Emergence of Strategies in a Logistic System Thanks to an Agent-based Model and Dynamic Graphs

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***Abstract*—The modeling of logistic system is a major issue of logistic research. Several researches use data about flow of goods to extrapolate the evolution of logistic systems, but these data might be difficult to acquire. We propose a complex system approach with agents and dynamic graphs to model logistic systems. It allows us to describe the local properties and functional rules of these organizations in order to observe the evolution of such a system in a dynamic context and with minimal initial data. This paper is the occasion to present the emergence of the best strategies used by logistics service providers to restock the warehouses and their customers. It shows how the mechanisms of our model allow the agents to react to disturbing events and to update their behaviors in order to stay efficient.**

***Index Terms*—agent-based model, dynamic graph, logistic system, modeling, complex system**

I. Introduction

In a logistic system, actors interact together in order to manage coherent flow of goods. They take decisions based on their available resources (such as infrastructures) but they also have to deal with the constraints of the system. The efficiency of a logistic system has an important impact on its economy or on its environment. The study of such a system is therefore a major issues of logistics research. Several efforts have been made in this way, in order to optimize [1] or to understand how flow of goods are organized [2]. In the literature on logistics, we can find different models, such as SMILE (Strategic Model for Integrated Logistic Evaluations) [3] which uses aggregated data about flow of goods in order to extrapolate the main roads followed by the goods. We also find some models like FAME (Freight Activity Microsimulation Estimator) [4], [5] or TAPAS (Transportation And Production Agent-based Simulator) [6], which use disaggregated data. This last model is designed to simulate three actors around the Baltic sea, and with a simplified transportation network. But, firstly, Tavasszy et al. [7] highlight that these models lack of dynamism (they mostly evolve on a month or even a year basis for each step), and secondly, the authors of FAME explains that the access to the needed data might be difficult. Choi et al. [8] describe the interests to consider logistic system as complex one. We also shown why logistic systems should be considered as complex in Demare et al. [9]. The complex system approach allows to model the behaviors of local entities of such a system in order to observe the evolution of the whole system thanks to auto-organization processes and emergence of properties. We present here a multi-agent model coupled with dynamic graphs. We describe in the first section which are the agents, how they interact dynamically, and how they behave thanks to different strategies. We also present the transportation network modeled by dynamic graphs. The model is strongly dynamic and it evolves on an hour basis. In the last section, we present some results: we show how the best strategies (considering an efficiency measure) emerge from local and distributed decisions. These results reveal that our model might be used to observe how a logistic system evolves according to dynamical (and possibly disturbing) events.

A. Model

In this section, we first present the actors of the logistics modeled as agent (see [10] for a full description). Then, we describe the transportation network modeled by a dynamic graph.

a) Actors as Agents: The figure 1 represents the actors modeled by an agent and how they interact together. The final consignee agents have local stocks. They decrease each day

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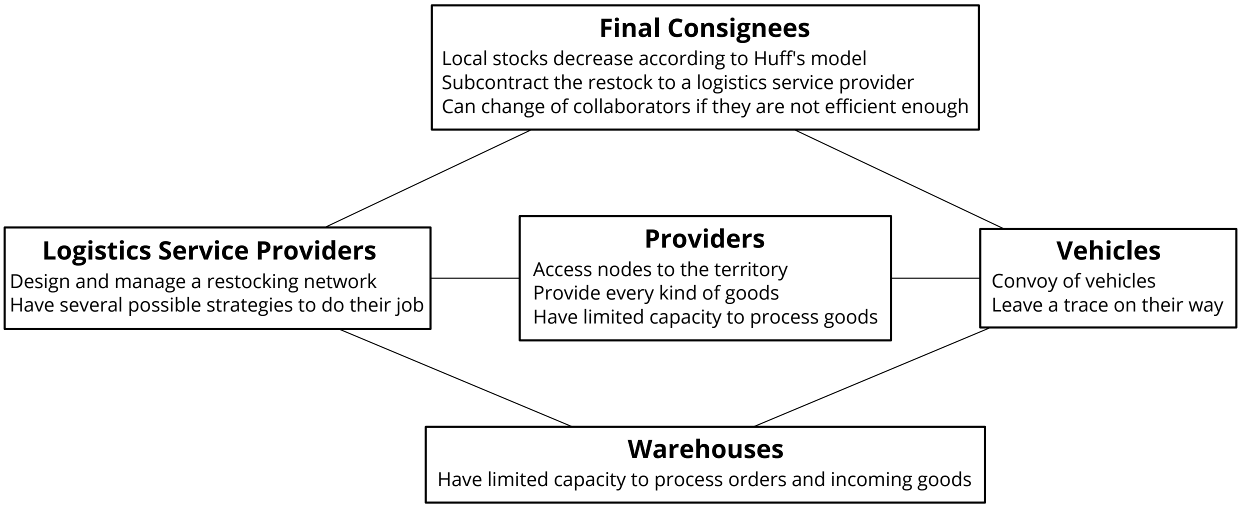


