Adaptive Behavior Modeling in Logistic Systems with Agents and Dynamic Graphs

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Inside a logistic system, actors of the logistics have to interact to manage a coherent flow of goods. They also must deal with the constraints of their environment. The article's first goal is to study how macro properties (such as global performance) emerge from the dynamic and local behaviors of actors and the structure of the territory. The second goal is to understand which local parameters affect these macro properties. A multi-scale approach made of an agent-based model coupled with dynamic graphs describes the system's components, including actors and the transportation network. Adaptive behaviors are implemented in this model (with data about the Seine axis) to highlight the system's dynamics. Agent strategies are evolving according to traffic dynamics and disruptions. This logistic system simulator has the capacity to exhibit large-scale evolution of territorial behavior and efficiency face to various scenarios of local agent behaviors.

CCS Concepts: • **Theory of computation → Graph algorithms analysis**; *Dynamic graph algorithms*; • **Computing methodologies → Modeling and simulation**; *Multi-agent systems*; *Agent/discrete models*; • **Information systems** → *Geographic information systems*; • **Applied computing** → *Sociology*;

Additional Key Words and Phrases: Agent-based model, dynamic graph, logistic system, adaptive behavior, complex system, geographical information system

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1 INTRODUCTION

A logistic system takes place on a territory and is composed of a set of actors and logistic infrastructures. The system is structured to support flows (of goods, of information, or financial),

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creating corridors between access nodes (maritime port, airport, etc.) and urban areas. The territory behind an access node is called a hinterland. Among the different actors, we can list the providers of goods, the logistics service providers, the transporters, the forwarding agents (they are mostly charged to manage the international transport), the final consignees, and many others. They are numerous and heterogeneous. However, no actor has a complete decisional power on the transport of goods. Instead, each manages only a small part of it. Therefore, they need to collaborate.

Choi et al. (2001) were among the first to make the proposition to see logistic systems as complex adaptive systems. Indeed, a system is said to be complex when its evolution emerges from the auto-organized behaviors of the entities composing the system. These entities are able to adapt their behaviors according to environmental changes or changes in the interactions between the entities. We call this phenomenon "adaptive behavior." The evolution of such a system is not precisely predictable at a microscopic level, but a simulation can help us to estimate overall tendencies that might be observable at a macroscopic level. It appears that the flow of goods observed at a macro level of logistic systems comes from the auto-organization of actors: it emerges from local decisions. The micro properties of the territory and local behaviors of actors (the local population densities, speed limits, number of lanes, etc.) force the goods to follow specific paths, which are the corridors detectable at a macro level. Moreover, the system is resilient thanks to the capacities of adaptation of its actors against various disruptions. Those are the reasons why we consider logistic systems as complex.

The hinterlands of access nodes see their size increase. Then, close access nodes compete against each other to deliver the goods on their overlapping hinterlands. According to the economical stakes of this competition, it is important to understand, first, how the modifications and adaptations of local decisions and, second, the evolution of the territory structure can impact the performance of the system. The goal of this article is to provide a model of a logistic system in order to observe the effects of local parameters on the macro properties of such a system. The simulation of this model allows testing of different scenarios. For instance, in Démare et al. (2017), we have already studied how the organization of flow of goods is affected by the attractivity of maritime ports. Here, we also would like to observe how the system reacts to disruptions in the traffic network. We want to understand how the actors adapt their behaviors to changes of the system. In this article, in particular, we are interested in the dynamic aspects of the model through the adaptation capacities of the agents. Moreover, the model and its simulation could provide a tool to test the effects of different strategies used by actors (e.g., to select warehouses or to manage stocks).

Usually, there are two main approaches to model such complex systems. First, it is possible to use dynamical systems such as those described by Surana et al. (2005), who tried to model supply chain networks. Second, there is the agent-based approach whose models are spatially organized, and process disaggregated and heterogeneous data. Later, we observed a fresh outbreak of these agent-based models in the domain.

In our article, we adopt a multi-scale approach, thanks to an agent-based model and dynamic graphs, to describe the complexity of these logistic systems. We model its local characteristics (actors and infrastructures, spatially spread over the whole region of the system) to explain the emergence of its macro properties.

Section 2 describes literature regarding models of goods traffic. We also define dynamic graphs since they are a main part of our model. Indeed, we mostly use dynamic graphs to model the transportation network. We also use them to represent the evolution of the interactions between the actors. In Section 3, we explain how we can see a logistic system as complex. We list the main actors, behaviors, interactions, and structural properties of such a system. We will see that we can represent the system in two parts (the port and the urban areas) connected by a logistic interface. It is the occasion to identify first macro properties emerging from local behaviors and interactions, which are characteristic of a complex system. Section 4 is about the modeling itself. It emphasizes the fact that a logistic system is seen as complex. In addition, since we want to keep control on local parameters and to use a spatial approach, we adopt an agent-based model coupled with dynamic graphs. It transcribes spatial constraints and actors' behaviors at a micro level. Both approaches (agent-based models and graphs) include dynamics that allow the system to evolve according to "feedback loop" mechanisms between the actors and the environment. Section 5 first describes the implementation of the model on a simulation platform (using data on the Seine axis) and then analyzes some results. In a first result, we highlight the emergence of optimal behaviors. We show that the actors adapt their behaviors progressively in order to achieve a better efficiency. In a second result, we observe, through the simulation, how the traffic evolves (adapts itself) when the system is disrupted (roads blocked).

2 RELATED WORKS

In this section, we first present some models of the literature on goods traffic. Then, we define dynamic graphs.

2.1 Models of Goods Traffic

Here, we consider models in which several independent stakeholders share a territory to supply common regions. We first will be interested in aggregated models and then disaggregated ones. They are called as such because they respectively use aggregated or disaggregated data as initial input. Eventually, we will describe models specifically designed to simulate traffic in maritime ports and urban areas.

One of the first models of goods traffic was proposed by Tavasszy et al. (1998): the Strategic Model for Integrated Logistic Evaluations (SMILE). This model is part of the aggregated models. It was inspired by models of passenger transportation and used a four-step approach.

- Step 1: Determine the quantities of goods produced in each zone and the quantities consumed in these areas according to aggregated input data.
- Step 2: Determine an Origin–Destination (OD) matrix with the quantities of goods that should be carried between two areas according to estimations made at the previous step.
- Step 3: Determine the share between each mode of transport to carry goods according to the OD matrix.
- Step 4: Compute the necessary number of vehicles (for each mode of transport) to carry the goods.

This model forecasts the evolution of traffic according to the initial input data of step 1. In SMILE, the world is divided into 77 regions, some of them extensive. This division was mainly due to a lack of data and leads to models that are not accurate enough. Moreover, the evolution of the simulation is year after year, and the structures of supply chain do not evolve. Therefore, the model is not very dynamic.

Numerous other models have been proposed (Jin et al. 2005; Maurer 2008; Tavasszy et al. 2001). Most of them are inspired by the four-step approach. The aim of their contributions is to improve specific parts: for instance, they introduce more complex logistics behaviors (Tavasszy 2006). More recently, another model, proposed by Zondag et al. (2010), studies the traffic competition between maritime ports according to their characteristics and their connection with their hinterlands. The authors consider that the hinterlands of ports might overlap with each other. Therefore, the traffic of a port might have effects on the traffic of other ports.

Chow et al. (2010) explain that aggregated models often fail to represent economical behaviors of stakeholders or to represent dynamic phenomenons such as urban congestion. Moreover, with such models, it is difficult to have a local impact on specific actors or specific parts of the environment owing to the aggregation. Therefore, researchers tried new approaches with disaggregated models. A first step in this direction is the model proposed by Ben Akiva and de Jong in two articles (Ben-Akiva and de Jong (2013) and de Jong and Ben-Akiva (2007)): the Aggregated-Disaggregated-Aggregated (ADA) model. It disaggregates input data according to number of employees in order to get annual firm-to-firm flows. Then, they simulate the evolution according to these disaggregated data and, finally, they aggregate the results in order to validate and to do spatial analyses.

Later, Samimi et al. (2010) proposed the model Freight Activity Microsimulation Estimator (FAME) model. It was designed as an agent-based model to simulate the traffic of goods between United States firms. The authors use disaggregated data on the characteristics of the simulated firms and on the road and rail transportation network. They also use aggregated data in order to determine how the firms interact. The agents have the possibility to create more sophisticated supply chains with intermediary distribution centers or warehouses. In a more recent article (Samimi et al. 2014), the authors explain that efforts should be made to apply their model to another territory owing to the difficulty in accessing the data.

