Improvement of the Road Traffic Management by an Ant-Hierarchical Fuzzy System

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***Abstract*—In view of dynamicity on road networks and the sharp increase of traffic jam states, the road traffic management becomes more complex. It is clear that the shortest path algorithm based only on road length is no longer relevant. We propose in this paper a hybrid method based on two stages based on ant colony behavior and hierarchical fuzzy system. This method allows adjusting intelligently and promptly the road traffic according to the real-time changes in the road network states by the integration of an adaptive vehicle guidance system. The proposed 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 adaptability.**

***Index Terms*—transportation, adaptive vehicle guidance, traffic assignment, ant colony, hiearachical fuzzy system, traffic simulation.**

I. Introduction

Nowadays, the Intelligent Transportation System (ITS) is an important component of human life and economic challenges is in growth phase on behalf of the monitoring and the control of road traffic. Some objectives of ITS are the vehicle guidance [1], the optimization of the road traffic flow [2], the management of the road network capacity [3], the improvement of the traffic safety, the minimization of the energy consumption, and others.

The road traffic management has as main objectives the improvement of the traffic fluency on road networks, the dynamic assignment of traffic flows, and the reduction of the number of traffic congestions states as well as their negative effects: delays, wasting time, drivers' stress, increasing air pollution, and blocking the passage of emergency vehicles [1] [4]. An accurate management will improve traffic efficiency over time and space with dynamic interventions. In this way, it appears the necessity of an intelligent vehicle guidance system helping drivers to attempt their destinations.

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 taking into account the real-time traffic quality of possible itineraries, avoiding congestions and jams states.

In view of the high dynamicity of traffic flow and the polynomial increase in the number of vehicles on road networks, the route traffic management becomes more complex. The selection of the shortest itinerary for a vehicle to reach its destination is no longer relevant [5] [6].

Since the road network is 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 [7] [8].

Furthermore, in order to enhance the problem of subjectivity, ambiguity, and uncertainty from road perceptions, the application of fuzzy set theory, using a set of 'if then' rules, is considered as an efficient framework to solve transportation problems [9].

Thus, the current trend of research work in traffic and transportation is to investigate in intelligent approaches integrating soft computing techniques [10], distributed and collaborative intelligence [11], bio-inspired intelligence [12], or hybrid approaches [6] [13]. The objective is to deal with the complexity and the dynamicity of transportation systems in order to provide intelligent transportation systems. This new topic of ITS is nowadays, in a growth phase of advancements.

We propose in this paper an adaptive hybrid method instigated from swarm intelligence, specifically ant colony behavior, well known for its good adaptability [3] [14]; and based on an hierarchical fuzzy system in order to improve the road traffic management by integrating important factors influencing the vehicle guidance. The idea is to increase the quality of the entire road network, especially in the case of congestions or jams.

The paper is organized as follows: section 2 presents an overview on related works on ITS based on swarm intelligence and fuzzy logic. 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.

II. Related Works

In this section, we focus our attention especially on road traffic management models which are based on swarm intelligence and Fuzzy logic.

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A. Road Traffic Management based on Swarm Intelligence

The swarm intelligence is well used to model complex traffic and transportation processes [12]. 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 [15]. 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.

Although Ant Colony Optimization (ACO) [16] was well used to solve transportation problems, especially industrial problems such as Travelling Salesman Problem (TSP) and Vehicle Routing Problem, the swarm optimization is not well used to solve road traffic management problem. In fact, the road traffic management problem cannot be solved using the classic ACO version that was well applied to TSP: Ants of the artificial colony are able only 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.

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

TABLE I
RELATED WORKS ON TRAFFIC MANAGEMENT BASED ON SWARM INTELLIGENCE

Auth.	Main objective	Approach features
[3], 2003	Road traffic management	Ant system for shortest path in weighted dynamic graph; neural network for regulation system.
[17], 2004	Synchronization of traffic lights	Colonies of social insects to adapt the traffic lights to give priority to the higher flow.
[2], 2004	Road traffic management	Extended ant-cycle algorithm to find the best path between two nodes.
[18], 2006	Traffic assignment problem	Ant colony for each origin-destination pair; stochastic user equilibrium algorithm to imitate the behavior of transportation system.
[13], 2007	Dynamic route planning	Finding both optimized shortest path and shortest time based on fuzzy logic, graph partitioning algorithm, and GA.
[19], 2007	Bus network optimization	Parallel ant colony algorithm to maximize traveller density (i.e. reduce transfers and travel time in bus network).

We notice:

- 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 a collaborative and adaptive road traffic management of the entire road network on the other hand.

B. Road Traffic Management based on Fuzzy Logic

In recent years, many developments in information acquisition technologies through Advanced Traveler Information Systems have been done. Thus, many factors that affect route choice decision such as travel distance, travel speed, weather conditions, travel time, personal preferences, work information, and other traffic information, are available for drivers in real-time. Table II summarizes the main features of some works on traffic management based on fuzzy logic.

