MODELING OF THE VULNERABILITY RELATED TO THE DYNAMIC ROAD TRAFFIC

Cyrille Bertelle Antoine Dutot Michel Nabaa* Damien Olivier
Université du Havre
LITIS
25, rue Phillipe Lebon
F-76085 Le Havre
{Cyrille.Bertelle; Antoine.Dutot; Michel.Nabaa; Damien.Olivier; }@univ-lehavre.fr

Pascal Mallet
CODAH
19, Rue Georges Braque
F-76085 Le Havre
Pascal.Mallet@agglo-havraise.fr

KEYWORDS

Dynamic Vulnerability Map, Decision Support System, Risk, Dynamic Graph, Communities Detection, Self-Organization, GIS, Traffic Flow

ABSTRACT

The utilization of the road network by vehicles with different behaviors can generate a danger under normal and especially under evacuation situations. In Le Havre agglomeration (CODAH), there are 33 establishments classified SEVESO with high threshold. The modeling and assessment of the danger is useful when it intersects with the exposed stakes. The most important factor is people. In the literature, vulnerability maps are constructed to help decision makers assess the risk. These maps are based on several types of vulnerability: socio-demographic, biophysical and other different types of hazards. Nevertheless, such approaches remain static and do not take into account the population displacement in the estimation of the vulnerability. We propose a decision support system which consists in a dynamic vulnerability map based on the difficulty to evacuate different sectors in Le Havre agglomeration. This map is visualized using the Geographic Information System (GIS) of the CODAH and evolves according to the dynamic state of the road traffic through a detection of communities in a large graph. This detection is realized by an ant algorithm.

INTRODUCTION

Le Havre agglomeration is exposed to several types of natural and industrial hazards: 16 establishments are classified SEVESO [1](EUROPEAN Community 1996) with very high threshold.

The examination of impacted populations remains a difficult exercise. In this context, the Major Risk Management Direction team (DIRM) of Le Havre Agglomeration (CODAH) has developed a model which estimates the nocturnal and diurnal exposed population allocation PRET-RESSE (Bourcier and Mallet 2006); the scale is the building. Although the model is able to locate the diurnal and nocturnal population, it remains static because it does not take into account the daily movement of people and the road network utilization.

For a better people evacuation in a major risk case, we need to have detailed information about the state of road traffic network to determine how to allocate the vehicles on the road network and model the movement of these vehicles. In fact, the panic effect of some people and the redundant drivers behaviors can lead to accidents and traffic jam, this can be very grievous and spread quickly.

In the literature, several models were developed to calculate a score for the vulnerability related to the road network utilization. Most of these models adopt a pessimistic approach to calculate this vulnerability: this case is met when a group of people in a hazardous area decide all to take the same route to evacuate this area, which unfortunately happens quite often in the real world evacuation situations. Although it helps decision-makers to estimate the risk by a census vulnerability map, this approach remains static and does not take into account the evolution of the road network traffic.

In this paper, we propose a dynamic and pessimistic approach related to the road network utilization. To this end, we model the road network by a dynamic graph (the dynamics is due to the traffic evolution). A simple model based on traffic flow will also be proposed and the interaction between micro and macro traffic simulation will be discussed. Then, we apply a self-organization algorithm (belonging to the collective intelligence algorithms) to detect communities in the graph. These communities correspond to clusters in the graph which evolve along the time. Each community is

*Corresponding author. Authors are alphabetically ordered. Michel Nabaa research is supported by Haute-Normandie Region.

[1]Directive SEVESO is an European directive, it lays down to the states to identify potential dangerous site. It intends to prevent major accidents involving dangerous substances and limit their consequences for man and the environment, with a view to ensuring high levels of protection throughout the Community.

a group of people in a neighborhood who share totally or partially, at a give time, the same route. The algorithm allows us to define the different vulnerable neighborhoods of the agglomeration in the case of a pessimistic evacuation due to a potential danger, while taking into account the evolution of the road network traffic due to the impact of the other flows coming from other neighborhoods. The result of this algorithm will be visualized into a GIS on a dynamic vulnerability map which categorizes various sectors depending on the difficulty of access to the road network. Finally, this vulnerability map will construct a tool to aid decision-makers in a better estimation of risk in the communes of the CODAH. This tool enriches the PRET-RESS static model developed at the CODAH, taking into account the mobility of the population.

