,\,s_r\,,g_r\,)$$

Similarly, objective function of supplier and logistics provider are:

$$f_s(x) = f\,(v_s\,,\,q_s)$$
$$\text{, where } v_s = \text{value of goods, } q_s = \text{quantity}$$

$$f_l(x) = f\,(d_l\,,\,v_l\,,\,k_l)$$
$$\text{, where } d_l = \text{distance, } v_l = \text{volume, } k_l = \text{vehicle capacity}$$

There are more than one retailer, supplier, logistics provider agent and different agent has different factors and constraints in objective function. These multiple agents with different objective function interact to reach a common goal of goods delivery from production unit to retailer shop (or consumer, depend upon the scope of model). Interactions among different agents contain different mechanism like negotiation, adaptive learning, cooperation, co-ordination etc. The system can have more agents other than supplier, retailer and logistics provider agents like mediator agents, administrative agent etc. With different settings, scenarios and regulations, different business cases can be created and simulated for better representation of city logistics process evaluate urban freight policy.

Challenges and potentials for multi-agent system in city logistics

In words of (Bonabeau 2002) “Agent based modeling is a mindset more than a technology and this mindset consists of describing a system from the perspective of its constituent units (i.e. Agents).” With many benefits of multi-agent system there exist many challenges too. The use of multi-agent system truly provides a new paradigm of process analysis but to create the multi-agent system which represent such a close to reality system is not an easy task. This paper attempts to list potentials of using multi-agent system for city logistics policy analysis and possible challenges in development of such a system.

Potentials

Mapping complexity of domain/time/disciples Decision making by different stakeholders at different domain (i.e. supply-demand, transportation network, traffic) decides the goods flow from one domain to another. In city logistics modeling, goods simulated entities (i.e. stakeholders, goods) follow all features at all level and so the "complexity" of domain to be modeled is same throughout the model, however, in multi-agent system the complexity varies with the level of domain which is more realistically captures the complexity. At the same time, the model captures different time scales at different level as for every kind of agent different mechanism representing time can be used (Brassel, Möhring et al. 1997). Agent can be given attributes to behave continuously or discretely and can play role according to need i.e. during event scheduling, synchronously or in round-robin manner. The decision making process in the urban freight transportation based not only on the economic objective function but also, sometimes significantly, on the type and magnitude of the relation between stakeholders (Hensher and Puckett 2005). The type of relation often depends upon factors like traits, expectation, length of relation etc. Thus, decision process counts this behaviors aspect which is connected with psychological discipline. Different types of vehicles available for the goods transportation in the city area require technical/engineering aspects in the modeling. Furthermore, among different stakeholders, some stakeholders are very inclined to take environmental measures in goods transportation and some completely ignore it, which include the social aspect in modeling agents. Agents can be applied various aspects, traits and different transition states to copy the real world scenarios and additionally, all these kinds of agents can be nested in each other. All these potential of multi-agent system allows integrating and simulating wider range of complexity of disciplines, which is distance aspect in any other classical simulation approaches.

Natural description of a system: Classical optimization theory can find solution to achieve highest efficiency for urban freight movements and minimize its negative effects. However, when each stakeholder is busy in pulling the rope on his side (i.e. maximizing his profit) the successful implementation of global optimization is more a benchmark than a practice. When the optimization is done at each retailer, supplier and carrier level, the concept of local optimization is more powerful and practical. City logistics processes are combination of activities (functions) by different individual, group or department. It is more realistic, when each agent (characterized with attributes to represents a stakeholder) carry out respective functions (i.e. ordering goods, scheduling vehicle etc), instead of performing the complete process (Bonabeau 2002). When all such “entities” interact with each other and work towards achieving a common goal (i.e. urban freight movements) while optimizing locally, the system provides natural description of domain to be analyzed. For example, a system has more natural description when different retailer, carrier and supplier agents decides their activities individually and their interaction creates the dynamics of domain then to come up with the equation that represents the dynamics of their decisions. Such description creates knowledge base about the processes for generating appropriate solutions of the problems associated with distributed decision making.