Fig. 1: The different kind of actors modeled by agents.

according to a biased random number (defined thanks to the Huff's model [11] [1]). A logistics service providers (LSP), chosen by the final consignee, manages the outsourced stocks. One LSP might have none or several final consignee(s), but one final consignee has only one LSP (selected randomly, biased by the distance). The goal of a LSP is to design and manage a supply network. The topology of this network is: a foreign goods provider connected to some regional warehouses, themselves connected to some local warehouses, connected to the final consignee(s) of the LSP. The topology is mostly the same from a LSP to another, but the way to select a warehouse may differ. Indeed, at the initialization of the simulation, each LSP is associated to one of the four strategies of selection. The first strategy (the control strategy) simply selects randomly the warehouses. The second selects the closest warehouse to the final consignee for a local warehouse, and the one which offers the largest storage surface for the regional level. The third selects the warehouses randomly but, with a bias: according to the distance with the final consignee for the local level, and according to the storage surface for the regional level. Finally the fourth strategy makes a first filter on the warehouses, according to the distance or the surface, and then select the ones which are the most accessible in the network (in term of the accessibility index proposed by Shimbel [12]).

Once the network is designed, the LSP monitors the stocks levels once a day. The agent browses each warehouse of its network thanks to a depth-first search algorithm. For each stock inside the warehouses of his 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 which defines the restock strategy of a LSP to determine when he orders a restock. The LSPs do not share the same "restock threshold" value. If the quantity of product is too low, then the LSP orders the restock to a node of higher level in the network.

During the simulation, each final consignee regularly takes measure of the efficiency of their LSP and compares it to the average efficiency measure of every LSPs. If the LSP is not efficient enough, then the consignee can decide to choose another LSP. The figure 2 describes this behavior. There are two heuristics to make this measure (inspired by the works of [13], [14]):

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

Due to this mechanism, the final consignee will tend to keep the best LSPs and let the worst ones. We will see in the results section that the best strategies emerge due to this behavior.

The foreign goods providers represent the access nodes. We consider that they aggregate every real foreign providers, and they can satisfy every orders of every kind of product. There are several provider agents only to model the different access nodes of the system.

b) Transportation Network as Dynamic Graph: The transportation network is a dynamic graph. It means that its topology can be updated in real time (*e.g.* road works,...) [16]. Moreover, the traffic on its edges evolve according to the vehicle traffic.

Vehicle agents carry goods on the network (see figure 3 for activity diagram of this kind of agent). At their creation, these agents compute a path from their initial location to their destination. As they move along this path (according to the speed limits), they leave, on each edge, a trace which is the amount of goods they carry. At each step, a coefficient makes decrease the trace on every edges, as the pheromones in ant colony optimization algorithms [17] which evaporate progressively. The trace is used to observe the traffic on the

[1]It considers the population densities and the accessibility to the network of shops to define their numbers of customers.