Another model, called Transportation And Production Agent-based Simulator (TAPAS), has been proposed by Holmgren et al. (2012). It models each customer, supplier, and transporters by different agents. The model is designed in two parts: a physical simulator (for the multi-modal transport network), and a decision-making simulator (for actors' behaviors and interactions). The model is planned for a reduced number of actors, and a simplified transportation network. The implementation of this model allows simulation of the traffic of three actors around the Baltic sea.

The issues behind these models often come from the difficulties in getting data used to simulate and also to validate the models. Moreover, these models offer a high-level representation of their associated systems. For instance, ports are seen as simple nodes in Zondag et al. (2010), and sometimes the transportation network is simplified, as in Holmgren et al. (2012). Thus, some authors worked on specific parts of such a system.

On the port side, Parola and Sciomachen (2005) developed a discrete-event simulation. It models intermodal container flows of two geographically closed maritime ports working together. The authors used this simulation to highlight congestion situations according to initial parameters and to test different scenarios in which some infrastructures are available or not.

Cortés et al. (2007) also worked on a discrete-event simulation. Their case study is about the inland port of Seville. This specific port has limited access owing to the presence of an estuary and a lock. Moreover, in contrast to Parola and Sciomachen (2005), they simulate different kinds of goods. Through the simulation of different scenarios, the authors show that the port of Seville should be able to absorb a growth of its traffic.

On the urban side, the models are often related to congestion issues of the transportation network and in a competitive context between goods and passenger traffic. Chow et al. (2010) explain that some works (Wisetjindawat and Sano 2003; Wisetjindawat et al. 2006) use the four-step approach discussed previously. However, due to the size of the studied regions, these models have to provide more precise output to be useful; therefore, they need more detailed input data (meaning disaggregated data). Roorda et al. (2010) also proposed a conceptual architecture of an agent-based model. Its goal is to simulate goods and passenger traffic. The authors were particularly interested in interactions between the actors of urban logistics. The interesting point in this model is its dynamics: there are different levels of temporality. The timestep is on a day basis, but agents have different kinds of behavior. They can make short-term decisions (e.g., restock a warehouse) or long-term decisions (e.g., open, close, or relocate a firm). Freight Market Interactions Simulation (FREMIS) implements a part of this model (Cavalcante and Roorda 2013). However, this implementation is still a work in progress since, once again, the authors have difficulties in getting the required data.

2.2 Dynamic Graphs

As discussed previously, we are going to use an agent-based approach to model logistic systems. This kind of model might be coupled easily with graphs since agents interact (making networks) and their environment itself can be represented by a graph (e.g., a transportation network). Moreover, the graph theory provides a lot of analytic tools that can help to determine some properties of the system.

Agent-based models are dynamic. Therefore, we cannot be content with the classic definition of static graphs. Thus, we explore in this section some definitions of dynamic graphs from the literature and finish with the definition that we use in our own model.

The concept of dynamic graphs has existed for a long time but it was only recently that researchers such as Harary and Gupta (1997) tried to formalize their definition. Actually, the dynamics can have many origins and ways to manifest from one domain to another. Thus, there are many definitions according to needs. For instance, Cortes et al. (2003) describe a kind of dynamic graph called a *cumulative graph*. Their goal was to study communication networks in which the nodes are the communication terminals and the edges represent communications between two terminals. The authors defined a graph as the sum of subgraphs corresponding to the snapshots of the communication network taken at regular intervals. The edges are then valued by the number of calls or by the total time of communications.

Evolving graphs have been described in an article by Ferreira (2002). The author presents a definition of a dynamic graph as a system $\mathcal{G} = (G, S_G)$, where G is the graph and S_G is an ordered sequence of subgraphs of G. These subgraphs match the active parts at specific dates (in a discrete time) of the main graph.

Casteigts et al. (2011) proposed another definition: they added two presence functions (one for the nodes, the other for the edges) and a latency function (to determine the time to cross an edge) to the classic definition of a static graph. The point is to get the dynamics on both the topology and labels of the graph.

However, we note that these previous models presuppose a knowledge on the dynamics. They allow only a replay of the dynamics of a graph. Thus, Savin (2014) proposed a model (that we use in our own model) in which the dynamics of a graph is defined through a process of evolution. To do so, Savin (2014) started with a definition of a graph for which its elements can have none or several attribute(s) associated to a value (e.g., an edge can have a "speed" attribute with the value 50km/h).

Then, Savin (2014) describes the dynamics that happen on such a graph through an evolution process. He defined an operator that applies a set of events (e.g., add or delete an edge or a node, update the attribute of a graph element) to a graph to make it evolve. Therefore, from an initial graph, this model allows one to build and update the graph iteratively.

To sum up, thanks to this model, a graph can evolve progressively in real time. Both nodes and edges can be added or deleted. Moreover, nodes and edges can be valued or labeled, but they also can have multiple and heterogeneous data that can be added, deleted, or updated at any moment. This model of dynamic graphs has been implemented in the graph library called Graphstream (Dutot et al. 2007).

3 COMPLEXITY OF LOGISTIC SYSTEMS

In this section, we study the main actors and infrastructures of a logistic system. It groups information from scientific research and discussions with logistics experts. It allows us to establish a state of the art about the main elements of such a system.

3.1 Logistic Systems: Limits and Issues

A logistic system is a geographical space composed of urban areas and of logistic structures. These structures are organized in order to support flow of goods. Goods are mainly transported between urban areas and they enter or leave the system through access nodes (such as a maritime port or airport). The transport axis between urban areas represents corridors of flow of goods. The size of the metropolises and growth of their demands imply a huge amount of traffic: 199 millions tons of freight went through the port of Antwerp in 2014 (according to the official annual report of 2014 of the port of Antwerp). It is source of financial attractiveness but the territory is also source of constraints: spatial, political, ecological, and the like. The numerous and heterogeneous actors of the logistics (importers, exporters, freight forwarders, logistic providers, etc.) have to deal with these constraints to satisfy the needs of the final customers. Moreover, the improvement of the logistics leads to the expansion of the system. It has grown so much that, today, an increasing number of close access nodes are in competition to deliver to the same urban areas. For instance, this is the case for Paris, whose goods mainly come from Le Havre and Antwerp.

The economical stakes are important in order to increase market share of ports. Concerning the Seine axis, the recent port reform, the creation of HAROPA[1] or also the number of scientific works and projects about this axis show the interest in improving the performance of the system. This is translated by a wish to understand the organization, advantages, and issues of a logistic system. More precisely, the problem here is to model the whole system, integrating the spatial constraints and the functional rules of its actors and infrastructures, in order to understand the global working of the system. The simulation of such a model should allow us to test different scenarios and therefore provide solutions to improve the logistic system.

3.2 Emerging Properties from the Auto-Organization of Actors

Here, we describe how the actors work and interact. We show that these interactions lead to properties observable at a higher level of study.

The actors of the logistics (De Langen et al. 2013) are mostly as follows:

- The foreign goods provider and final consignee: In the interest of the final customers' demands, they initiate the flow of goods via a contract between the provider and final consignee.
- The freighters: Those who take charge of the goods during the transport (depending on the contract).
- The freight forwarders: They organize the transportation of goods on behalf of the freighter.
- The transporters (shipowner, road transporter, etc.): They move the goods according to the requests of the freight forwarder (destination, preferred path, duration, etc.).
- The logistics service providers: They handle goods in the hinterland within and between logistic structures (warehouses, distribution centers, etc.). They outsource the stocks of a freighter (Jayaram and Tan 2010; Liu et al. 2014; Rodrigue 2012). The structured organization of logistic infrastructures is called the *supply network*. The logistic infrastructures answer

[1] This is an Economic Interest Group (EIG) grouping within the same structure of the ports of Le Havre, Rouen, and Paris in order to help the collaboration.

(a) Logistic buildings in a join network.

(b) Logistic buildings in a fork network.

Fig. 1. Two kinds of network of logistic buildings.

