An Adaptive Vehicle Guidance System instigated from Ant Colony Behavior

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Abstract—In view of the high dynamicity of traffic flow and the polynomial increase in the number of vehicles on road networks, the route choice problem becomes more complex. A classical shortest path algorithm based only on road length is no longer relevant. We propose in this paper an adaptive vehicle guidance system instigated from the ants behavior, well known for its good adaptativity; this system allows adjusting intelligently and promptly the route choice according to the real-time changes in the road network situations, such as new congestions and jams. This method is implemented as a deliberative module of a vehicle ant agent in a collaborative multiagent system representing the entire road network. Series of simulations, under a multiagent platform, allow us to discuss the improvement of the global road traffic quality in terms of time, fluidity, and adaptativity.

Index Terms—Transportation, adaptive vehicle guidance, traffic assignment, ant colony, traffic simulation.

I. INTRODUCTION

Nowadays, an important component of human life and economic challenges is in growth phase on behalf of the monitoring and the control of road traffic: the Intelligent Transportation System (ITS). It has as objectives, a real-time route choice (or vehicle guidance) [1], an optimization of the road traffic flow [2], a management of the road network capacity [3], an improvement of the traffic safety [4], a minimization of the energy consumption, and others.

A Vehicle Guidance System (VGS) assists each driver in selecting the best route (itinerary), from a set of feasible routes between an origin and a destination on a road network, while avoiding congestions and jams situations. This system should improve the fluency of road network, to allow a dynamic assignment of traffic flows, and to reduce the number of traffic congestions as well as their adverse effects: delays, wasting time, drivers' stress, increasing air pollution, and blocking the passage of emergency vehicles [5][6][7].

This objective cannot be accomplished without an efficient adaptive route choice system which is able to propose the best itinerary for each driver destination, while taking into account the real-time traffic quality of the road network. An adaptive system should control the traffic flow of the road network and which may involve, in real-time according to jam situations, accidents, or other factors that decrease the quality of the road flow. This adaptive involvement can be dealt with by changing the proposed itinerary for drivers under travel in order to reach destinations under better available conditions, ignoring some inaccessible roads, or adapting the timers to traffic lights.

In view of the high dynamicity of traffic flow and the polynomial increase in the number of vehicles on road networks, the route choice problem becomes more complex. The classical shortest path algorithm based only on road length is no longer relevant [8][9]; more than ever an off-line design based approach.

Since the road network is a geographically distributed, the use of an intelligent decentralized approach is interesting. In fact, the multiagent approach allows to model complex systems where numerous autonomous entities interact and collaborate to produce global solution. The global system behavior is made of several emergent phenomena that result from the behavior of individual entities and their interactions [10][11].

Thus, the current trend of research work in traffic and transportation is to investigate in intelligent approaches integrating soft computing techniques [12], distributed and collaborative intelligence [13], bio-inspired intelligence [14], or hybrid approaches [9][15]. The objective is to deal with the complexity of transportation systems in order to provide smart transportation systems. This new area of ITS is nowadays, in a growth phase of advancements.

We propose in this paper an adaptive VGS instigated from swarm intelligence, specifically ant colony behavior, well known for its good adaptativity [3][16]; this system allows adjusting intelligently and promptly the route choice according to the real-time changes in the road network situations.

The idea is to increase the quality of the entire road network, especially in the case of congestions or jams. On the one hand, this consists in maximizing the capacity of the network by minimizing travel times while taking into account the current road traffic flow; and on the other hand, in reducing the number of traffic congestion phenomenon when many vehicles try to use the same road at the same time.

The paper is organized as follows: section 2 presents an overview on related works on ITS based on swarm intelligence. Section 3 describes the proposed approach for adaptive VGS. The simulation and discussion of results are presented in Section 4. Finally, we conclude by summarizing the obtained results and pointing to some future research directions.