STATE OF THE ART

Traditional methods evaluating the risk for population do not treat generally the behavioral of evacuee (e.g. initial response to an evacuation, travel speed, family interactions / group, and so on.); they describe prescriptive rules as the travel distance. These traditional methods are not very sensitive to human behavior for different emergency scenarios. The computerized models offer the potential to evaluate the evacuation of a neighborhood in emergency situations and overcome these limitations (Castel 2006).
Recently, some interesting applications have been developed by including the population dynamics, the models of urban growth patterns and land use.
For computer modelers, this integration provides the ability to have computing entities as agents that are linked to real geographical locations. For GIS users, it provides the ability to model the emergence of phenomena by various interactions of agents in time and space by using a GIS (Najlis and North 2004). So, combining several layers as houses, road network, population... allows us to model different types of agents into a GIS environment.
In (Cutter et al. 2000), the authors present a method to spatially estimate the vulnerability and treats the biophysical and social aspects (access to resources, people with evacuation special needs, people with reduced mobility ...).
Several layers are created in the GIS (a layer by a danger), and all these layers are combined into one composed of intersecting polygons to build a generic vulnerability map. To complete this, it was necessary to take into account the infrastructure and various possible routes of evacuation. So, a new map has been constructed and a new layer has been incorporated. This work has been applied to the George Town canton in which we find various natural and industrial risks, and where there are different types of people.
In the neighborhood evacuation cases on a micro scale, a number of studies based on micro simulation have been developed.
In their paper (Church and Cova 2000), the authors presented a model to estimate the necessary time to evacuate a neighborhood according to the effective of the population, the number of vehicles, roads capacity and the number of vehicles per minute. The model is based on the optimization in order to find the critical area around a point at a potential danger in a pessimistic way. This model has been coupled with a GIS (ArcInfo) to visualize the results (identify evacuation plans) and construct an evacuation vulnerability map for the city (Santa Barbara).
Cova and Church (Church and Cova 1997) opened the way on the study based on geographic information systems to evacuate people. Their study identified the communities that may face transport difficulties during an evacuation. Research has modelled the population by lane occupation during an evacuation emergency using the city of Santa Barbara.
An optimization based model (graph partitioning problem) was realized to find the neighborhood that causes the highest vulnerability around each node in the graph and a vulnerability map around nodes in the city was constructed. A constructive heuristic has been used to calculate the best cluster around each node. This heuristic was developed in C and the result was displayed on a map (with ArcInfo).
Nevertheless, in this approach, we predefine the maximum number of nodes in a neighborhood, which may not always be realistic and does not take into account the traffic evolution during the calculation of critical neighborhoods. So, the vulnerable neighborhoods don't evolve according to traffic state.
Since an individual panic under evacuation situation may cause a collective panic and the changes that may occur in the environment (buildings collapse, reverse route direction), the evolution of the system is unpredictable; so, in our work, we try to build a dynamic vulnerability map evolving with the traffic dynamics, in which the nodes number of in a critical neighborhood, is not predetermined and can change depending on actual traffic state.

DYNAMIC MODEL

Problem description

In this paper, the term "vulnerability" depends on the access to the road network. To address this vulnerability, we have to finely represent the population and the dynamic state of road traffic. In PRET-RESSE model developed within the major risks management team of CODAH, we have ventilated the *day / night* population at the building scale. The model was able to locate people during the day both in their workplace and their residence (the unemployed and retirees). It has been estimated that people will be in their residence during the night.
PRET-RESS will be enriched by our model that will try to dynamically assess the vulnerability related to the road traffic evolution; so we are interested in the allocation of the vehicles on the road network, the regulation of the traffic flow and trying to dynamically estimate the vulnerability according to the traffic.

System architecture

Our system consists of two modules as shown in the figure 1.

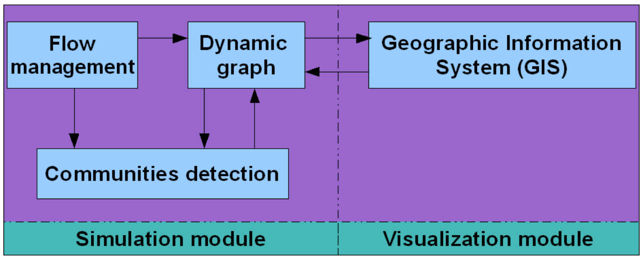

Figure 1: System architecture

The simulation module contains three components:

- The dynamic graph extracted from the road network layer and detailed in the following section,
- The flow management component consists of vehicles flow simulator applied on the graph,
- The communities detection component, detailed in the "Communities Detection" section. Its input is the extracted graph and the current flow. It returns the communities that are formed according to the current state of road traffic.