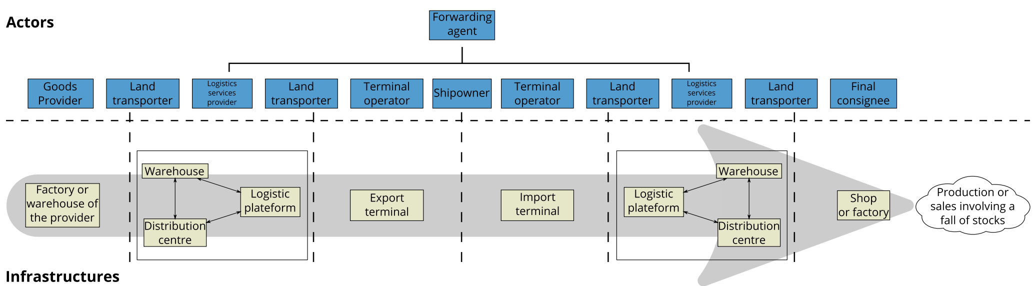


Fig. 2. Each actor manages a part of the flow.

to particular needs and are arranged by the logistics service provider into networks in order to atomize or massify the flow of goods as in Figures 1(a) and 1(b).

This list is not exhaustive, however. The actors of the logistics are numerous and heterogeneous. They interact with each other owing to their behaviors but also owing to the constraints of the environment (such as spatial restriction from the network). Each manages a part of the flow but they are auto-organized in order to build a coherent flow (Figure 2). This auto-organization leads to the creation of communities or clusters. For instance, if we represent the interactions between the actors of the system, the density of interactions is higher between actors of the port than anywhere else. The port community can be seen as a strong cluster of actors sometimes collaborating and sometimes in competition. This multi-scale point of view, with local rules on one hand and global communities on the other hand, reveals the complexity of the studied system.

This complexity also appears in the organization of the infrastructures.

3.3 Emerging Properties from the Distributed Organization of Infrastructures

This section will explain how the infrastructures of a logistic system work and interact. We also observe macro properties coming from the local organization of these infrastructures.

The goods move in a physical environment which appear as a structured and organized multimodal network, managed by actors (see Figure 2). Each kind of network provides particular constraints (size of vehicles, speed, etc.). Some subnetworks allow the transport of more goods at the same time (e.g., river network vs. road network), while some others allow reaching more destinations quicker (e.g., road network vs. rail network on short circuit). Some of its infrastructures (e.g., terminals) have the function of moving the goods from a kind of network (here, maritime lines) to another (e.g., road network). The other kind of infrastructures, the logistic buildings, exist in order to outsource the stocks of another building and/or to provide extra-logistics activities (e.g., container packing, quality control, cross-docking, etc.). The size of these buildings, the activities that they provide, and how they are included in a supply network define a particular structure in which the buildings are organized into a hierarchy. Therefore, the transportation network is also source of complexity.

The important volumes between different nations or continents, such as between Asia and Europe, allow massification of the transportation of goods by the use of cargo ships in order to bring down costs. However, ships of maritime lines can be delayed: the precision of the estimated time of arrival (ETA) can be low, with sometimes one day of difference from the actual arrival time. The port terminals need to process these sometimes delayed but huge flows (Lévêque and Serry 2014). Moreover, handling or customs clearance can increase the time to leave the port. In contrast, actors in urban areas manipulate flows whose ETA can be precise to the hour or even less. Moreover, because urban areas are more or less spread over the territory of importation, the import flow of goods has to be atomized. The flow rate and frequency are not the same between these two kinds of logistics. In computer science, we use the term *buffer* to designate a memory area where data is stored temporarily in order to facilitate its transfer between two processes or devices that do not have the same bit rate capacities. The regularity and atomization of urban logistics is made possible by a buffer interface between the port and metropolises. This interface corresponds to this structured multi-modal network: its topology as a fork network (on the import side) allows the atomization; the outsourcing logistic buildings play the role of buffer in order to compensate for the irregularity of international transport.

Even if it is possible to observe local movements of goods at a micro level, overall patterns emerge at the macro level of the logistic system. The local constraints on the network lead the flows over the main paths and drive to the congestion of these axes. It again reveals a complex system. In the next section, we will use concepts of complexity science to model a logistic system.

4 AGENT-BASED MODEL AND DYNAMIC GRAPHS

The previous section explained how the actors behave and how they interact with each other, and with their environment, in reality. Now, we propose a model based on this information.

This model needs to provide the keys to understanding a logistic system and to provide help for decision making in spatial and logistics planning. First, the model must have the ability to adapt itself to different scenarios. For instance, two different logistic systems do not havethe same spatial constraints and the actors can be subjected to different regulations. Second, we should be able to update the behaviors of actors individually. Finally, the model has to provide measures of macro properties, such as traffic, congestion, time of transportation, costs (financial, or possibly environmental), and the like.

We saw that logistic systems can be seen as complex. Moreover, we are looking for a disaggregated model allowing the possibility to act on local parameters (in contrast to aggregated models; see Section 2.1). We also want our model to be dynamic in order to observe its evolution over the time. We designed our model in order to have a temporality on an hourly basis (which is more precise than the models presented in Section 2.1). This is why we chose an agent-based approach coupled with dynamic graphs. They are both known to be well suited for a complex system, they can report the spatial dimension of the system, they are configurable, and they are dynamic. The graph theory also provides a lot of analytic tools in order to highlight traffic and congestion issues, for instance.

4.1 Actors as Agents

Each actor of the system is represented by an agent. Their autonomous decisions are taken from their own behavior, which depends on the kind of actor that they model. Figures 3, 5, 6, and 7 describe each modeled actor and how they interact with each other. Their perceptions of the environment or their interactions with other agents can modify their behavior and, therefore, their

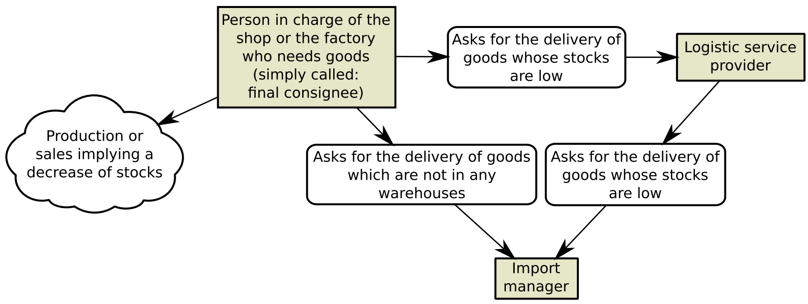


Fig. 3. Diagram of possible interactions between agents (person in charge of the shop or factory, logistics service provider, and import manager).

decisions. In these figures, the colored rectangles represent the agents. The rounded white rectangles are the interactions between couples of agents. The direction of the arrows indicates which agent initiates the interaction.

In Figure 3, there are three agents:

- the person in charge of the shop or the factory who is the final consignee
- the logistics service provider whose the goal is to manage the outsourced stocks of the final consignee
- the import manager who manages the orders of goods when even the outsourced stocks are too low

The final consignee has local stocks that are determined according to the surface (in m^2) that they occupy. One agent might have several different products (the number is defined by the user before the simulation). For each product, there is a maximal stock quantity. The quantity of each product decreases each day according to a biased random number. We use the model by Huff (1964) to define the bias and determine how quickly the stocks decrease. This model was originally designed to determine the number of customers of a shop. It considers the population densities around the shop and its accessibility to the network. The total number of potential customers of a shop j is computed as follows:

$$T_j = \sum_{i=1}^{m} \left(\left(\frac{\frac{S_j}{T_{ij}}}{\sum_{k=1}^{n} \frac{S_k}{T_{ik}}} \right) \times C_i \right),$$

where

- m is the number of geographical areas considered (e.g., cities, district, region)
- n is the number of shops
- S_j is the surface of the shop j
- T_{ij} is the time for a customer to go from i to j
- C_i is the population of i

We use the model by Huff (1964) to sort the final consignees in order to associate each x agent to a "diminution coefficient" dc_x based on its rank in the sorted list:

$$dc_x = \frac{1}{((p - q)/(n - 1)) \times r + q},$$

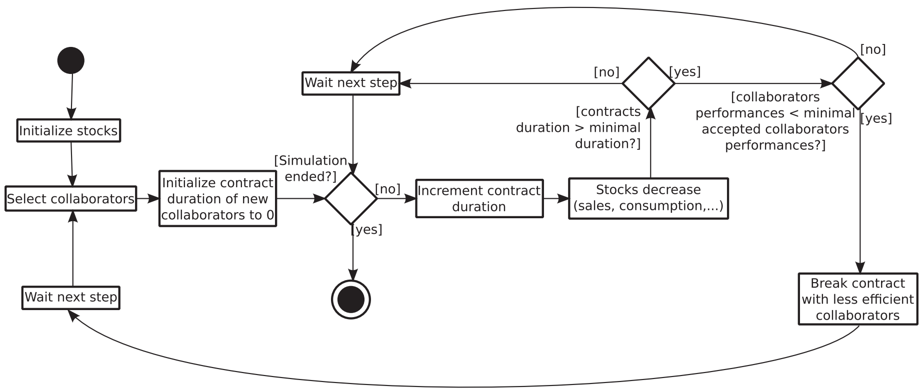


Fig. 4. Activity diagram of the agents representing the final consignees.

where

- r is the rank of the agent in the sorted list
- n is the number of final consignee agents
- $1/q$ is the minimal coefficient (defined by the user)
- $1/p$ is the minimal coefficient (defined by the user)

Each day, the quantity of product (whose maximal quantity is $q_{\max}$) will decrease to a random number between 0 and $q_{\max} \times dc_x$.