Authors, year	Main objective	Approach features	Road network and simulation data	Ant as a vehicle	Multiagent consideration	System design
[3], 2003	road traffic management	ant system for shortest path in weighted dynamic graph; neural network for regulation system.	simulated virtual network	no	yes	off-line
[20], 2004	vehicle routing	multiple ant colony optimization to find good solution to the VRP.	simulated virtual network	no	no	off-line
[21], 2004	synchronization of traffic lights	colonies of social insects to adapt the traffic lights to give priority to the higher flow.	real network, city of Porto Alegre, Brazil	yes	yes	on-line
[2], 2004	road traffic management	extended ant-cycle algorithm to find the best path between two nodes.	simulated virtual network	no	no	off-line
[25], 2006	traffic assignment problem	ant colony for each origin-destination pair; stochastic user equilibrium algorithm to imitate the behavior of transportation system.	real network, cities of Salerno and Naples, Italy	no	no	off-line
[15], 2007	dynamic route planning	finding both optimized shortest path and shortest time based on fuzzy logic, graph partitioning algorithm, and GA	real network, city of Singapore	no	no	off-line
[22], 2007	bus network optimization	parallel ant colony algorithm to maximize traveller density (i.e. reduce transfers and travel time in bus network).	real network, Dalian City, China	no	no	off-line

II. RELATED WORKS ON INTELLIGENT TRANSPORTATION BASED ON SWARM INTELLIGENCE

The swarm intelligence, a branch of artificial intelligence, is well used to model complex traffic and transportation processes [14]. A self-organization of the social insects is based on relatively simple rules of individual insect's behavior. Among these social insects, the ant succeeds in finding food by following the path with highest pheromone quantity deposited by other ants [17]. The pheromone signal represents the communication tool between individual ants. It contributes to the formation of the collective intelligence of the social ant colonies, viewed as multiagent systems.

Moreover, Ant Colony Optimization (ACO) [18] is a probabilistic technique for solving computational problems which can be reduced to finding optimal paths through graphs. It is used to solve the Travelling Salesman Problem (TSP) [19], the Vehicle Routing Problem (VRP) [20], the dynamic VRP, the VRP with time window, the open VRP, the period VRP, the generalized VRP, and other integrated problems. It has also been applied to the synchronization of traffic lights [21] and the bus network problem [22]. Some of these problems are also solved with Practical Swarm Optimization [23], and the Bee Colony Optimization [24]. The similarity between these approaches is the information incompleteness when solving the problem. But, with multiagent consideration, social agents have the information about the quality of the partial solutions.

Table I summarizes the main features of some works on traffic management based on swarm intelligence. We notice:

- Initially, ant colony is well used to solve transportation problem, especially industrial problems;
- Vehicles are not considered as ants. Ants' colony is used mostly to find the shortest path with minimum time. So, systems are designed as off-line learning;
- The hybridization of ITS based on swarm intelligence and the multiagent simulation is not yet prominent.

This leads us to develop an on-line design when considering the vehicle as an ant, for the vehicle guidance system on the one hand, and for an adaptive management of the entire road network on the other hand.

III. PROPOSED METHOD BASED ON ANT COLONY BEHAVIOR

This section details a vehicle guidance method as well as a road traffic management instigated from ants' behavior and based on multiagent approach. Each vehicle is considered as an ant-agent evolving on the road network designed as a multiagent system.

The purpose is to increase the global velocity on the road network while selecting the best itinerary for each vehicle according to the real-time traffic flow and the shortest path.

A. Road Network Architecture

A typical road network control and management is based on traditional stationary equipments installed in the main roads, such as:

- Sensors for counting the number of vehicles;
- Cameras to detect congestion situations especially at road junctions;
- Information screen for passengers showing the road status;
- And other equipments.

Using these road equipments, it is complicated to obtain traffic information in real-time for the entire road network. In fact, an accurate management cannot be done with modest traffic information and without vehicles information. Moreover, the integration of these equipments in all roads, in each city, is expensive. The use of an advancement road network model for the road management system is hence necessary.

Accordingly, a satellite navigation system such as GPS (Global Positioning System) [26] is well suited to collect the localization data, vehicle's velocity, and motion direction, at regular time intervals. Recent developments on this equipment promote the research field in real-time road traffic information in order to improve route choice decision [1][27].

However, the GPS is not popularized especially in developed countries. Since the proposed traffic management method needs real-time traffic information, we advise computing the traffic flow on each road via the Cellular network data-based such as GSM (Global System for Mobile communications) [28]. The latter can be considered as an intelligent vehicle agent. So, it can provide an approximate measure of the traffic density obtained by means of Phone Company data. Each switched-on mobile phone turns into a traffic probe as anonymous source of information. In fact, the Phone Company can locate its customers, anonymously analyze those who have coordinated inside roads with a motion velocity exceeding the walking passenger's one. This technique provides the average velocity of each vehicle in real-time without additional infrastructures.