The visualization module consists of the road network layer integrated into the GIS. This module communicates with the simulation module: the graph is constructed from this module, which in turn get the simulation result and visualize it as a dynamic vulnerability map.

Environment modeling

The road network is integrated as a layer in the Geographic Information System (GIS). From this layer, we extract the data by using the open source java GIS toolkit Geotools. This toolkit provides several methods to manipulate geospatial data and implements Open Geospatial Consortium (OGC) specifications, so we can read and write to ESRI shapefile format. Once data road network are extracted, we use the GraphStream tool (Dutot et al. 2007) developed within LITIS laboratory of Le Havre to construct a graph corresponding to the GIS network layer. This tool is designed for modeling; processing and visualizing graphs.

Figure 2 represents the network layer into the GIS and the figure 3 is the graph extracted with geotools and visualized with GraphStream by using the same points coordinates.
The data extracted from network layer contains the roads circulation direction, roads id, roads type, their lengths and geometry.
The extracted multigraph $G(t) = (V(t), E(t))$ represents the road network at time t where $V(t)$ is the set of nodes at t and $E(t)$ the set of arcs at t. We deal with a multigraph because we have sometimes more than one oriented arc in the same direction between two adjacent nodes due to multiple routes between two points in Le Havre road network. GraphStream facilitates this task because it is adapted to model and visualize multigraphs. In the constructed multigraph:

- The nodes represent roads intersections,
- The arcs represent the roads taken by vehicles,
- The weight on each arc represents the needed time to cross this arc, depending on the current load of the traffic
- Dynamic aspect relates to the weights of the arcs, which can evolve in time, according to the evolution of the fluidity of circulation.

We have also constructed a Voronoi tessellation (Thiessen polygon) around nodes and projected the population in buildings on these nodes. The population in buildings is extracted from PRET-RESS model.

Vehicles flow

For a better people evacuation in a major risk situation, we need to know the state of the road network to determine how to allocate the vehicles on this network and to model the movement of these vehicles. Different types of models can be adopted:

- The microscopic model details the behavior of each individual vehicle by representing interactions with other vehicles and in general by using a spatialization. It is used on the scale of a sector or a neighborhood. It has the advantage to model vehicle behavior in an evacuation of a neighborhood, people panic, interactions between vehicles, accidents... So, if we have vehicles with different behaviors and interacting between them, these vehicles sometimes self organize and with a top down approach, we can examine the global behavior of the system and try to locally modify the environment, when necessary, to ameliorate the system,
- The macroscopic model is based on the analogy between vehicular traffic and the fluid flow within a canal. It allows us to visualize the flow on the roads rather than individual vehicles. It is used at many sectors or the entire city scale,
- The hybrid model allows coupling the two types of dynamics flow models within the same simulation. Several works have already borrowed this direction (Hennecke et al. 2000, Bourrel and Henn 2002, Magne et al. 2000), however, this approach is relatively new and very few have adopted it to our knowledge (Hman et al. 2006). The use of a hybrid model is very important to us: changing the scale from micro to macro in a region where we haven't a crisis situation (everything is normal) allows to economize the computation and the

Figure 2: The initial network layer

change from macro to micro in a critical situation allows to zoom and detect the behaviors and interactions between entities in danger.

In this paper, we used a simple model of macroscopic flow:

- A flow of cars moving from one arc to another adjacent one,
- The arcs are limited in capacity,
- The flow can be broken and two or more flows can gather on a node,
- Traffic jams may appear in certain places of the road network; those places will be more vulnerable than others.

We have adopted a macroscopic model in which flows circulate normally (no accidents) because the goal now is to establish a dynamic pessimistic vulnerability map which is not always the case in the real world (e.g. 90% of people takes an exit route and the rest takes another route for example). Hence, it is important to have in the near future a micro approach with a change of scale (from micro to macro and vice versa during the simulation) to simulate scenarios of danger in real time (accidents, behavior of drivers, vehicles interactions ...), a study on which we are working actually.