The outsourced stocks of the final consignees are managed by logistics service providers (LSPs). One final consignee has only one LSP, but one LSP might have none or several final consignee(s). We will explain later exactly how LSPs work. For now, we focus on the interactions between these two agents. Figure 4 illustrates the dynamics of the interactions between a final consignee and its LSP.

At initialization, each final consignee randomly selects one of the LSPs. A contract is made between them and cannot be undone before a minimal period defined by the user. During the simulation, a final consignee regularly measures the performance of his LSP. There are two heuristics to make this measure (based on the works of Teresa and Evangelos (2015) and Šrámková et al. (2015)):

- the number of stock shortages
- the time taken to deliver the goods to the final consignee

If the average performance measured by one final consignee is lower than the average measure of all final consignees, then the agent can decide to break the contract with the LSP and choose another one. Therefore, only the best LSPs will conserve their contract. We will see in the results section that the best strategies emerge owing to this behavior.

If the stocks are too low (even the outsourced ones), then the agents need to make contact with a foreign goods provider. Figure 5 describes the agents involved in this process.

The import manager can be an independent agent, part of the final consignee agent, or the LSP. It depends on the studied system. In our implementation, the import manager is part of the LSP. At initialization, the import manager chooses one of the foreign goods providers. When the stocks are too low, the import manager takes an order of a specified quantity of the missing product.

In our implementation, we consider that the foreign goods providers aggregate every real foreign provider. We assume that they can satisfy every order of every kind of product, no matter

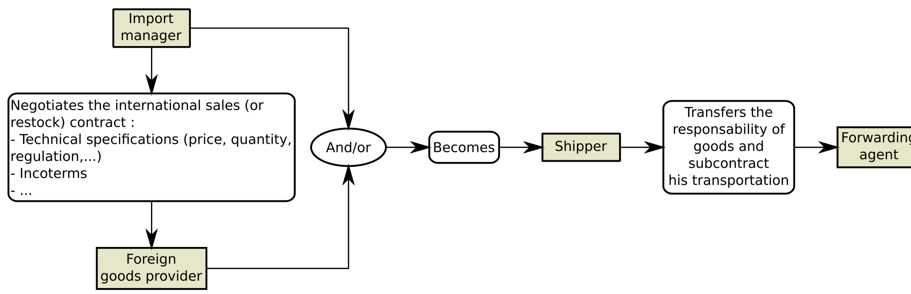


Fig. 5. Diagram of possible interactions between agents (import manager, foreign goods provider, shipper, and forwarding agent).

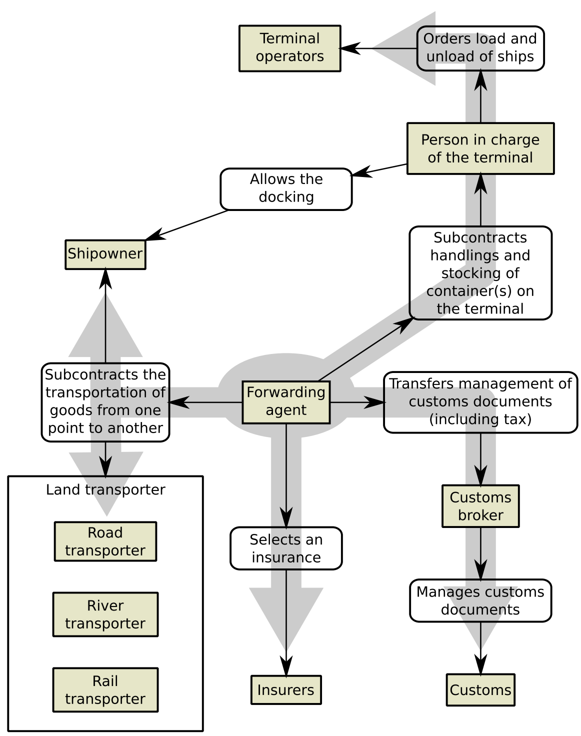


Fig. 6. Diagram of possible interactions between agents (forwarding agent, person in charge of the terminal, terminal operators, shipowner, land transporters, insurers, customs broker, and customs).

the quantities asked. Indeed, the foreign goods providers represent the access nodes. Thus, there are several provider agents but only to model the different access nodes. However, one can be interested in implementing several foreign goods providers connected to the system to model the different origins of the goods (e.g., from Asia and America).

Once the order is made, the forwarding agent organizes multi-modal transportation with the transporters from the foreign goods provider to a warehouse (the delivery address is here given by the import manager but, actually, the warehouse is managed and chosen by the LSP). Figure 6 describes the interactions between the forwarding agent and the others. The forwarding agent

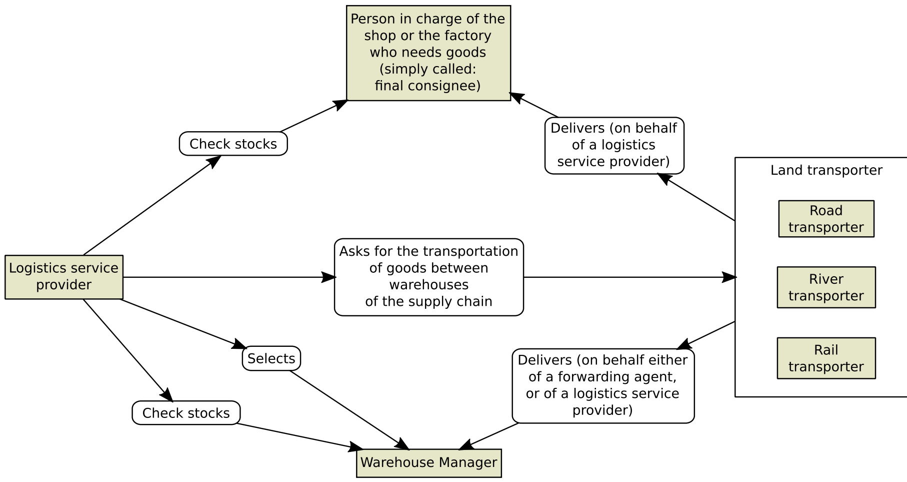


Fig. 7. Diagram of possible interactions between agents (land transporter, warehouse manager, logistics service provider and person in charge of the shop or factory).

is clearly at the center of these interactions. The forwarding agent plays the role of orchestra conductor in order to manage the transportation of the goods.

The forwarding agent computes the shortest path between the foreign goods provider and the warehouse in the multi-modal network. The user must choose before the beginning of the simulation whether the algorithm should consider the time of the route or its financial costs to compute the shortest path. There is one transporter agent by mode of transport. The forwarding agent makes contact with each transporter who will carry the goods. Then, the transporters will take care of the goods on their respective parts.

Figure 6 also presents the insurers, customs broker, and customs. These 3 agents might have an impact on the financial costs. More specifically, customs can also be a source of delays for the goods to enter the territory in some situations. However, their implementation is not mandatory. We did not implement them ourselves (see Section 5). It mostly depends on the characteristics of the studied system and on the level of details requested. Nevertheless, their implementation can stay really simple.

