Efficient Vehicular Crowdsourcing Models in VANET for Disaster Management

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***Abstract*—Route planning in a vehicular network is a well known problem. Static solutions for finding a shortest path have proven their efficiency, however in a dynamic network such as a vehicular network, they are confronted to dynamic costs (travel time, consumption, waiting time, ...) and time constraints (traffic peaks, ghost traffic jam, accidents ...). This is a practical problem faced by several services providers on traffic information who want to offer a realistic computation of a shortest path. This paper propose a model based on the communication between vehicles (Vehicle to Vehicle: *V2V*) to reduce the time spend by travels taking into account the travel time registered and exchanged between vehicles in real time. In our model, vehicles act as ants and they choose their itineraries thanks to a pheromone map affected by the phenomenon of evaporation. The presented algorithms are evaluated in real world traffic networks and by modeling and simulating extreme cases such as accidents, act of terrorism and disasters.**

***Index Terms*—V2V, ant algorithm, travel time, disasters**

I. Introduction

The computation of the shortest path is a fundamental component in route guidance systems in urban environment. Methods widely used as Dijkstra's, Bellman-Ford, Astar and Floyd-Warshall algorithms are efficient in a static graph, but loose their performance in a dynamic network. They don't use real time information and they do not consider the neighborhood ; that may can lead all vehicles on a same road at time t. We identify two problems : the information access in real time and the cooperation between actors. Centralized approach to solve the problem, has an eye on all the network, but the quantity of data to treat make it difficult to achieve in real time, so we focus on decentralized bio-inspired solution. Crowdsourcing insects rely on their collective brain power. In this context, we propose Vehicular Crowdsourcing Models (*VCM*) where the vehicle is an ant and gathered information in the urban environment in order to find its path. This information has a delay and a reliability for the vehicles as the ants' pheromone. Our decentralized approach use vehicular ad hoc network and turns every participating car or infrastructure device into a node to connect and create a network. The paper is structured as following : a related works on bio-inspired shortest path problem is presented in Section II. After a formalization of the problem in Section III, we describe different *VCM* models in Section IV. In Section V, we test and compare our models on simple scenario and on a real map. Finally we test extreme cases such as accidents or disasters in Section VI, and we conclude in Section VII.

II. Related works

Among approaches for solving the shortest path problem, most are inspired by ant behavior (1). They collect real data and incorporate them in the bio-inspired algorithm by modifying the heuristic and pheromone functions. Wang *et al.* (2) include traffic density in the pheromone function to solve the shortest path with real time traffic information. When data are unavailable, Salehinejad *et al.* (3) use historical and statistical traffic data as input into the ant algorithm. In the paper of Huang *et al.* (4), the distance of adjacent intersections and the traffic saturation are introduced in the path optimization process. Other articles are inspired by the ant algorithm, as in (5), authors improve the initial algorithm. When ant deposits pheromone to evaluate the quality of a route, it also deposits pheromone describing the different regions this route passes through. The algorithm will require less iteration to find meaningful results. More recently Jyothi *et al.* (6) extend the traditional Ant Colony Optimization to a dynamic decision system for choosing the shortest best route in highly congested areas. Jindal *et al.* (7), propose a repulsion effect in the algorithm to avoid the congestion. Then they improve it with a particle swarm optimization algorithm (8). Few method explore extreme situations as Peinado *et al.* (9) who describe a model which is useful in a particular limitation of an emergency situation.

III. Problem Statement

In this section, we present definitions needed in our vehicular crowdsourcing models.

Definition : Global graph G
A road network can be represented by a graph $G = (V, E)$, where $V = \{v_1, v_2, ..., v_n\}$ is a finite set of intersections and $E = (e_{ij})_{ij}$ is a finite set of road sections. A road section is determined by two intersections $e_{ij} = (v_i, v_j)$ and G is directed, $e_{ij} \neq e_{ji}$.
Definition : Vehicle Path P^m
A vehicle m has a departure and a destination : O^m and D^m respectively. It uses a path P^m to join O^m to D^m. $P^m = \{R_1, ..., R_n\}$ with $R_i = e_{jl} \in E$, $R_1 = O^m$, and

$R_n = D^m$. The length of a path is the Euclidean distance noted : $L(P^m)$. And the travel time with the maximum speed allowed on each edges of the path is noted: $TT(P^m)$.