COMMUNITIES DETECTION

Our aim is to identify communities in graphs, i.e. dense areas strongly linked to each other and more weakly linked to the outside world. If the concept of communities in a graph is difficult to define formally, it can be seen as a set of nodes whose internal connections density is higher than the outside density without defining formal threshold (Pons 2005). Thus the goal is to find a partition of nodes in communities according to a certain predefined criteria without fixing the number of such communities or the number of nodes in a community. Interesting works were developed in the literature on the detection of structure in large communities in graphs (Clauset et al. 2004, Newman 2004a;b, Pons and Latapy 2006).
In our problem, we look for a self-organization in networks with an algorithm close to the detection of communities in large graphs and belonging to collective intelligence algorithms. Organizations connect elements, events or individuals by interrelations so that they become components of a whole. They assume the solidarity and robustness of these links, and ensure that the system will eventually be long lasting despite random perturbations. The organizations, therefore : transform, produce, tie and maintain. Time is present generating the dynamic and we will try to fight against these organizations, in the case of risk management, to avoid bottlenecks which do not facilitate the evacuations.

Thus we will considered the graph at time t, $G(t) = (V(t), E(t))$ where the edges are weighted, this weight being noted $|e|$ for the edge e and represents the needed time

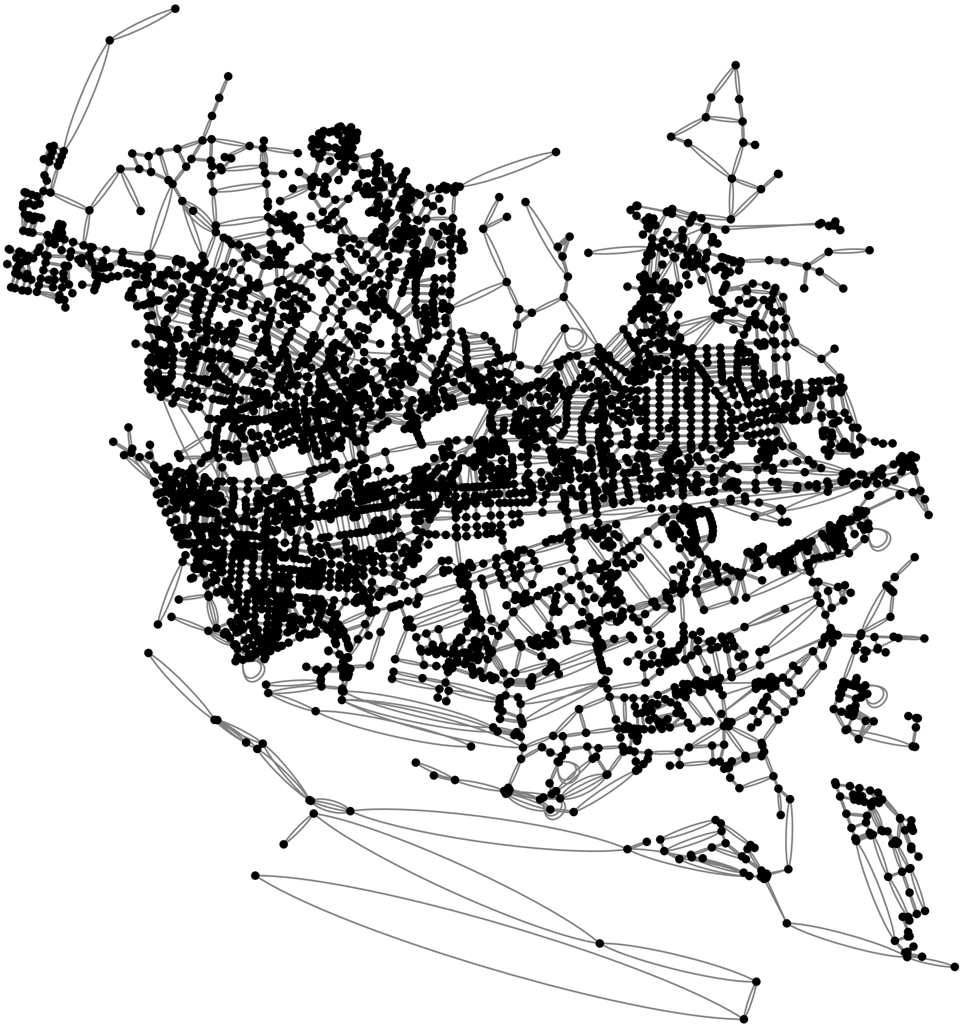

Figure 3: The extracted graph

to cross this arc, depending on the current load of the traffic and we try to define a colored dynamic graph $G(t) = (E(t), V(t), C(t))$.
The algorithm used can be referred to as an *ant algorithm* (Dorigo and Stützle 2004). Our ant algorithm use several colonies of ants, each of a distinct color. Ants travel inside the graph an lay down pheromones, information that can be detected by other ants. Pheromones are also colored. Ants tend to be repulsed by pheromones of other colors. Furthermore, ants tend to favor edges with important weights.
The colored dynamic graph precedently mentionned is defined such that:

- $V(t)$ is the set of vertices at time t. Each vertex v is characterized by:
  - a color $c \in C(t)$,
- $E(t)$ is the set of edges at time t. Each edge e is characterized by:
  - a weight $|e| \in \mathbb{N}^+$ that corresponds to interaction importance between the elements at each end of edge e.
  - a quantity of pheromones of each color.
- $C(t)$ is a set of colors representing the ant colonies at time t.

The algorithm principle is to color the graph using pheromones. Each colony will collaborate to colonize zones, whereas colonies compete to maintain their own colored zone (see figure 4). Solutions will therefore emerge and be maintained by the ant behavior (see figure 5). The solutions will be the color of each vertex in the graph. Indeed, colored pheromones are deposited by ants on edges. The color of a vertex is obtained from the color having the largest proportion of pheromones on all incident edges (see algorithm 1).
We have an interaction between each two local adjacent nodes according to the attraction force that exists between them. This force depends in our case on the report of *the number of vehicles on the arc between 2 nodes neighbors / vehicles capacity of the arc*. This report was chosen because, in every community, we will have a large number of vehicles