The traffic management system involves also the presence of a Route Guidance System (RGS) for the interaction between the driver and the vehicle agent, and the presence of a Geographic Information System (GIS) providing a digital map of the road network. Wireless connection equipment (i.e. radio frequency) can ensure communication between RGS and the remote server. These systems can be integrated into a dashboard of vehicle or into a third generation mobile phone.

Fig. 1 illustrates a modern road network architecture using advanced communication technologies. The accuracy of the sensor data coming from the network components is implicitly assumed to be correct and complete. This network is designed as a hierarchical multiagent system based on agent-group-role organization [29][30].

In this architecture, vehicles are grouped by both city and road. It can be applied for urban or interurban road network. It allows managing traffic on road network in real-time which
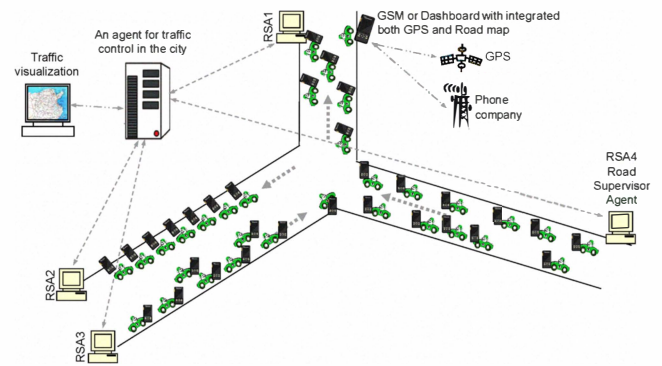

Fig. 1. Modern road network architecture

will lead to better management of driver's requests during the travel. The architecture involves three types of agents: City Agent (*CA*), Road Supervisor Agent (*RSA*), and Intelligent Vehicle-Ant Agent (*IVAA*) which will be detailed in the next subsection.

B. Description of the Adaptive Vehicle Guidance (AVG) Method

Actually, the Vehicle Guidance Problem can not be well resolved using the classic ACO version applied to TSP [19]. In fact, ants of the artificial colony are able to generate successively shorter feasible tours by using information accumulated in the form of a pheromone trail deposited on the edges of the TSP graph.

However, the proposed method in this paper considers that each vehicle is represented by an ant having a road as a source and another road as a destination. The route guidance is based on traffic flow of the road network. Thus, the pheromone deposited by ants on the road, is quantified by the traffic flow on this road.

In terms of multiagent technology, the method consists of three parallel and distributed processes embedded in *IVAA*, *RSA*, and *CA* (see Fig. 2).

1) Intelligent Vehicle-Ant Agent (IVAA): it stands for a vehicle and encapsulates a deliberative module for the selection of the best itinerary alternative. In practice, it is a software agent that can be integrated into the dashboard of the vehicle or into a mobile phone equipped with GPS for localization and GIS for the digital map of the road network. This agent represents the ant as with the ant colony algorithm.

The *IVAA*'s process starts by an initialization of the source and destination of the vehicle. The search of the best itinerary reiterates at every intersection until reaching the destination. Indeed, the search of the best itinerary should be adaptive according to the high dynamicity of the road network and to the traffic flow information in real-time.

The itinerary selection algorithm starts by a search of a set of itineraries as follows:

- From the current intersection, search the shortest itinerary from each next possible road intersection to road destination, based on itinerary length;
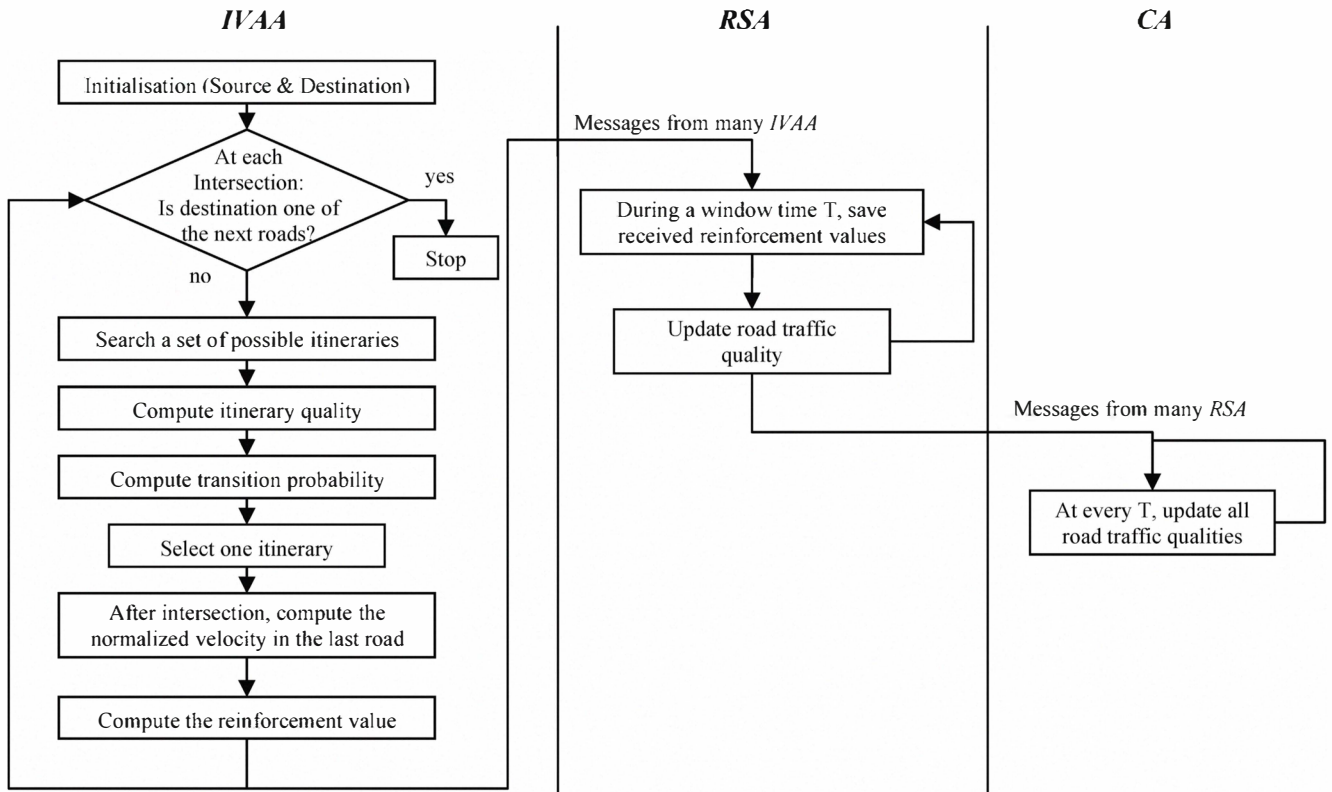
Fig. 2. Flowchart of the Adaptive Vehicle Guidance Method

- Shortest itineraries that go back by the current intersection are removed.

An itinerary quality is computed for each itinerary by (1). It represents the average of itinerary qualities on roads belonging to the itinerary.

$$q^i_{itinerary} = \frac{\sum_{k=1}^{n} q^k_{road_i}}{n} \quad (1)$$

with i is the itinerary number and n is the roads number belonging to the itinerary.

The road quality represents the pheromone quantity deposited in the path. This quantity, computed by Equation (2), is equal to the average velocity of the vehicle on the road, computed after travelling the road.

$$\overline{V}_i = \frac{road\_length(meter)}{time(seconds)} \quad (2)$$

with i is the travelled road number.

Since the velocity of the vehicle depends on the maximum velocity allowed on the road, it is more judicious to consider the normalized average velocity to identify the road quality (See (3)).

$$\hat{V}_i = \frac{\overline{V}_i}{V_i^{max}} \quad (3)$$

with i is the road number. So, the road quality obtains a normalized value between 0 and 1. This quality is initialized

to 1 as a fluent road.

As the classical ant algorithm, a transition probability is computed, by (4), for each possible itinerary from the searched possible probability set. This probability depends on the itinerary quality and the itinerary length.

$$p^i_{itinerary} = \frac{(q^i_{itinerary})^\alpha \left(\frac{W_{shortest\_itinerary}}{W^i_{itinerary}}\right)^\beta}{\sum_{j=1}^{iti\_nb} (q^j_{itinerary})^\alpha \left(\frac{W_{shortest\_itinerary}}{W^j_{itinerary}}\right)^\beta} \quad (4)$$

with $q^i_{itinerary}$ is the quality of the itinerary i, $W^i_{itinerary}$ is the itinerary weight representing the itinerary length, $W^i_{shortest\_itinerary}$ is the length of the shortest possible itinerary.