Definition : map of pheromone
$G^m(t)$ is the graph known by the vehicle m at the time t in term of travel time. This is a subgraph of G with $E^m \subset E$. Weights on edges in E^m represent information in pheromone known by the vehicle m at time t. We note $w_{ij}^m(t_0)$, the travel time on the edge e_{ij} registered at time t_0 by the vehicle m. The rate in pheromone is given by:

$$\tau_{ij}^m = \frac{w_{ij}^m}{w_{ij}^m(t_0)} \tag{1}$$

w_{ij}^m is the travel time on e_{ij} with the maximum speed. A pair of data is associated to each edge: (τ_{ij}^m, t_0); τ_{ij}^m represents the quality of the edge in term of travel time and t_0 is the time when the vehicle m registers this value, it represents the validity of the pheromone.

Definition : Carry and Forward
We consider the situation where a vehicle m crosses a vehicle l at time t. $G^m(t)$ is the graph of knowledge of the vehicle m and $G^l(t)$ the graph of the vehicle l. The vehicle m keeps the latest information and updates it (rules are symmetric).

$$\forall e_{ij} \in E^m \cap E^l : (\tau_{ij}^m, t_0) \leftarrow (\tau_{ij}^l, t_0') \text{ if } t_0 < t_0' \tag{2}$$

$e_{ij} \in E^l / E^m$ means that the vehicle m does not have information on e_{ij}, therefore it saves (τ_{ij}^l, t_0') for this edge.

Definition : Evaporation of pheromone
With time, the reliability of the information decreases, we define it by its evaporation as the ants process. Lets t the current time, t_0 the time when the vehicle has registered the pheromone value on e_{ij}, $(t - t_0)$ represents the time since the value is registered on e_{ij}. Higher this value is, older the information is and its useless for the vehicle m. The evaporation is defined at each time step by:

$$\begin{cases} (\tau_{ij}, t_0) \leftarrow ((1-\varphi).\tau_{ij}, t_0) & \\ (\tau_{ij}, t_0) \leftarrow (0.5, -1) & \text{if } (t - t_0) \geq T \end{cases} \tag{3}$$

$$\text{With } \varphi = \frac{t_0}{t} \tag{4}$$

φ is the gradient of the evaporation. T is the life time of the travel time measured. When $(t - t_0) \geq T$, the vehicle initializes the edge at 0.5, it means the value is too old.
Using these definitions, we will present three Vehicular Crowdsourcing Models, based on vehicles cooperation.

IV. Vehicular Crowdsourcing Models

In the ant algorithm, each ant m computes a set of feasible path at each iteration, and moves to one of these in probability. The probability of choosing a path by the ant m is defined by the quality of its edges defined by the quantity of pheromone. We will propose three models to find this path. In the two first models, the vehicle will use all information of pheromone gathered on its map to compute the best path to its destination. In the last model, the vehicle use only pheromone information around it as a real ant which searches its itinerary.

A. Pheromone on K-Paths: PKP

If the vehicle chooses edge by edge without considering its destination as a real ants, the exploration can be excessively too long. Thats why we use a k-path algorithms, which will give a direction to the destination and avoid useless itinerary too far from the arrival position. For PKP, the cost on each edge corresponds to the best travel time to cross it (ie with the maximum speed). Then the probability to choose a path $P_n = \{R_1, ..., R_n\}$ among the k-paths is:

$$p(P_n) = \frac{\frac{\sum_{i=1}^{n} \gamma.\tau_i}{n.L(P_n)}}{\sum_n \sum_i \frac{\gamma.\tau_i}{n.L(P_n)}} \tag{5}$$

If τ_i is known $\gamma = 1$ else $\gamma = \beta$.

β allows to give less importance to the unknown pheromone values. The vehicle chooses the path with the higher probability. Then if two of them have the same one, the algorithm chooses the path with the smaller variance in pheromone level (indeed, the vehicle prefers to take two edges with a medium fluidity rather than a congested edge and then a fluid edge).

B. K-Pheromone Paths: KPP

In the second method, the algorithm computes the k-shortest path directly on the pheromone map. The probability to choose a path P_n among the k-paths is given by is the same probability defined for the PKP. As the previous model if two paths have the same probability, the algorithm chooses the path with the smaller variance in pheromone level.