Finally, Figure 7 represents the interactions with the LSP. The main goal of this agent is to supervise the outsourced stocks of the customers (the final consignees). For this purpose, an LSP designs and manages a supply network made of warehouses.

This supply network is a dynamic graph. The nodes are either a provider, warehouse, or a final consignee. The edges are oriented and describe the fact that a node can restock another node. When an LSP gets new customers (thus, the LSP gets new interactions with final consignees), then the graph gets new nodes and edges. If the LSP loses a contract, however, the graph is also updated as a consequence. The topology and the dynamics of this graph affect the traffic of the transportation network and the efficiency of the agents. The characteristics of such a graph are crucial to understanding the system.

When an LSP is selected by a final consignee, the LSP must select warehouses and organize them into a network. The topology of this network and the properties of the warehouses (such as the surface or location) allow outsourcing of the stocks and atomization of the flows. The network plays the role of logistic interface. The way to organize the topology and to select the warehouses depends on different parameters, such as the financial means or the kind of goods (food needs a short circuit compared to furniture, for instance). We consider that the algorithm that builds the supply network should be determined by the user when the user implements the model according to the kind of industry or logistic system studied. However, the supply network of an LSP is connected to only one foreign goods provider. Therefore, the network is similar to the fork network of Figure 1(b): there is one provider, many final consignees, and some intermediary warehouses on one or several level(s). We note that the network is not necessary a tree.

When the network is designed, the LSP needs to monitor the stock levels once a day with a depth-first search algorithm. For each stock inside the warehouses of the LSP's network, the LSP determines if the current quantity of goods is too low according to this formula:

$$q < q_{\max} \times S,$$

where q is the current quantity of goods, $q_{\max}$ is the maximal quantity of goods for this stock, and S is the restock threshold. This last parameter is a percentage that defines the restock strategy of the LSP: when does the agent order a restock? The model gives two modes to use this parameter: either each LSP is initialized with a random value contained between an upper and lower bound or every LSP shares the same value, defined by the user. If the quantity of product is too low, then the LSP orders the restock to a higher-level node in the network.

The efficiency of each LSP will be different from one agent to another according to the restock threshold value, the supply network topology, and the warehouses' properties (see Section 5.3.1 for an analysis of the effects of these parameters on efficiency).

All interactions between the agents of this model are used to build and keep updated a dynamic graph in which the nodes are the agents and the edges are the interactions. This graph evolves in real time with the simulation. For instance, if an LSP has been chosen by a final consignee at step i, we then add an edge between the two corresponding nodes at the same date in the graph. If the final consignee breaks the contract with this LSP at step $i + k$, we then delete this edge. The reason to maintain such a graph is mostly for analysis purposes. It might be interesting to understand how the topology and dynamics of such a graph might affect the system. For instance, are there specific configurations of this graph that lead to congestion of the transportation network? The graph could also be used to detect communities of actors working together that have a higher level of efficiency in the system. Then, we could find a way to identify the properties that make them more efficient.

4.2 Territory as Agents and Dynamic Graphs

The environment of our model is the transportation network. It is represented by a dynamic graph that allows us to follow the traffic evolution in real time (congestion on edges) and to integrate dynamic phenomena such as accidents and roadwork (deletion or addition of an edge and, therefore, modification of the topology).

To be more precise, the transportation network in which the goods move is represented by different modes of transport. Each mode has its own dynamic graph. They are connected with each other by agents representing nodal infrastructures, such as terminals or warehouses (see Figure 8). However, even if the model is suitable for multi-modality transport modeling, the current work presented in the following is based only on one mode of transport. The topology of the network can be updated in real time: for instance, a road can become unavailable due to an accident or roadwork. The increase of traffic on a specific road leads to a decrease in speed, representing a congestion or a traffic jam.

Vehicle agents carry goods in the network. Their behavior is described by the activity diagram of Figure 9. According to the level of granularity defined by the user, these agents can model one vehicle or possibly a convoy transporting all goods from the same order. At their creation, these agents compute a path from their initial location to the final destination. They move along this

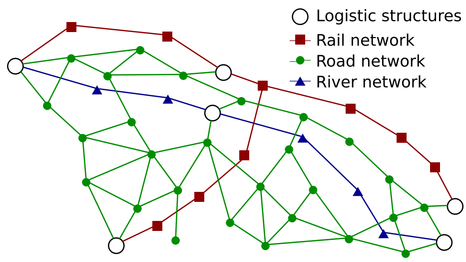


Fig. 8. Representation of the multi-modal network and how it is coupled with the agent-based model.

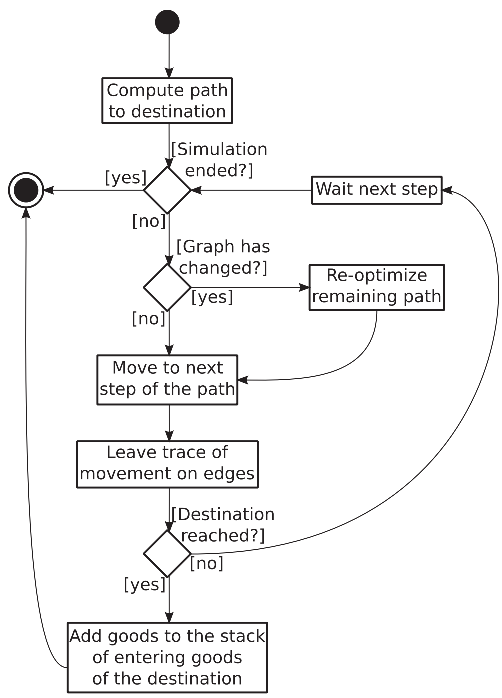


Fig. 9. Activity diagram of the vehicle agents carrying goods on the transportation network.

path according to the speed limits. They leave a trace of their movement. This trace is the amount of goods that the agent carries. At each step, a coefficient decreases the trace on every edge. This mechanism is inspired by the pheromones used in ant colony optimization algorithms (Colorni et al. 1992; Dorigo 1992) in which the pheromones evaporate progressively. The trace is used to observe the most congested edges of the network (they are colored according to the value of the trace). If an edge is no longer used for some reason, the evaporation process will dynamically highlight this change.

When the vehicle agents reach a nodal infrastructure, the goods that they carry are added to the infrastructure's stack of the entering goods. Figure 10 shows that each nodal infrastructure manages two FIFO (First In, First Out) stacks: entering and leaving goods. Each infrastructure has a maximal capacity per step to process goods. It represents the bulk breaking necessary to make the transfer and the limited means provided by the logistic structure. Therefore, if there are too many entering or leaving goods, it can lead to congestion within the infrastructure.

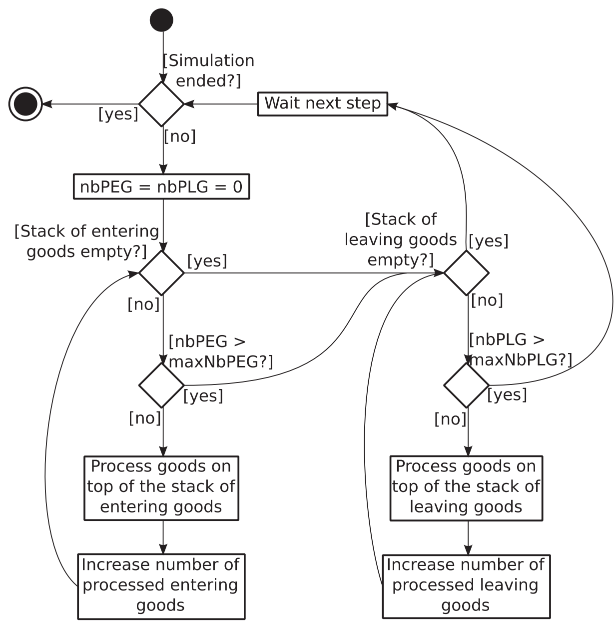


Fig. 10. Activity diagram of the agents representing the logistic infrastructures. nbPEG: the number of processed entering goods; maxNbPEG: the maximal number per step of processed entering goods; nbPLG: the number of processed leaving goods; maxNbPLG: the maximal number per step of processed leaving goods.

4.3 Coupling the Actors and the Territory

The actors can have an impact on the network because they increase traffic on the most accessible and/or efficient part of the network, leading to congestion and traffic jams. Since the actors update their decisions in real time, the environment also has an impact on these decisions: parts of the environment with congestion are less efficient and accessible. Thus, they become less attractive and are selected less, which leads to less congestion. This is a feedback loop mechanism of the model.