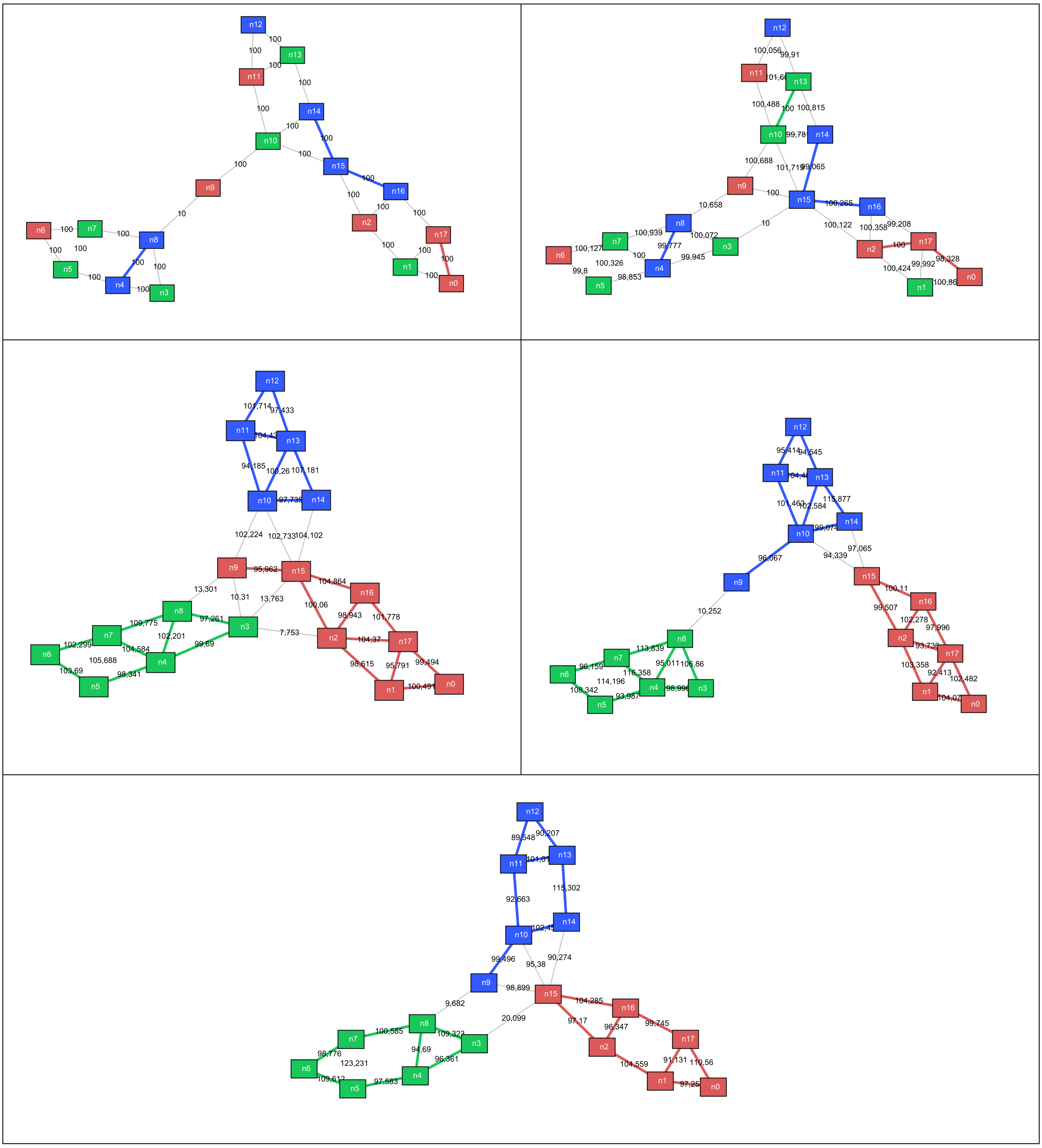

Figure 5: *Example of a dynamic evolution and communities detection.*

which all decide to exit through a single road in the case of a potential danger; this responds well to one of the purposes listed in beginning to have a pessimistic approach in the calculation of vulnerability. The algorithm has the advantage of not allowing the breaking of a link between 2 adjacent nodes to maintain the structure of the road network. When the traffic evolves, the algorithm detects that and communities can change or disappear as a result of local forces that change between the nodes locally.

Dynamic vulnerability map

At each simulation time step, the flow on the arcs changes following traffic conditions and the attraction may change also. Once communities are formed on the graph, the result will be transmitted to the road network layer into the GIS to

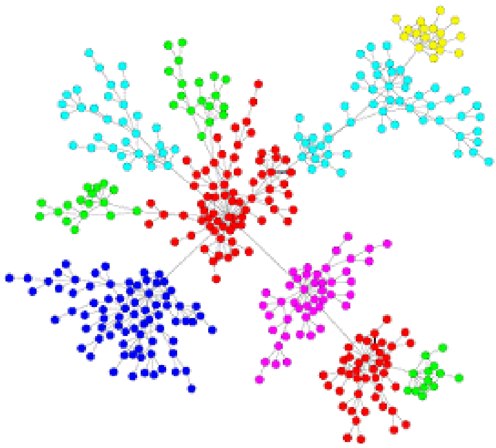

Figure 4: Communities detection in a graph

Algorithm 1: Ant behavior

n: current node
t: current time
A: fear of hostile environment threshold
T: resting time
Δt: time counter
if *degree(n)=0* **then**
    Jump randomly on another node
else
    $w \leftarrow$ Sum of all weights on each incident edge to n
    $\tau \leftarrow$ Sum of all pheromones of all colors on each incident edge to n
    $\tau_c \leftarrow$ Sum of pheromones of the ant color on each incident edge to n
    $a \leftarrow \frac{\tau_c}{\tau}$
    if $\Delta t < T$ **then**
        Choose an edge to cross in a weighted random fashion, using edges weight (if available)
        Lay down a small amount of pheromone of the ant color on this edge
        $n \leftarrow$ vertex at the other end of the chosen edge
        $\Delta t \leftarrow \Delta t + 1$
    else
        if $a < A$ **then**
            Jump randomly on another node
            $\Delta t \leftarrow 0$
        else
            Choose an edge to cross in a weighted random fashion, using edges weight (if available)
            Lay down a small amount of pheromone of the ant color on this edge
            $n \leftarrow$ vertex at the other end of the chosen edge

be visualized.