C. Pheromone on Paths Exploration: PPE

The third method is close to the real ants behaviour. The probability p_{ij}^m of moving on the edge e_{ij}, for an ant m, depends on the combination of two values, the attractiveness μ_{ij} of the edge e_{ij}, computed by some heuristic indicating the desirability of that move and the level of the move in pheromone τ_{ij}, indicating how was the efficiency of this particular move in the past.
In this model PPE, the vehicle acts like an ant by exploring its environment. First of all the algorithm computes all possible paths P in all direction around the vehicle according the following condition: $TT(P) < T$. We recall that T is the life time of the pheromone value registered by the vehicle and $TT(P)$ is the travel time on the path P with the maximum speed allowed on it. Then the probability to choose a path $P_l = \{R_1, ..., R_l\}$ among the computed paths is given by:

$$p(P_l) = \frac{\sum_{j=i}^{s} \beta.\tau_j^{\alpha}(1-\beta).\mu_{js}}{\sum_k p(P_k)}$$
$$\text{with } \mu_{js} = \frac{L(R_j \to D^m)}{L(P_n) + L(R_s \to D^m)} \tag{6}$$

R_i is the current position of the vehicle m. $L(R_s \rightarrow D^m)$ is the euclidean distance of the shortest path between R_s and the destination of the vehicle m, D^m. If the pheromone value is known by the vehicle, then $\alpha = 1.5$ else $\alpha = 1$, indeed we give more importance to the pheromone values known by the vehicle. β allows to give less importance to the pheromone values or to the length of the path.

V. Numerical Results

A. Environment of the simulations

We use an open source microscopic and continuous road traffic simulation package, *SUMO* (Simulation Of Urban Mobility). We have to calibrate the different parameters: T which is the life time of the pheromone value and β which determines the importance of unknown edges. For PKP and KPP, we choose the value $k = 4$. Vehicles, in our simulations, travel between 300 meters or 800 meters ; beyond 4 paths, the trips become too long. We test different values on the *Manhattan map* (10; 11). 200 vehicles travelled on the grid at random with a maximum speed limited to 50 km/h. We simulate three iterations of this configuration. Vehicles exchange information to nearest neighbours, therefore a wide distance of communication is not really important especially in a congested traffic (the range of communication is set to 60 meters for all simulations).

We evaluate travel and waiting time for each models. For PPE it appears that $T = 25$s and $\beta = 0.2$ are the best values. For PKP and KPP, $T = 15$s and $\beta = 0.4$ are the best values. We notice that unknown edges implies hazard in the path computation specially for the model PKP. For KPP, short range for the pheromone evaporation are better. The table I shows the different parameters. It appears that T has to be small, that means information around the vehicle is important for the future path.

Parameters/Models	PKP	KPP	PEE
Limit time of the information T (s)	15	15	25
Importance of unknown information β	0.4	0.4	0.2

TABLE I: Pheromone parameter set

B. Results

1) Real map: We test PKP, KPP and PPE on a real map. For a realistic scenario, we used the TAPASCologne dataset (12) - reproducing the urban traffic in the city of Cologne. The dimension of the map is 1200m x 800m, the simulation begins at 6.00 am to 6.15 am with 1200 vehicles. We compare our models with the model $PDLAIS$ - *Partial, Decentralized and Locally Autonomous Strategy* - presented in (13). In this article strategic points in the city (most congested intersections) are equipped in order to reroute vehicles thanks to the local information. We also compare our models with the centralized solution called *CS*. We evaluate the gain in travel time and waiting time compared to the scenario *NK*, with No Knowledge (Figure 1) and we present the standard deviation for each model (Table II).

	NK	PKP	KPP	PPE	CS	PDLAIS
SD of TT (min)	8	7.5	7	10.6	6.1	7.5
SD of WT (s)	37.6	33.1	29.6	35.3	23.7	34.5

TABLE II: Standard Deviation (*SD*) of Travel Time (*TT*) and Waiting Time (*WT*) for the different models

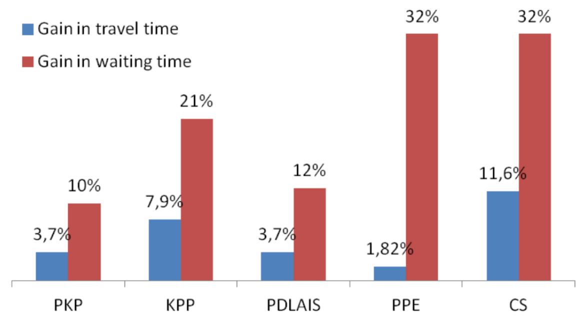

Fig. 1: Results of gain in travel time and waiting time for the different models on a real map

The three models of crowdsourcing vehicular PKP, KPP and PPE have good results and improve travel time and waiting time compared to a situation without information, for intance KPP is the best in travel time. Further results are close to the centralized solution as the gain in waiting time for the PPE model, however its standard deviation is higher than the other models (see Table II).