Flexibility: Urban freight transportation is very dynamic domain with continuous entry and exit of different stakeholders. Under this continuous change different stakeholders have to take decision which serves them best. Multi-agent system provides flexibility of entry and exit (birth and death) of agent in the system. Not only that but the agents can adjust/modifying their behavior, characteristics, learning ability, rationality etc. according to new situation (De Wolf and Holvoet 2003). Imitating urban freight domain, different stakeholder agents can create groups and sub groups (i.e. Retailers using service from urban consolidation center) to represent unique attributes under varying circumstances. Furthermore, it is possible to experiment with aggregate group, sub-group or single stakeholder-agent with different levels of description co-existing within a model. These stakeholder-agents have the ability to move within their environment, in different directions at different velocities which makes multi-agent system very flexible in terms of potential variables and parameters that can be specified. Neighborhoods can also be specified using a variety of mechanisms and implementation of agent interactions can be coordinated according to space, networks, or a combination of structures. Thi would be far more complex to model using traditional mathematics.

***Emergent behavior*:** Emergence is a special characteristic of complex domain like city logistics. Emergent behavior can appear when number of entities (agents) in an environment operates or interact and form a complex behavior as collective (Gilbert and Terna 2000). Two bakery owners in a town, though selling same goods choose different suppliers and different logistics service based on their calculation, decision factors variety and information availability. Similarly, other store owners use different supply facility and different transportation facility (including owning transport vehicles). This interaction among different suppliers, logistics providers and shop owners result in complex urban freight traffic. Together with characteristics like heterogeneity, dynamism, non-linearity, limited information sharing even a simple multi stakeholder system can exhibit very complex behavior pattern. Also, the number of interactions between city logistics stakeholders increases combinatorially with the number of stakeholders, thus potentially allowing for many new and subtle types of behavior to emerge which can be described as ‘aggregate complexity’. Such a complex emergent behavioral pattern is hard to capture with conventional methods used for city logistics modeling (such as optimization, statistical and probabilistic methods (Taniguchi and Thompson 2002)) for they consider static movements of goods and aggregate them in one equation. Properties of multi-agent system to describe system in a natural and flexible way give its an ability to capture such emergent behavior of system (Berry, Kiel et al. 2002) A modeler can model and simulate the behavior of the system's constituent units (i.e. agents) and their interactions, capturing emergence from the bottom up during simulation. It should be noted that in an emergent phenomenon the whole system cannot be reduced to the system's part (Bonabeau 2002) because the whole is more than the sum of its parts (due to interaction of parts).

Challenges

Role: In the process of city logistics, a stakeholder plays different roles in different situation and so his decision variable varies accordingly. For example, a typical retailer deals differently with logistics provider and differently with supplier. To add more complexity, it is possible that he/she may deal differently with two different suppliers. Thus, not all the relation that held with one supplier implies to other supplier too (Troitzsch 2009). While modeling any real entity in multi-agent system, it should be noted that it part of different settings at the same time. Thus it is noteworthy challenge to put different behavior or decisional characteristics in an agent, especially when an agent should be capable of understanding what behavior it should adopt in what situation.

Scale: Micro, Macro or Meso: As mentioned, multi-agent system focuses on Meso level analysis to understand interaction process of city logistics decision making for better policy analysis. However, implementing micro, macro or (especially) meso level is not as easy as describing them. Meso level is the intermediate level between macro and micro. It's the ladder process and meso level analysis connects micro and macro steps (Schenk, Moll et al. 2007). Fundamental objective is to create smooth city logistics process, i.e. at macro level. For that the starting point is to build model based on basic system elements (stakeholders), i.e. at micro level. Implementing policy regulation at macro level creates movements at micro level system elements (i.e. stakeholders). The interactions among stakeholders create meso scale and determine behavior at macro scale, i.e. city logistics traffics. Thus, the model is iterative process encountering all three levels but focusing on meso level.