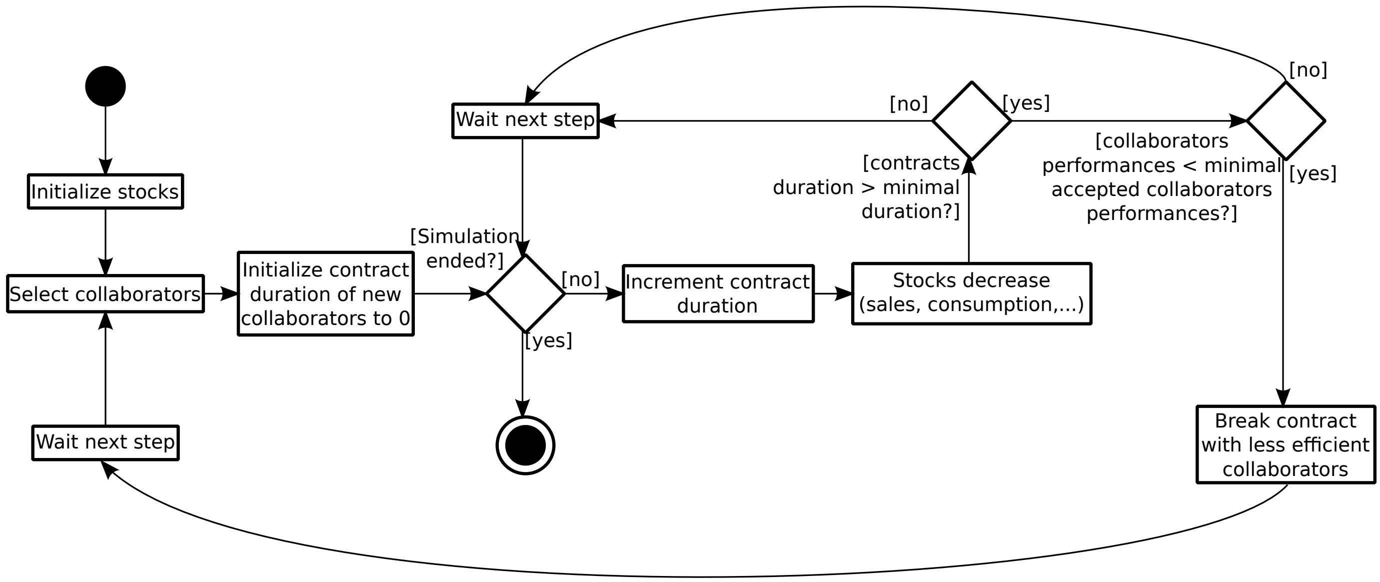


Fig. 2: Activity diagram of the final consignee agents describing how they manage their collaboration with a LSP.

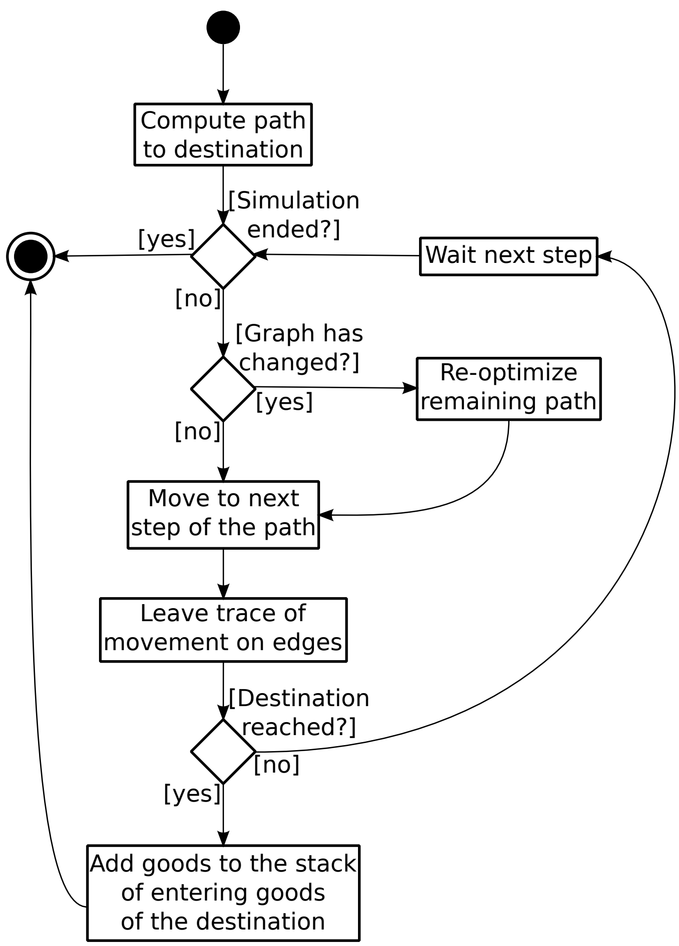


Fig. 3: Activity diagram of the vehicle agents carrying goods on the transportation network

network: if an edge is no more used for some reasons, the evaporation process will dynamically highlight this change.