α and $\beta \in [0,1]$ represent the itinerary intensities. If $\alpha > \beta$, then the traffic flow criteria is more important than itinerary length criteria. A good trade off between these two criteria improves the management of the road network.

Two methods are candidates for the selection of the next proposed road according to the selected itinerary:

- *Heuristic method*: selects the itinerary having the highest transition probability;
- *Probabilistic method*: using a cumulative table as follows:
  - Normalize the transition probability of the set of possible itineraries. Normalization means dividing the probability value of each itinerary by the sum of all probability values, so that the sum of all resulting probability values equals 1;

- The set of itineraries is sorted by descending probability values;
- Accumulated normalized probability values are computed. The accumulated probability value of an itinerary is the sum of its own probability value and the probability values of all the previous itineraries. The accumulated probability of the last itinerary should evidently be equal 1;
- A random number R between 0 and 1 is chosen;
- The selected itinerary is the first one whose accumulated normalized value is greater than R.

This probabilistic method is more advantageous in rush hour. In fact, suppose that many vehicles from the same road select the same itinerary having the highest probability, the quality of roads in this itinerary will decrease quickly. So, the probabilistic method tries to propose other good itineraries without decreasing the traffic quality of the network.

Just after travelling on the road, each vehicle has to evaluate and inform the *RSA* about the quality of the road. So, in order to update the road quality with real-time information, a reinforcement value dq of the road, quantified by the normalized average velocity, is computed by (5).

$$dq^i = \hat{V}_i \qquad (5)$$

with i is the vehicle number.

2) Road Supervisor Agent (RSA): represents a software agent implanted in the server. It monitors the state of the traffic flow on the road, uses control actions for management, sends security information for passengers, and carries out the coordination with *CA* (detailed below) and *IVAA*. The number of *RSA*s in the city is equal to the number of roads with a single direction (i.e. a road with two directions requires two agents).

After each window time T, the *RSA* receives a set of dq values from vehicles. The newer road quality is computed based on Widrow-Hoff delta rule by (6).

$$q_{road}^{new} = q_{road}^{old} + \gamma(\hat{dq} - q_{road}^{old}) \qquad (6)$$

with q_{road}^{old} is the old road quality, $\hat{dq}$ is the average of all received dq values during T, and $\gamma \in [0,1]$ is the importance factor of quality value change.

3) City Agent (CA): represents a software agent to manage the road network in the city in order to obtain a better exploitation of the network. It communicates and cooperates with other city agents according to the *RSA* request. It maintains the traffic quality of the roads in the city.

IV. SIMULATION AND DISCUSSION OF RESULTS

As it may be very expensive to carry out the real plan to test our method, taking into account the variation of traffic information, and to visualize the evolution of the road network, we choose to implement a multiagent simulation [31]. In fact, this kind of simulation is very helpful to explain collective behaviour as a result of individual actions. This is the best achievable opportunity to make predictions in a scientifically proven way, to test, and to evaluate several use cases without having resort to expensive and complicated tests [32].

In this paper, we develop a micro-simulation which is greatest strength to model congested road networks by means of queuing conditions. The micro-simulation tries to simulate the individuals' behaviour over time, and reflects, even relatively, small changes in the physical environment such as topology, lanes narrowing, or the change between signalized and unsignalized intersections. Furthermore, the macroscopic level is used to offer the diagram of traffic flow on the road network and to show the influences of congestions in the traffic density.

A. MultiAgent Simulation

The multiagent simulation is based on the idea that it is possible to represent entities behaviours in one environment, and agent's interaction phenomenon. At each simulation step, each agent can receive a set of information describing the surrounding situation in the environment [31].

For few years, we have noted the birth of some multiagent platforms. These platforms provide both a model for developing multiagent systems and an environment for running distributed agent-based applications. In order to develop our simulator, we choose the MadKit [1] platform as a generic multiagent platform [33]. Our choice is initially based on published comparison between well known multiagent platforms [34] [35].

In addition, among MadKit's advantages, it is possible to make traffic services fully extensible and easily replaceable. It allows a fast development of distributed agent system by providing standard services for communication and life cycle management of the agents. With TurtleKit tool [36], the MadKit platform can support thousands of vehicles agents which interact and perform tasks together by defining an agent with reactive intelligence.

In order to control simulations, we define a launcher agent with the role of setting up, launching, and managing the simulation (see Fig. 3a).