The model is also multi-scale: even if the buildings are spread over the territory and are connected to the transportation network, they also belong to another level of network: the supply chain. Figure 11 illustrates this: the agents who model a logistic provider make the decision to include some infrastructures to a supply chain according to these predefined rules. The goods must follow a particular path before reaching their final destination: for instance, the goods within a container must be unstuffed before the final delivery.

5 RESULTS

In this section, we discuss the model's implementation. The first subsection describes the technical characteristics of the implementation. We follow with a presentation of the four implemented strategies used by the LSPs to build a supply network. We then provide an analysis of results. The implementation is a first step to check the validity of the model. The behaviors of the agents lead to auto-organization processes that are the source of emerging properties. Thus, the implementation is used to analyze these dynamic properties.

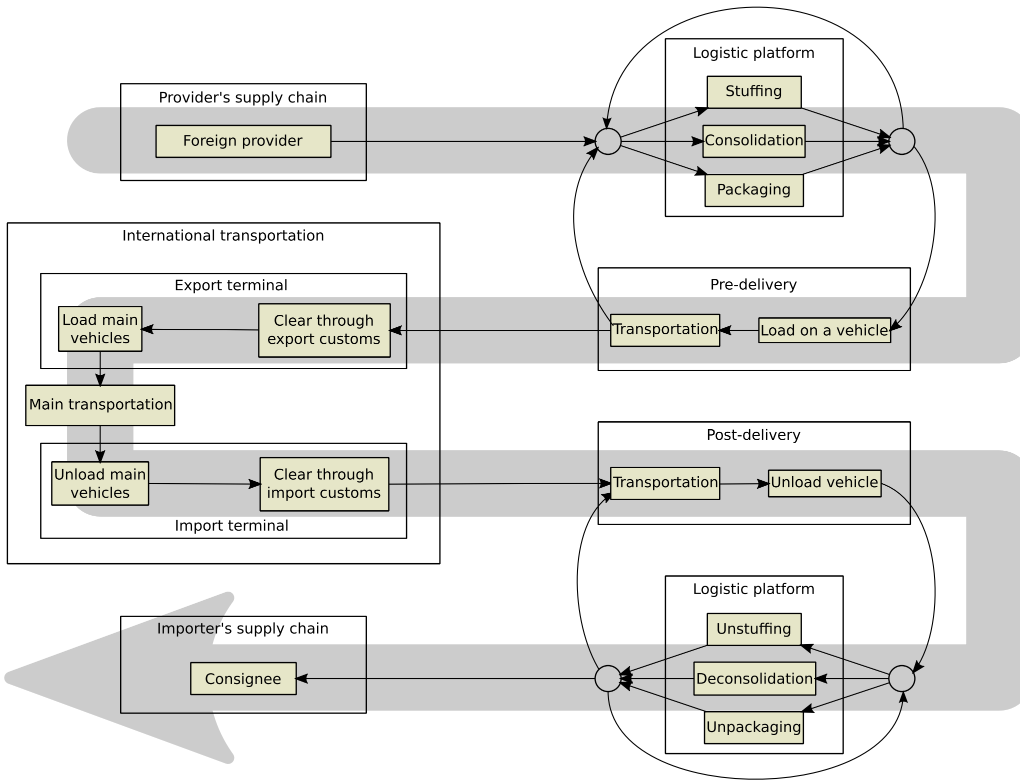


Fig. 11. Simplified representation of the different steps followed by containerized goods during international transportation.

5.1 Implementation Choices and Characteristics

5.1.1 Simulation Platform Choice. The model has been implemented into a simulation platform called GAMA (Grignard et al. 2013; Taillandier et al. 2012)[2]. The GAMA platform is appropriate for the needs of the implementation (Allan 2010; Railsback et al. 2006) because it has tools that allow it to integrate geographical data.

The source code of this model is available for reproducibility purposes at this address: https://github.com/ThibautDemare/DALSim.

5.1.2 Presentation of the Case Study and Origin of the Data. The simulation works with real data on the Seine axis in France. It is a logistic system located between (and including) the maritime port of Le Havre and Paris. The road network is mostly used to transport the goods in this logistic system. Therefore, we do not use the multi-modal network for the simulations presented hereafter but rather only the road network. We decided to implement reactive agents in order to have more control on parameters and their effects on the output. One simulated step represents 1 hour in real time.

We implemented a foreign goods provider connected to the port of Le Havre, but we also created another one connected to the port of Antwerp (and added the road network between Antwerp and

[2]The model code can be found at https://www.openabm.org/model/5645/version/1/.

the Seine axis). This is owing to the competition between these two ports to deliver goods to the Seine axis (mostly to Paris).

The other data have not been automatically generated: they are real data that have been gathered and organized by the Devport project team[3] but comes from various origins.

The Shapefile of the road network comes from Euro Global Map[4]. It represents the main roads (national and regional motorways and highways) and provides information about speed.

There are around 3000 warehouse agents. The data comes from the SITADEL2 database[5] which has been open access since 2017. This database inventories the building permits from 1980 to today. We kept only the data about buildings whose surface is greater than $2000m^2$ and used for nonresidential purposes.

We have around 7700 final consignee agents. We used the Sirene database[6] from the INSEE[7]. This database inventories all active business in France, but we focused only on wholesale.

Finally, there are around 2250 LSP agents. Those come from the official list of businesses specializing in goods transportation, managed by the Minister of Ecological Transition and Solidarity[8].

Of course, a similar study on a different logistic system is possible if the data for this region are available.

5.2 Strategies to Build a Supply Network

Now, we present how we implemented the strategies used by the LSPs to build a supply network. First, the network is always a fork network (see Figure 1(b)) of two levels. It means that an LSP connects his goods provider to a first level of regional warehouses, which are connected to the second level of local warehouses, themselves connected to the final consignees. It is the most common supply network on the Seine axis. What differs from one LSP to another is the way to select the warehouses that belong to the supply network. For this purpose, at the initialization of the simulation, each LSP is associated to one of the four strategies of selection. Then, they keep the same strategy during the simulation.

The first strategy randomly selects the warehouses. This is the control strategy. The three other strategies integrate a criterion—such as the distance to the consignee, the storage surface, or the accessibility of the warehouse—to the transportation network. They are some of the most important properties found in the literature about warehouse selection (Agrebi et al. 2015; Demirel et al. 2010). Thus, the second strategy selects the closest warehouse to the final consignee for the local level and the one that offers the largest storage surface for the regional level. For the local level, the proximity to the consignee is important to get reactivity. For the regional level, it allows grouping of more stocks of different consignees in the same place and limiting of the technical means. The third selects the warehouses randomly but with a bias: according to the distance from the final consignee for the local level and according to the storage surface for the regional level. Finally, the fourth strategy does a first filter on the warehouses according to the distance or the surface and then selects the ones that are the most accessible in the network (in terms of the accessibility

[3]This is a multidisciplinary research team that works on the study of the logistic system of the Seine axis. Website: http://www.projet-devport.fr/en/.

[4]https://www.data.gouv.fr/fr/datasets/euroglobalmap-donnees-topographiques-au-1-1-000-000-couvrant-45-pays-et-territoires-en-europe/.

[5]http://www.statistiques.developpement-durable.gouv.fr/sources-methodes/enquete-nomenclature/1542/0/base-sitdel2.html.

[6]https://www.data.gouv.fr/fr/datasets/base-sirene-des-entreprises-et-de-leurs-etablissements-siren-siret/.

[7]INSEE: Institut national de la statistique et des études économiques.

[8]https://www.ecologique-solidaire.gouv.fr/liste-des-entreprises-inscrites-au-registre-electronique-national-des-entreprises-transport-route-et.