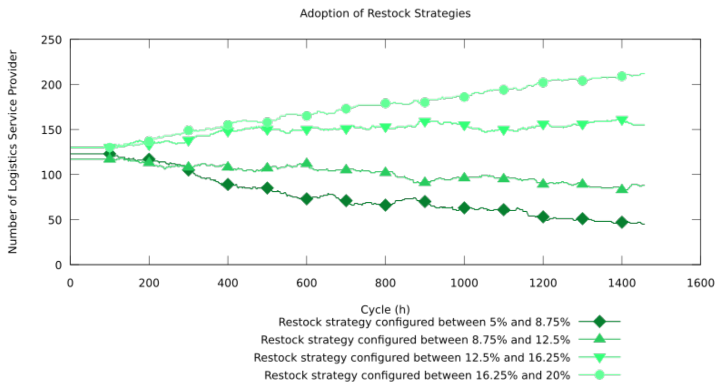
II. Results

In this section, we present some results: how the best restock strategies emerge from local and distributed decisions.

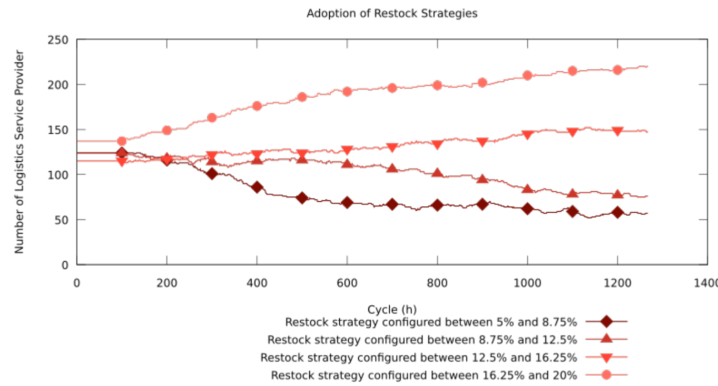
We implemented our model in the GAMA Platform. Our case study is the Seine axis logistic system. Indeed this particular system offers several urban areas with a large population (whose mainly Paris) and the logistic activities are numerous and various. The geography of this system is also interesting since the Seine river draws a natural corridor between the port of Le Havre and the region of Paris. Moreover, the Seine axis logistic system is related to many research interests due to the competition with the port of Antwerp which deliver an important part of the flow of goods to Paris. Therefore, our simulation might help to understand the strengths and weaknesses of this system. The data about the actors and the infrastructures were provided by the Devport project[2]. There are around 3000 warehouses agents which provide storage surfaces of more than $2000m^2$. The 7700 final consignees agents are retailers. There are two foreign goods providers (one connected to the port of Le Havre and the other one connected to the port of Antwerp). And there are around 2250 LSP agents. We notice that the number of simulated agents, and considering the dynamics of our model, is a main innovation compared to other researches like TAPAS [6] or FAME [4], [5].

The figure 4 concerns the choice of a restock strategy. On each chart, we measure the number of LSPs chosen by the final consignees. We associate the LSPs to a curve according to the value of their restock thresholds. For these simulations,