VI. Investigating the impact of urban incidents

An incident refers to anything that stops the traffic flow. There are few options to simulate this kind of events in SUMO, however some tools allow to create similar conditions. We test vehicular crowdsourcing models in three situations, a car accident (or road work), act of terrorism and disaster to test the robustness in a dynamic environment.

A. Car Accident or Road Work

To simulate a car accident, we just have to stop cars for a limited period. Road works can be similar to a car accident in term of simulation in *SUMO*, stopping a car produces same effect as a road work. In order to accentuate the scenario we block an edge during a long time. Unlike a car accident which is a short event (several hours), road work lasts longer.

1) Simulation and results: We evaluate the travel time and the waiting time of vehicles, that are not found stuck. We also note the number of vehicles arriving according to simulated model, this parameter allows to evaluate the effectiveness of the model. Higher the number of vehicles able to bypass the area, the more efficient the model is. Models with the greatest number of vehicles avoiding the area of the congestion, are KPP and PPE (Figure 2). However, the standard deviation of the travel time for KPP is $11,11$ min and $7,34$ min for PPE, which means that bypasses found by KPP are longer than those find by PPE. PKP and $PDLAIS$ have same results as without system. It is important to note that their

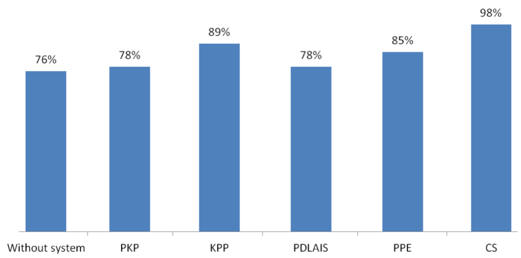

Fig. 2: Results in case of road work: number of vehicles arriving at destination in percentage

mean percentage are lower than others because the number of arriving vehicles is lower. $PDLAIS$ results depend on the position of connected intersections in the city, if they are far from the congestion it fails. PKP computes the k paths without traffic information at the beginning, this can create a handicap for vehicles that cross the congested area. By increasing the value of k, we could perhaps improve the performance of this model on a larger map but the complexity of the algorithm Yen and its calculation time will also increase.

B. Terrorism

Several evacuations explore strategies by taking into account the distribution of the population and vehicle behaviours. Alazawi *et al.* (14) propose a system to collect information from various sources and locations to propagate them into the network through the V2V communication and the cloud during an explosion of hazardous materials in a glass factory. Waine *et al.* (15), analyze the impact of a nuclear attack on Washington DC. And Lambert *et al.* (16) study the transportation demand and performance in the case of 'dirty bombs'. They study how detonation can degrade the transport system, especially during peak periods. They show that the main streets of the neighborhoods reach their maximum capacity. During an attack, the number of travellers that leave the buildings to go home, multiply by two the number of car that evacuate the area. In addition, the percentage of vehicle that completely leave the area is 13% of total trips. We use these observations and analysis to simulate a terrorist attack in a neighborhood of the city of Cologne. We test our models to disseminate information and remove vehicles from the danger zone (see Figure 4).

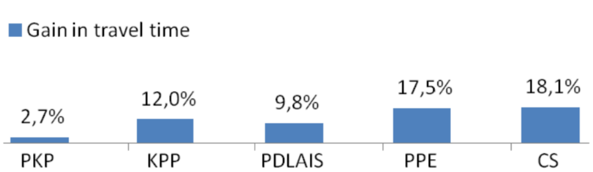

Fig. 3: Results in case of a act of terrorism

1) Simulation and results: A terrorism scenario has an impact in all the town, therefore we evaluate travel time of the entire network. The model PPE which uses local information pheromone around the vehicle, gets the best results in travel times despite a greatest standard deviations ($13,13$ min), which means that some vehicles are affected by the others. KPP and $PDLAIS$ have good results with the best standard deviations ($8,09$ min and $8,35$ min respectively). They are closest to the centralized solution ($7,09$ min for standard deviation). However $PDLAIS$ is dependent on the infrastructure, if the connected intersection is in the danger zone, these results can not be insured. Models of crowdsourcing vehicular do not depend on the infrastructure and can be effective regardless of the location of the explosion.