Since the inexistence of an available road network benchmark with a set of origin-destination travels by time, we designed a virtual urban road network map (see Fig. 3b), as an instance of the observer agent of TurtleKit tool. This network has 14 roads with 1 direction and 2 lines, and 35 roads with 2 directions among them, 3 roads with 1 line and 32 roads with 2 lines; and 34 intersections equipped with traffic light signals. Each road has a maximum velocity value. The allowed speed for roads in the downtown (the interior of the network) is 16 m/s (meter/second) and the other roads are considered as relatively high speed roads with 20 m/s (72 km/h). In the simulation environment, one pixel represents 120 meters, and the traffic signals vary every 20 seconds. The guidance algorithm is running with $\alpha = 1$, $\beta = 1$, and $\gamma = 0.7$.

To easy understand the example of the road network map, we model it by a directed weighted graph $G = (V, E)$ with

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[1]Madkit: Multiagent Development Kit. http://www.madkit.org
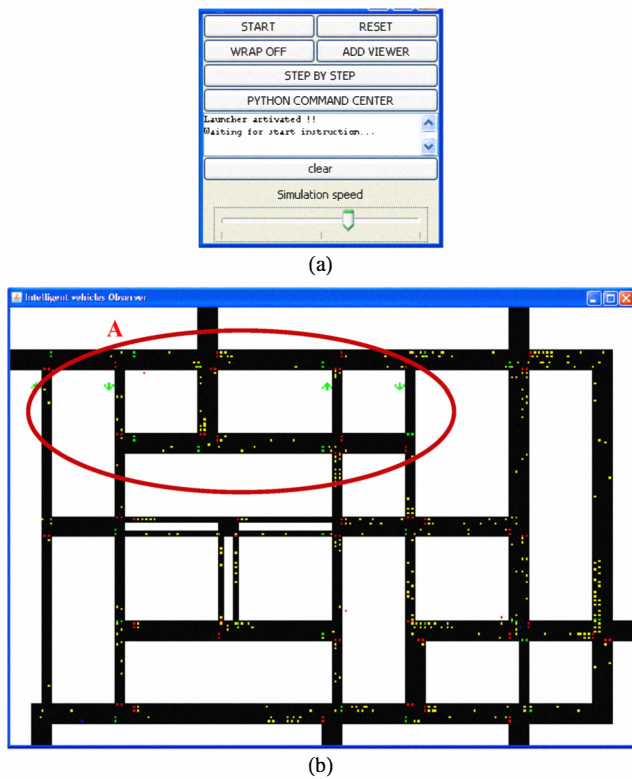
(a)

(b)

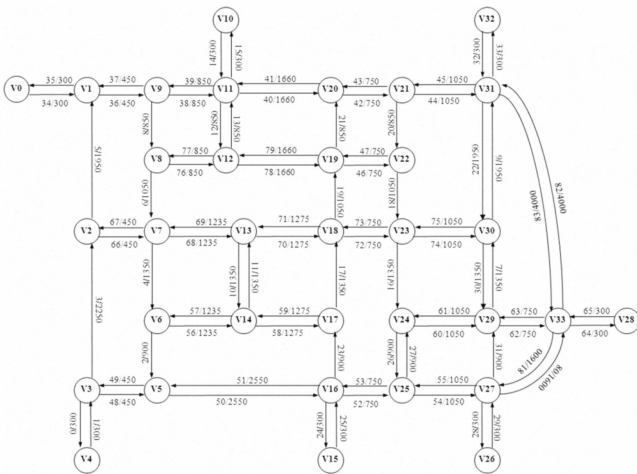Fig. 3. The simulator: (a) Launcher agent, (b) Example of simulated road network in the observer agent

Fig. 4. Illustration of the road network as a directed weighted graph

$|V| = 34$ road intersections and $|E| = 84$ roads with one direction. Fig. 4 illustrates the graph with Vertex number and Edges labelled by the number / weight (length road).