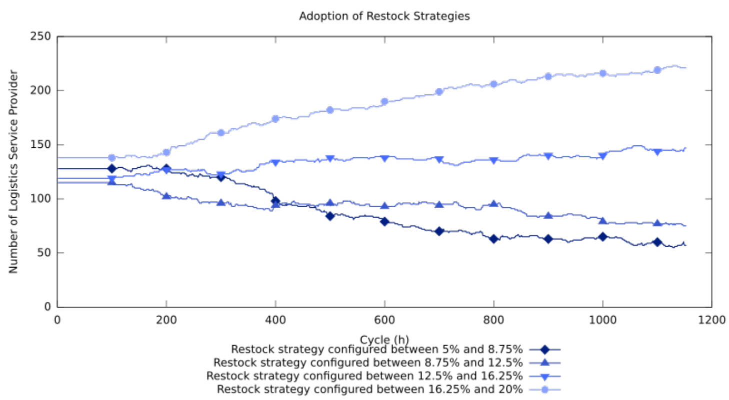
[2]It is a multidisciplinary research team who works on the study of the logistic system of the Seine axis



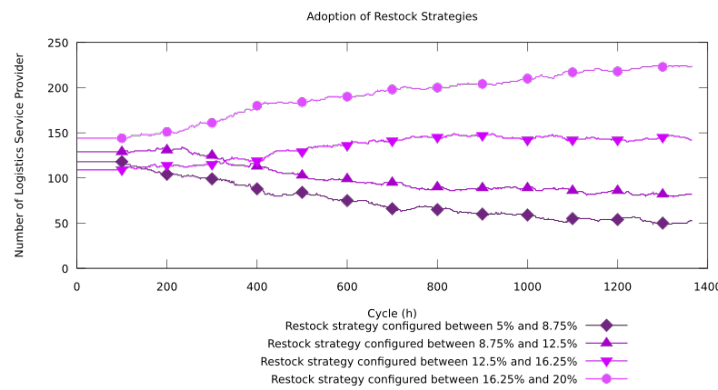
(a) Restock strategy emergence with fixed warehouse selection strategy. Simulation 1 - Warehouse selection strategy: random biased according to distance/surface..



(b) Restock strategy emergence with fixed warehouse selection strategy. Simulation 2 - Warehouse selection strategy: also consider the accessibility..



(c) Restock strategy emergence with fixed warehouse selection strategy. Simulation 3 - Warehouse selection strategy: closest or largest..



(d) Restock strategy emergence with fixed warehouse selection strategy. Simulation 4 - Warehouse selection strategy: pure random..

Fig. 4: Emergence of the best restock strategies

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 the LSPs used the same method to select the warehouses of their supply network. Here, the efficiency measure used by the final consignee is the number of stock shortages.

On the figure 4, we can notice the emergence of the same results whatever the strategy used by the LSPs: agents with the highest restock threshold are preferred.

A high threshold implies more deliveries, more often. Therefore the final consignees have less stock shortages with this strategy. Considering the efficiency measure, it is the best strategy. Nevertheless, with this strategy the financial costs should be more important for the final consignees since there are more goings and comings. In the simulation, the efficiency measure used by the agents never consider the costs. Therefore, the implementation of another measure, based on another criterion, might produce different results on the emergence of strategies. Moreover, thanks to this mechanism of emergence, if we disturb the system, the agents are able to react and to update their behaviors in order to stay efficient.

Thus, we have shown here that the emergence of optimal behaviors is enforced by our approach.

Of course, the strategies developped here are simple and they generalyze the main work habits of actors of the logistics. However, we could implement other strategies more specific to some particular problems such as the issues related to urban logistics. For instance, we could use the simulation to observe the effects of innovative strategies on the congestion of the urban traffic.

III. Conclusion

To put it in a nutshell, we describe in this article an agent based model coupled with dynamic graphs which represent a logistic system. We had a complex system approach in order to model the local behaviors and properties of logistic systems. It allows us to observe its evolution in a dynamic context and despite a lack of data about flow of goods. More specifically, we present the mechanisms behind the emergence of the best strategies used by logistics service providers to restock the warehouses and their customers (the final consignees). This mechanism allows the agents to react to disturbing events as in the reality. Therefore, with this model, we can observe how the system evolves according to different scenarios.

As perspective of this work, we would like to implement in the near future the different modes of transport on the network.

Indeed, the simulation only considers the road to carry goods. We also want to develop other kind of efficiency measure, for instance, based on financial costs or on the carbon footprint. This last measure could be used to study the effects of ecotaxation.

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