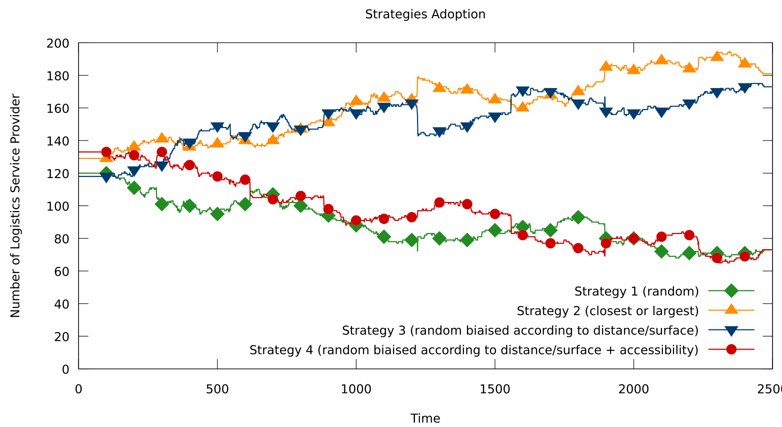


Fig. 12. Choice of different strategies for the creation of a supply network.

index proposed by Shimbel (1953)). We also note that, for each strategy, a warehouse selected as local cannot be selected as regional (or the reverse) in the same supply network.

5.3 Analysis

5.3.1 Adaptive Behaviors. We now focus on the behavior modifications realized by the agents. As we have seen in Section 5.2, four different strategies can be chosen by LSPs to include warehouses in their supply network. Figure 12 illustrates how the choice of these strategies evolves over time. At the beginning of the simulation, one of these strategies is assigned to each LSP. The final consignees randomly chose one of the LSPs and must maintain their business relationship for a minimum duration. During the experiments, a 3-month duration was used. Even if such a short duration is not realistic, longer ones do not change the results. However, lengthening the contract's minimum duration only increases the delay before the emergence of a particular behavior. During the initialization step, we modify some starting dates of contracts in order to avoid a heavy synchronization of the actions done by the agents; thus, some initial contracts may last less than 3 months. The first 100 steps of the simulation are constant because this is necessary to generate enough data for the performance evaluation.

Figure 12 describes the evolution of the choices (made by the final consignee agents) of the LSPs who are sorted by the strategy that they use to build a supply network. During the simulation of Figure 12, the performance measure is based on the average duration of the deliveries (the time between the order and arrival of the goods). The lower that the average duration was ensured by the LSPs, the better they were evaluated by the consignees.

Two strategies are clearly chosen more according to Figure 12. Strategy 2, based on the selection of the closest or largest warehouse, comes first. Strategy 3, based on a random selection with a bias regarding the distance (or surface) of the warehouse, is next. The results of these strategies are very close; sometimes, as the simulation is not deterministic, strategy 3 is the best one. The results of strategies 4 and 1 are very similar and are significantly lower. This figure represents only one simulation but the emergence of the same strategies (2 and 3) at the end of other simulations has been reproduced on every other simulation that we ran (20 runs, in this case).

Indeed, strategies 2 and 3 are the smarter ones and the choice of these selection methods by the agents seems to be natural. Nevertheless, this is a real auto-organized process that emerged from local interactions. It should be noted, however, that the choice of these strategies is bound to the efficiency measure used by the final consignees. Another performance measure and a more

Table 1. Average Number of the Selected LSPs Sorted According to Their Restock Strategy After 1000 Simulated Steps and Computed with 17 Different Simulations

Type of strategy	Restock strategy configured between 5% and 8.75%	Restock strategy configured between 8.75% and 12.5%	Restock strategy configured between 12.5% and 16.25%	Restock strategy configured between 16.25% and 20%
Average number of LSPs per strategy (in %)	16.93	22.06	28.43	32.57
Standard deviation	3.22	3.28	2.1	5.43

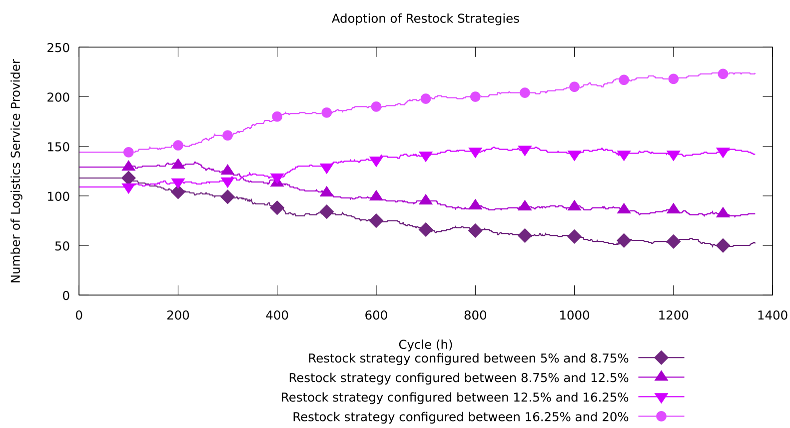


Fig. 13. Restock strategy emergence with fixed warehouse selection strategy. Simulation 1—Warehouse selection strategy: pure random.

accurate strategy could generate more realistic results. However, the strength of this first approach is to prove that the emergence of optimal behaviors is enforced by our model.

Table 1 and Figures 13 to 16 concern the choice of a restock strategy. For these simulations, a restock threshold between 5% and 20% is attributed to each LSP. In order to limit any bias during the adoption of the strategies, all LSPs used the same method to create their supply network (indicated in each legend).

In Table 1 and Figures 13 to 16, note the emergence of the same results whatever the strategy used by the LSPs: agents with the highest restock threshold are preferred.

Each figure represents only one simulation, but we also reproduced the emergence of similar results with other simulations. Table 1 is the result of 15 simulations: the same rank between the restock strategies emerges each time.

Nevertheless, a high threshold implies more deliveries; therefore, the financial costs should be more important for the final consignees. In the simulation, the agents use an efficiency measure based on one criterion regarding the time to deliver: they never consider the costs. Therefore, the implementation of another measure, based on another criterion, might produce different results on the emergence of strategies.

5.3.2 *Traffic and Transport Network.* Two features of the simulation are now considered: the first allows vehicles to leave a trace on their way in order to observe the traffic; the second one allows blocking some roads dynamically to disrupt the system (with the dynamic graph used to

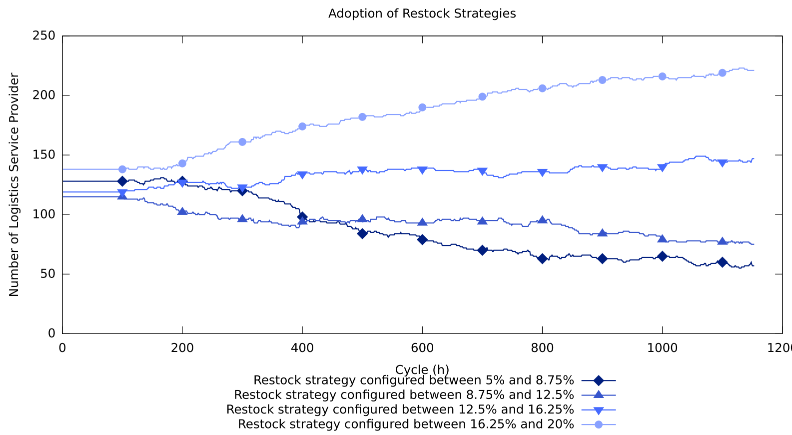


Fig. 14. Restock strategy emergence with fixed warehouse selection strategy. Simulation 2—Warehouse selection strategy: closest or largest.

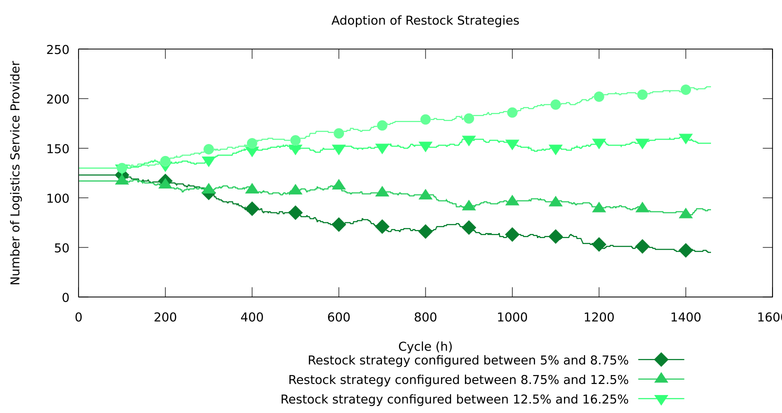


Fig. 15. Restock strategy emergence with fixed warehouse selection strategy. Simulation 3—Warehouse selection strategy: random bias according to distance/surface.

model the transportation network) so that one can observe how the system behaves when the transport network fails. As done before, we limited possible bias due to dynamic interactions between agents. To do so, the simulation has been executed without any modifications of the supply network, built with strategy 2.