Complexities arise while interaction (i.e. meso scale) no longer allows any stakeholder-agent to be completely controlled merely as individuals. Correspondingly, at this scale, intelligence embedded within agents is often not enough to build up intelligent systems. Thus the very notion of situated intelligence demands accuracy in design of agent society and agent environment. Thus a system should be designed at abstractions to support social intelligence, i.e., intelligence exhibited by agent societies, which canot directly be ascribed to individual intelligent (component) agents (Ciancarini, Omicini et al. 2000); also at the same time one needs to deploy suitable infrastructures shaping the agent environment so as to fully enable and promote the exploitation of both individual and social intelligence. The trade-off between these two criteria requires extra accuracy from the modeler. Transforming city logistics domain knowledge and knowledge about stakeholders in the system components and system level is one of the biggest challenges.

Environment: The complexity of urban freight domain is also an outcome of its setting, i.e. environment. Details for instance, information level, routes, physical distance between stakeholders, size of warehouses, number, size and technical advancement of vehicle and other factors affecting goods movements are very essential to create real-life model. The accuracy of such details gives perfection to the simulation model. Environment in multi-agent system is infrastructure where agents interact with domain objects, resources and other agents. Just like without adequate infrastructure a machine cannot work properly, in absence of proper environment a multi-agent system cannot produce desired result. As different agents have different scope and different degrees of freedom, the service and information available to them varies. By clearly defining the access level for each agent, environment should be able to restrict the information flow and ability of agent to influence the whole system. Thus, at *what* level and *how* the topology of real world should be embedded in multi-agent environment to synchronize scope of agents is to be determined cautiously.

Negotiation: Collaboration and coordination: In urban freight domain, different interaction occurs during decision making process for goods order, logistics contracting, routing, scheduling etc. This type of interactions can be information exchange, request for action or create consensus by cooperation or coordination (i.e. cargo consolidation). However, perhaps the most fundamental and complex interaction is *negotiation* – the process by which a group of stakeholders come to a mutually acceptable agreement on some matter, i.e. logistics contracting, collaboration, consolidation etc. Negotiation underpins attempts to cooperate and coordinate. As the agents are autonomous entities, agents need to understand or predict mechanism of other agents in order to close the deal (negotiation). Agent negotiation is considered to deal with three broad topics (Lomuscio, Wooldridge et al. 2003) (Jennings 1993) (Jennings, Faratin et al. 2001): 1) *Negotiation Protocols*: the set of rules that govern the interaction. 2) *Negotiation Objects*: the range of issues over which agreement must be reached i.e. price, quality, timings, penalties, terms and conditions, etc. 3) *Agents' Decision Making Models*: The sophistication of the model, as well as the range of decisions that have to be made, are influenced by the protocol in place, by the nature of the negotiation object, and by the range of operations that can be performed on it.

The relative importance of these three topics varies according to the negotiation and environmental context. In some circumstances the negotiation protocol is the dominant concern (Vulkan and Jennings 2000). For example, when a large retailer firm is hiring logistics services through auction then the system designer should determine what particular form of auction (e.g. English, Dutch, Vickrey etc.) can best organizes the negotiation. This mechanism choice constrains the types of operations that can be performed on the negotiation object (no counter-proposals or issue extensions) and prescribes the behavior of the stakeholder-agents' decision making models (e.g.

strategic behavior is pointless and the agents' dominant strategy is to simply bid up to their true reservation value). In other cases, however, when strategic negotiation closes the deal its stakeholder-agent's decision making model that is the dominant concern. Here, the protocol does not prescribe an optimal strategy for the agent and there is scope for strategic reasoning to determine the best course of action. In such cases, the relative success of two agents is determined by the effectiveness of their reasoning model – the better the model, the greater the agent's reward (Rosenschein and Zlotkin 1994).