B. Results and discussion

Series of simulation are performed when varying the number of vehicles, sources and destinations, travel time, congestion/jam position. The results are compared to the static method of route choice based on itinerary length (using Dijkstra's algorithm).
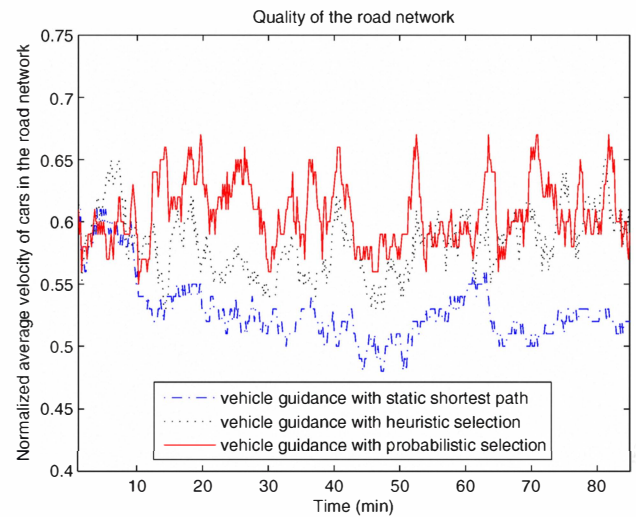

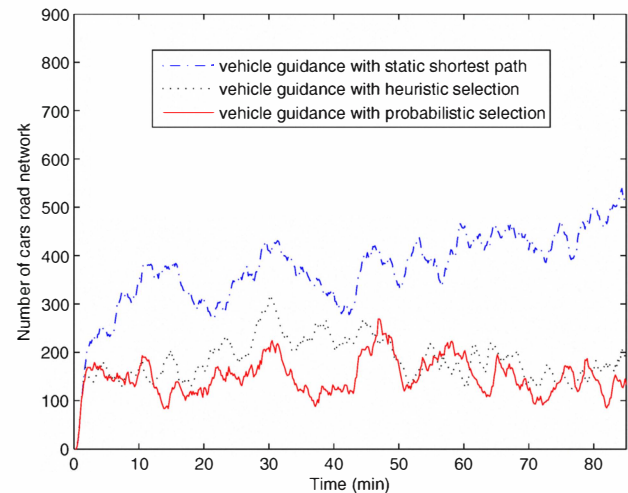Fig. 5. Variation of the road traffic quality of the road network

Fig. 6. Number of vehicles circulating on the road network

As regards to the quality of traffic flow on the road network with normal random variation, Fig. 5 shows the advantage of the proposed AVG method, in the raise of the average velocity in the entire road network. In fact, a highest number of vehicles reach their destinations early, compared to the classical shortest path selection (see Fig. 6).

In order to test the influence of congestion and to verify the efficiency of our method to minimize congestion and jam situations, we add a high number of cars at the same time on nearest roads. When forcing congestion from 16th till 23th minute, by adding 300 vehicles in area A (see Fig. 3b), Fig. 7 and Fig. 8 bear out the adaptativity of the entire network in terms of road traffic quality and number of circulating vehicles.

Let's focus on the adaptativity of the proposed AVG in one vehicle; table II details the itinerary proposed to one vehicle using different methods of selection itinerary into the
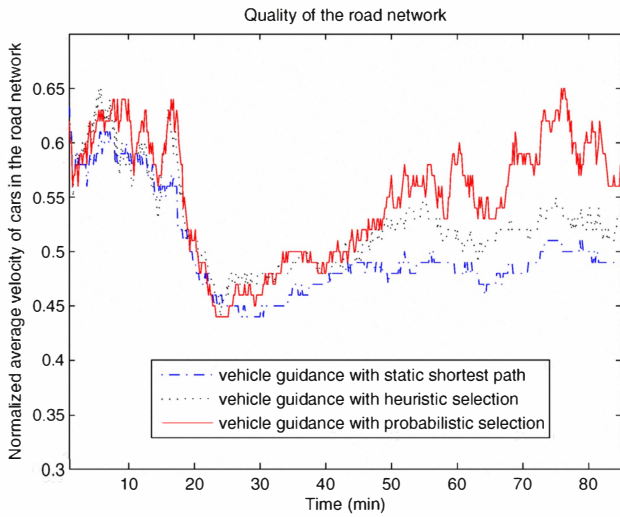
Fig. 7. Variation of the road traffic quality of the road network with congestions in some roads
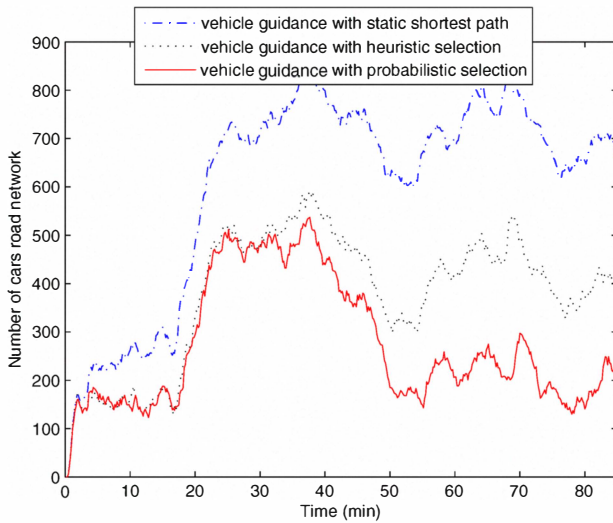