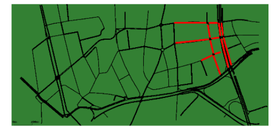
Fig. 4: Location of a terrorism act

C. Disaster

Natural disasters in the recent years as the earthquake in Japan and tsunami disaster increase the importance of emergency response systems. The questions of who evacuates and what factors influence the evacuate/stay decision are frequently investigated, mostly in the social sciences, but more recently by engineers as well. During an earthquake, the locations of failures on the road cannot be predicted in advance, however Wisetjindawat *et al.* (17) propose a model with the probability that a road is broken according the intensity level of the disaster. We use this model to simulate an earthquake in an urban network in order to test the dynamism of our model in case of disaster. The probability that a link r on the network is passable is formulated as follows:

$$p_r = e^{-\lambda . l_r}$$

λ is the constant representing the breakage rate of the road section, according to the intensity of the earthquake (locations / km) and l_r is the length (km) of road section r. λ is obtained from the report by the Disaster Management Working Group under the Cabinet Office. An intensity equal to 4 on the scale of the Meteorological seismic Agency of Japan (*JMA*) does not cause breakage, 5 *JMA* could cause between 0.035 and 0.11 breaks per kilometer, 6 *JMA* concerned around 0.16 breaks per kilometer and finally 7 *JMA* concerned 0.48.

1) Simulation and results: An intensity of 7 *JMA* (maximum intensity on the scale) is a too catastrophic situation to be exploited. We use a value of 0.11 which corresponds to 5 *JMA*. We apply the probability on roads in the area of the city of Cologne used previously. We assume that the traffic lights are not available after the disaster. Figure 5 shows the percentage of chance for an emergency vehicle to arrive at its destination. We note that PKP and KPP are not performing, it comes from the computation of the k paths to the destination which limit the possibilities (the k roads are long and therefore the possibility to meet a broken roads is high). The model $PDLAIS$, more efficient, uses local information, but it is highly dependent on the state of infrastructure and the position

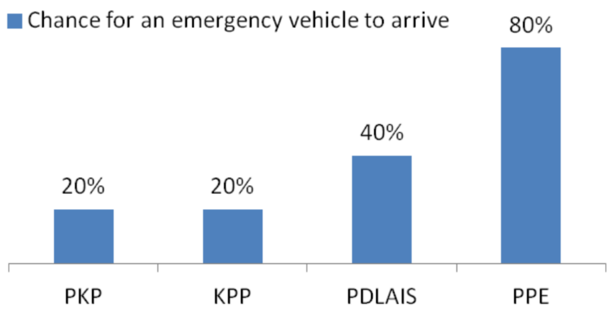

Fig. 5: Results in case of disaster

of connected intersections compared to the ambulance trip. Finally, the local solution PPE is the most robust for this catastrophic event.

VII. Discussion and Conclusion

The vehicular crowdsourcing models presented in this paper consider the vehicle as an ant searching the best path to its destination thanks to a pheromone map constructed with information sent by other vehicles. They have good results in travel time and waiting time in different urban area with a reduction until 32% in waiting time and results similar to the model with connected intersections, $PDLAIS$ (13). The next step would be to optimize the complexity of KPP and PKP, focusing on the entire way of the vehicle. We would test the greatest values of k on a larger map. However, the Yen algorithm adds complexity and computation time. The latest model, PPE, which uses only local information pheromone is an interesting alternative. This model coupled to $PDLAIS$ with the V2I communication at strategic points in the city, could give interesting results to study. Both models could complement, or disturb each other. Next, we will evaluate the latency limits and the network load. In extreme situations, packet loss occurs without performance impact, but we need to evaluate the limits. With these bio-inspired methods, more vehicles are able to get around unpredictable road works. In case of terrorist acts, they react quickly allowing faster evacuation despite the larger number of vehicles. Finally in case of natural disaster where a part of the city is destroyed, the information exchanged between vehicles will allow emergency vehicles to circulate, particularly with the PPE model which uses local information. The impact of these events is few studied in literature and crowdsourcing models, with only local information exchanges, show their robustness.

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