For the negotiation mechanism design three approach are widely used; namely, game theoretic, heuristic and argumentation-based approaches. However, this is not exhaustive list and so given the wide variety of possibilities, it should be clear that there is no universally best approach or technique for automated negotiation. Rather, there is an eclectic bag of methods with properties and performance characteristics that vary significantly depending on the negotiation context. This makes negotiation process in multi-agent system interesting and challenging. While developing a business cases to check the collaboration possibilities among different stakeholders, one needs to carefully evaluate the real –life negotiation process. This requires examining the space of negotiation opportunities for autonomous stakeholders, to identify and evaluate some of the key techniques involved. This evaluation can provide a list of negotiation objects and negotiation protocols. With the help of these detail information agents' decision model determined. The care should be taken, nonetheless, that the negotiation among different stakeholders reaches to consensus and fulfills the objective of each agent.

Scope and delimitation: A multi-agent model for a town, a city or a cluster of cities give different information about decision processes even though the characteristics of agents are same. This fact forces us to define the scope of model and is highly depends upon the goal and objective of model (Troitzsch 2009). As claimed multi-agent system can track complex system, however, definition of complex system or complexity should have clear meaning or measure for particular model development. Complexity in city logistics emerges from dynamic interaction of different stakeholders and reacting to other agents' actions. So depending on number of stakeholders, interactions may arbitrarily high which leads to state space of agents with large number of dimensions. The model should be abstraction of reality to achieve the understanding of different factors affecting it. In case of city logistic defining a limit regarding number and types of stakeholders involved, physical boundary to be modeled, time representation (i.e. day, month or year), negotiation etc. is very essential and painstaking effort is unavoidable in performing that task. Also, the urban freight domain involves human beings (i.e. stakeholders) who possess potentially irrational behavior, subjective choices, and complex psychology. These factors are difficult to quantify, calibrate, and sometimes justify. This complicate the implementation and development of a model, as well as the interpretation of the simulation output. Furthermore, agent-based models can be more difficult to analyze, understand and communicate than traditional analytical/ mathematical models, as it is difficult to provide detailed descriptions of the inner workings of such models.

Conclusion

Multi-agent system holds key for many unrequited policy analysis problems in various domains that is impossible with other classical methodologies. However, at the same time precision required for developing such a system to reap all those benefits is challenging task and that goes without saying for city logistics domain as well. Along with multiple benefits, there are multiple challenges associated with multi-agent system development. In fact depending on the complexity desired and complexity of domain to be modeled more challenges will surface in future. Multi-agent systems are developed for many different domains and few attempts in logistics fields are (see literature review) also observed. In this paper we have tried to give a general ideal about potentials and challenges for multi-agent system focusing on urban freight transportation domains. Apart from common challenges most multi-agent system development faces, designing role, developing appropriate environment to inscribe agents, synchronizing with scale (i.e. macro, meso, micro), drawing boundary and developing negotiation skills for agents are found to be most important for the successful development of urban freight multi-agent model. Overcoming these challenges requires painstaking effort but assures in-depth understanding about urban freight transportation process for successful city logistics policy analysis.

Reference

Bankes, S. (2002). "Agent-based modeling: A revolution?" Proceedings of the National Academy of Sciences 99(Suppl 3): 7199.

Berry, B., L. Kiel, et al. (2002). "Adaptive agents, intelligence, and emergent human organization: Capturing complexity through agent-based modeling." Proceedings of the National Academy of Sciences 99(Suppl 3): 7187.

Boerkamps, J., A. van Binsbergen, et al. (2000). "Modeling behavioral aspects of urban freight movement in supply chains." Transportation Research Record: Journal of the Transportation Research Board 1725(-1): 17-25.

Bonabeau, E. (2002). "Agent-based modeling: Methods and techniques for simulating human systems." Proceedings of the National Academy of Sciences of the United States of America 99(Suppl 3): 7280.