In Figure 17(a), the traffic is in a standard state, which is used as the control state. The main urban areas are connected by more or less important flow of goods. Paris, as the biggest logistic activity area, is the most attractive city. Indeed, we observe two main logistic corridors: one on the Le Havre-Paris axis, and the other one on the Antwerp-Paris axis. The capital city attracts most of the traffic. Orléans seems to be restocked by flows from both Le Havre and Antwerp (through Paris).

Now, we provoke some disruptions in the system by blocking different roads on the Antwerp-Paris axis. This allows us to observe how the flow is reorganized. Figure 17(b) shows how the flow of this axis is bypassed south to avoid the blocked area. The flow is divided into two subflows:

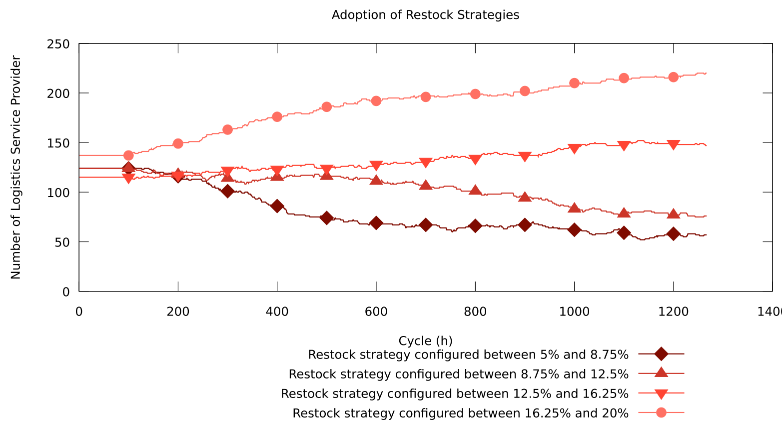


Fig. 16. Restock strategy emergence with fixed warehouse selection strategy. Simulation 4—Warehouse selection strategy: based on (i) a random bias according to distance/surface and (ii) on accessibility.

one joins the northeast of Paris (one of the most important logistic areas of this district) and the second uses a southeast pathway.

If the disruption is amplified, as in the Figure 17(c), and so on, almost all pathways from Antwerp become blocked; one can see that the system initiates a new organization. Some parts of the flow from Antwerp seem to go through the Rouen urban area.

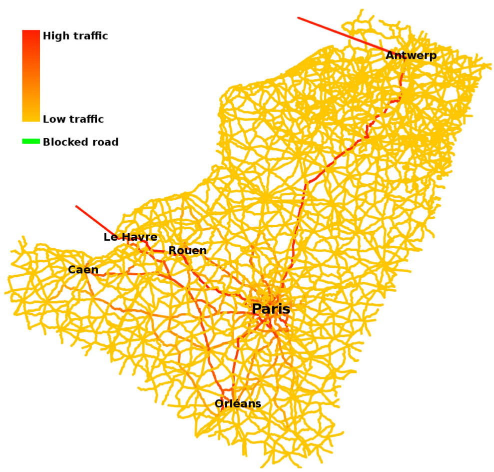
This approach to analyzing the traffic illustrates the resilience ability of the system. It could help users to have a better understanding of the evolution of the traffic in the case of disruption. It shows how the flow is reorganized and which alternative roads are taken. This study has been done at a regional scale, but it is possible to make it at a wider or smaller scale, or a different region of the world, with a different database.

6 DISCUSSION AND CONCLUSION

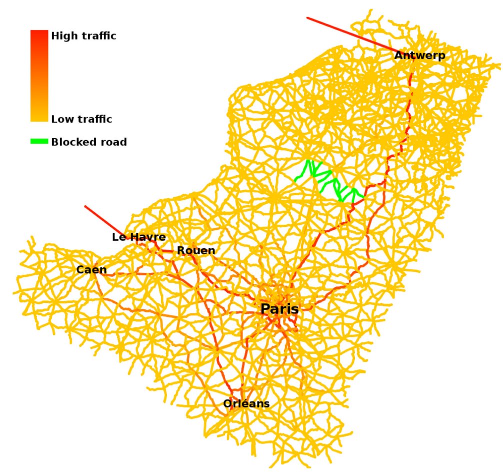
The complex system approach of this article proposes a model of a logistic system to study how it is structured and how its dynamics work according to adaptive behaviors and a multi-scale approach. The goal is to acquire a global knowledge about the system from the behaviors and interactions at a local scale. Our approach described the behaviors, properties, organizations, and constraints (spatial, political, economical, etc.) of each actor and infrastructure of the system. We saw that this kind of system is also defined by the interactions between the system's components. The daily, and even hourly, decisions taken by the actors according to their collaborators or competitors influence the environment that itself has an effect on the behaviors of the actors. This mechanism of feedback loops leads to the emergence of properties at different levels of study, revealing a complex system.

Our agent-based model coupled with dynamic graphs allow integration of the particular characteristics of logistic systems: the spatiality, dynamics (on an hourly basis), and the functional rules of each actor and infrastructure. Moreover, the model is adaptable to different logistic systems: each system can have different constraints or its actors can have different working habits. Regarding the dynamic graphs, they are mainly used here to represent the transportation network and its evolution. There is one dynamic graph for each kind of transport mode, connected by agents. The graphs are also used to describe the interactions between the actors. It could allow detection of the clusters of actors such as the port cluster or even the most efficient set of collaborators.

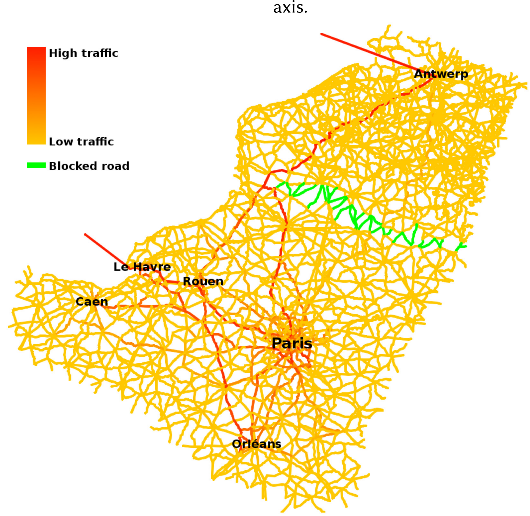
The model also allows experimentations with different scenarios using the simulation. The last section shows how the model is used to observe the emergence of optimal behaviors (adaptive



(a) Goods traffic with usual conditions.



(b) Goods traffic after a small disruption on the Antwerp-Paris axis.



(c) Goods traffic after a major disruption on the Antwerp-Paris axis.

Fig. 17. Goods traffic according to different states of the road network.

behaviors) according to predefined efficiency measures. It shows that the simulation could be used to compare two different strategies in a complex system. This comparison might be done during a simulation when the system is disrupted. The user is able to test whether some strategies achieve better (or inferior) results when disturbances occur in the system. In addition, the user can propose and test other strategies besides the one already implemented. The results of the second study show the dynamics of the network when it is disrupted at a regional level. It highlights the resilience capacity of the system and how it is reorganized via secondary roads.

Some critics of the model should be taken into consideration. First, in the real world, there are more than two access nodes, and it is difficult to implement the model with a realistic number of them. Also in the real world, a part of the transported goods are not always addressed to somewhere inside the system. We could use an aggregated model to represent these flows to affect the traffic of our simulation.

To gain more perspectives, we would like to implement the multi-modal network to provide more flexibility to agents by using new transport possibilities. It would help us to test the effects of new scenarios, such as the future creation of the "Seine–Nord Europe" canal, which will connect the Seine basin and Belgium, Germany, and the Netherlands. Then, we would like to integrate different kinds of costs, such as financial or the carbon footprint. Costs could be used to study the effects of other scenarios: for instance, how eco-taxation can impact decisions and performances. We also want to take some time to validate our model and compare the flow data generated by the simulation with real data. We intend to use a database such as ETISPlus[9] to do so. Eventually, we want to develop the concept of community (or cluster) detection to highlight the most efficient actors so that we could understand why they are efficient and try to transfer this knowledge to other actors in order to make them more efficient.

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