CONCLUSION

In this paper, we have proposed a decision support system to assess the danger depending on the road network usage by the vehicles population using the network. This tool enables decision makers to visualize, on a geographic information system, a dynamic vulnerability map related to the difficulty of evacuating the various streets in the metropolitan area of Le Havre agglomeration. We simulated road network traffic by using a simple model of vehicles flow. A communities detection algorithm in the large graphs was adopted. It enabled us to form communities in a graph thanks to local forces propagation rule between adjacent nodes. The communities evolve according to the current state of the road network traffic. The result of the evolution of communities is visualized by using a GIS. The adopted approach allowed us to estimate the risk due to the use of the road network by vehicles and categorize Le Havre agglomeration areas by their vulnerability. We will complete our work by using real traffic data retrieved from a displacements survey with Le Havre population which will help us to better locate people during the day and therefore having a more realistic vulnerability dynamic map.

REFERENCES

Bourcier J. and Mallet P., 2006. *Allocation spatio-temporelle de la population exposée aux risques majeurs. Contribution à l'expologie sur le bassin de risques majeurs de l'estuaire de la seine: modèle PRET-RESSE. Revue internationale de Géomatique*, 16(10), 457–478.

Bourrel E. and Henn V., 2002. *Mixing micro and macro representation of trafic flow : a first theoretical step*. In Proceeding of the 9th Meeting of the Euro Work-ing Group on transportation.

Castel C., 2006. *Developing a prototype agent-based pedestrian evacuation model to explore the evacuation of King's Cross St Pancras underground station*. Center for advanced spatial analysis (university college London): working paper 108, ACM, London, 427–437.

Church R. and Cova T., 1997. *Modelling community evacuation vulnerability using GIS. International Journal of Geographical Information Science*, 11(8), 763–784.

Church R. and Cova T., 2000. *Mapping evacuation risk on transposion networks using a spatial optimization model. Transportation Research Part C: Emerging Technologies*, 8(1-6), 321–336.

Clauset A.; Newman M.E.J.; and Moore C., 2004. *Finding community structure in very large networks. Physical review E 70*, 6, 066111.1–066111.6.

Cutter S.; Mitchell J.; and Scott M., 2000. *Revealing the vulnerability of people and places: a case study of Georgetown County, South Carolina. Annals of the Association of American Geographers*, 90(4), 713–737.

Dorigo M. and Stützle T., 2004. *Ant Colony Optimization*. MIT Press.

Dutot A.; Guinand F.; Olivier D.; and Pigné Y., 2007. *GraphStream: A Tool for bridging the gap between Complex Systems and Dynamic Graphs*. In *EPNACS: Emergent Properties in Natural and Artificial Complex Systems*.

EUROPEAN Community, 1996. *COUNCIL DIRECTIVE 96/82/EC of 9 December 1996 on the control of major-accident hazards involving dangerous substances*. URL `http://eur-lex.europa.eu/smartapi/cgi/sga_doc?smartapi!celexapi!prod!CELEXnumdoc&numdoc=31996L0082&model=guichett&lg=en`.

Hennecke A.; Treiber M.; and Helbing D., 2000. *Macroscopic simulation of open systems and micro-macro link. M Schreckenberg, D Helbing, H J Herrmann, editor, Traffic and Granular Flow: Social, Traffic, and Granular Dynamics*, 2, 383–388.

Hman M.E.; Abouaäissa H.; Jolly D.; and Benasser A., 2006. *Simulation hybride de flux de trafic basée sur les systèmes multi-agents*. In 6e Conférence Francophone de MOdélisation et SIMulation - MOSIM 06.

Magne L.; Rabut S.; and Gabard J.F., 2000. *Toward an hybrid macro and micro traffic flow simulation model*. In INFORMS spring 2000 meeting.

Najlis R. and North M.J., 2004. *Repast for GIS*. In Proceedings of Agent 2004 : Social Dynamics: Interaction, Reflexivity and Emergence, University of Chicago and Argonne National Laboratory, IL, USA.

Newman M.E.J., 2004a. *Detecting community structure in networks*. *Eur Phys J*, 38, 321–330.

Newman M.E.J., 2004b. *Fast algorithm for detecting community structure in networks*. *Phys Rev*, 69, 066133.

Pons P., 2005. *Détection de structures de communautés dans les grands réseaux d'interactions*. Septièmes Rencontres Francophones sur les aspects Algorithmiques des Télécommunications, Giens, France.

Pons P. and Latapy M., 2006. *Computing communities in large networks using random walks*. *Journal of Graph Algorithms and Applications*, 10(2), 191–218.