Brassel, K., M. Möhring, et al. (1997). "Can agents cover all the world?" LECTURE NOTES IN ECONOMICS AND MATHEMATICAL SYSTEMS: 55-72.

Browne, M., M. Piotrowska, et al. "Literature Review WM9: Part I - Urban Freight Transport ".

Ciancarini, P., A. Omicini, et al. (2000). "Multiagent system engineering: the coordination viewpoint." Lecture Notes in Computer Science: 250-259.

Davidsson, P., L. Henesey, et al. (2005). "An analysis of agent-based approaches to transport logistics." Transportation Research Part C 13(4): 255-271.

De Wolf, T. and T. Holvoet (2003). Towards Autonomic Computing: agent-based modelling, dynamical systems analysis, and decentralised control, Citeseer.

Durfee, E., V. Lesser, et al. (1989). "Trends in cooperative distributed problem solving." IEEE Transactions on knowledge and data Engineering 1(1): 63-83.

EU-Report "An overview of the European research and policy."

Gilbert, N. and P. Terna (2000). "How to build and use agent-based models in social science." Mind & Society 1(1): 57-72.

Haken, H. (1977). Synergetics: an introduction: nonequilibrium phase transitions and self-organization in physics, chemistry, and biology, Springer.

Hensher, D. A. and S. M. Puckett (2005). "Refocusing the Modelling of Freight Distribution: Development of an Economic-Based Framework to Evaluate Supply Chain Behaviour in Response to Congestion Charging." Transportation 32(6): 573-602.

Jennings, N. (1993). "Commitments and conventions: The foundation of coordination in multi-agent systems." Knowledge Engineering Review 8: 223-223.

Jennings, N., P. Faratin, et al. (2001). "Automated negotiation: prospects, methods and challenges." Group Decision and Negotiation 10(2): 199-215.

Lomuscio, A., M. Wooldridge, et al. (2003). "A classification scheme for negotiation in electronic commerce." Group Decision and Negotiation 12(1): 31-56.

Meimbresse, B. and H. Sonntag (2001). "Modelling urban commercial traffic with the model wiver." Actes des 13`emes Entretiens J. Cartier, Montr´eal, Etudes et Recherches LET.
Muñuzuri, J., J. Larrañeta, et al. (2005). "Solutions applicable by local administrations for urban logistics improvement." Cities 22(1): 15-28.
Roorda, M. J., R. Cavalcante, et al. "A conceptual framework for agent-based modelling of logistics services." Transportation Research Part E: Logistics and Transportation Review 46(1): 18-31.
Rosenschein, J. and G. Zlotkin (1994). Rules of encounter, MIT press Cambridge, MA.
Routhier, J. and P. Aubert (1999). FRETURB, un modèle de simulation des transports de marchandises en ville.
Schenk, N., H. Moll, et al. (2007). "Meso-level analysis, the missing link in energy strategies." Energy Policy 35(3): 1505-1516.
Taniguchi, E. and R. G. Thompson (2002). "Modeling city logistics." Freight Transportation 2002(1790): 45-51.
Troitzsch, K. G. (2009). Perspectives and challenges of agent-based simulation as a tool for economics and other social sciences. Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems - Volume 1. Budapest, Hungary, International Foundation for Autonomous Agents and Multiagent Systems.
Van Duin, J. and H. Quak (2007). "City logistics: a chaos between research and policy making? A review." Urban Transport XIII-Urban Transport and the Environment in the 21st Century: 135-146.
van Duin, J. H. R., L. A. Tavasszy, et al. (2007). "Real time simulation of auctioning and re-scheduling processes in hybrid freight markets." Transportation Research Part B: Methodological 41(9): 1050-1066.
Vulkan, N. and N. Jennings (2000). "Efficient mechanisms for the supply of services in multi-agent environments." Decision Support Systems 28(1-2): 5-19.
Wisetjindawat, W., K. Sano, et al. (2007). Micro-simulation model for modeling freight agents interactions in urban freight movement, Citeseer.