Fig. 8. Number of vehicles circulating on the road network with congestions in some roads

same road traffic simulation conditions. This table confirms the global results illustrated by Fig. 6 and explain the improvement of AVG in terms of average velocity and travel time with the same distance, compared to static selection.

Table III presents the same simulation with some congestions on different roads. The probabilistic selection is better than the heuristic selection since its good adaptativity.

Thus, the probabilistic selection proposes itineraries taking into account the real-time and changed traffic quality on the road network without a great loss on individual travel time. The probabilistic selection consists in distributing vehicles among different best roads. It has sometimes similar results as the heuritic ones, but when road congestions arise, it offers a better global road traffic quality and avoids congested / jammed situations.

TABLE II
ITINERARY SELECTION OF ONE VEHICLE

	From road 36 to road 62		
Intersections	Static method	Heuritic selection	Probabilistic selection
1	8-6-68-70-72-16-60-62	**8**-76-78-46-18-16-60-62	**8**-38-12-78-46-18-74-30-62
2	–	**76**-78-46-18-16-60-62	**38**-12-78-46-18-74-30-62
3	–	**78**-46-18-16-60-62	**40**-42-20-18-16-60 (*)
4	–	**46**-18-74-30-62 (*)	**42**-20-18-74-30-62 (*)
5	–	**18**-74-30-62	**20**-18-74-30-62
6	–	**74**-30-62	**18**-74-30-62
7	–	**30**-62	**74**-30-62
8	–	–	**30**-62
Average velocity (m/s)	11.06	12.27	12.17
Trav. Time (s)	683	616	621
Distance (m)	7560	7560	7560

(*) indicates a change in the previous proposed itinerary

TABLE III
ITINERARY SELECTION OF ONE VEHICLE WITH CONGESTED ROADS

	From road 36 to road 62			
Inter.	Congested roads	Static method	Heuritic selection	Probabilistic selection
1	–	8-6-68-70-72-16-60-62	**8**-76-78-46-18-16-60-62	**8**-38-12-78-46-18-74-30-62
2	76,12,79	–	**6**-4-2-50-52-27-60-62 (*)	**38**-12-78-46-18-74-30-62
3	70,17,73	–	**4**-2-50-52-27-60-62	**40**-42-20-18-16-60-62 (*)
4	68,11,71,46,20	60-62	**2**-50-52-27-60-62	**42**-20-18-16-60-62
5	16,27,61,74,71,22	–	**50**-52-27-60-62	**44**-22-30-62 (*)
6	14,38,13,41	–	**52**-54-31-62 (*)	**83**-63-62 (*)
7	6,66,68	–	**54**-31-62	**63**-62
8	–	–	**31**-62	–
A.V.(m/s)		7.86	10.99	11.60
Tr.T.(s)		961	855	781
Dis. (m)		7560	9400	9060

(*) indicates a change in the previous proposed itinerary

V. CONCLUSION AND FUTURE WORK

In this paper, we present an adaptive vehicle guidance system based on ant behavior. This system allows adjusting intelligently and promptly the road traffic on the network according to the real-time changes. Multiagent simulation results confirm that the proposed algorithm with probabilistic itinerary selection offers a better road traffic quality of the entire road network without a great loss of individual travel time. The proposed algorithm can manage, in real-time, unexpected events of congestion as well as the appearance of new road constraints or the changes on road network typology.

Evaluating best itinerary is an incredibly difficult task. So, as perspective, it is necessary to take into account some other factors influencing the route choice as familiarity of the driver with the itinerary, the quality of the road, safety, and the weather conditions. Furthermore, we intend in the near future to control also the light traffic signals in order to improve the management of the road network. Furthermore, we intend to evaluate the adaptativity degree of our agents by means of the system proposed in [37].

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