TABLE II
RELATED WORKS ON TRAFFIC MANAGEMENT BASED ON FUZZY LOGIC

Auth.	Main object.	Approach features
[20], 2004	Traffic assignment	Choice function based on fuzzy preference relations for travel decisions considering the spatial knowledge of individual drivers.
[21], 2004	Route choice model	Calibration method and knowledge base composition, using a combined approach of fuzzy logic and neural nets, to compute the final route utility.
[6], 2004	Route choice model	Fuzzy model using hybrid probabilistic-possibilistic model to quantify the latent attractiveness of alternative routes.
[22], 2005	Route choice model	Hybrid model using concepts from fuzzy logic and analytical hierarchy process with respect to travel time, congestion and safety.
[23], 2006	Route choice model	Fuzzy neural approach to modelling behavioural rules.
[24], 2009	Traffic management	Traffic advisory system using fuzzy logic to determine the threshold capacity of a road segment.
[25], 2011	Urban traffic managament	Multi-agent system based on type-2 fuzzy decision module for traffic signal control in a complex urban road network.

It is clear that for an accurate selection, route choice model have to consider all available information. In order to enhance the problem of subjectivity, ambiguity, and uncertainty of perceptions, the application of fuzzy logic is considered as an efficient framework to solve transportation problems.

We notice that until now, itinerary selection based on fuzzy logic is applied by evaluating only two or three alternatives with a few number of selection criteria. This encourages us to go on further and to develop a hierarchical fuzzy system, in a cooperative multiagent system, for traffic management. It can take into account a large number of selection criteria and compare a variable number of feasible routes in order to select the best itinerary.

III. PROPOSED MODEL

This section details the proposed road traffic management system. The first subsection presents the road network architecture, based on multiagent approach, detailing the different components of the system. Then, we present the main two stages of the deliberative agent for vehicle guidance: the first is instigated from ants' behavior in order to select the best itinerary based on road traffic quality and itinerary length. The second is based on a hierarchical fuzzy model in order to include other criteria influencing the route selection.

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 road traffic quality and other factors related to the infrastructure, the environment, and the driver.

A. Route Selection Architecture

The proposed road network architecture involves equipments such as the Global Positioning System (GPS). The GPS is well suited to collect the localization data, vehicle's velocity, and motion direction, at regular time intervals. Recent developments on GPS promote the research field in real-time road traffic information in order to improve route choice decision [1] [26]. An approximate measure of the traffic density can obtained using GPS or a cellular network data based such as the Global System for Mobile communications (GSM) [27]. In fact, each switched-on mobile phone turns into a traffic probe as anonymous source of information. So, 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 can provides the average velocity of each driver in real-time without additional infrastructures.

In order to obtain traffic information in real-time for the entire road network, it is more interesting to use the advanced equipments instead of the use of traditional stationary equipments (sensors and cameras) that must be installed in the each road.

The proposed 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 servers. The system can be integrated into a dashboard of vehicle or into a third generation mobile phone.

Since the road network is geographically distributed, we proposed a hierarchical multiagent approach to model the road network that allows to model complex systems where numerous autonomous entities interact and collaborate to produce global solution [28]. Solutions like this depend on global knowledge of the road conditions, the ability to transmit route plans to all vehicles, and the compliance of drivers to follow the route plan. Thus, in the proposed road network architecture, vehicles are grouped by both city and road. It involves three types of agents: City Agent (*CA*), Road Supervisor Agent (*RSA*), and Intelligent Vehicle Agent (*IVA*).

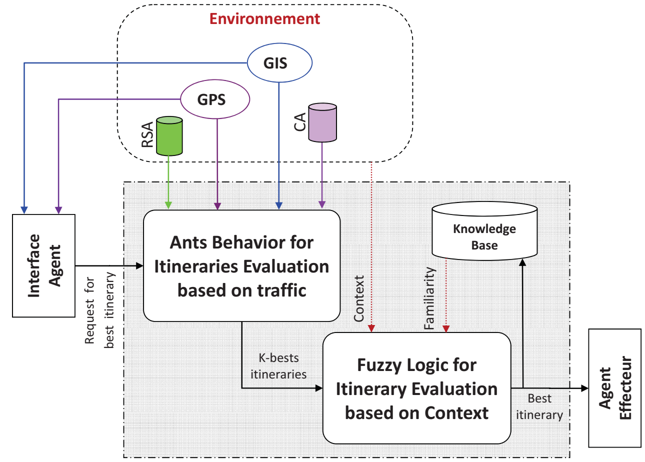

Fig. 1. Intelligent vehicle agent architecture

Figure 1 presents the architecture of the proposed intelligent vehicle agent, and especially the deliberative agent responsible to propose the best itinerary to the driver to reach its destination taking into account the real-time road network state. In order to deal with this goal, the architecture involves two main stages: the first is instigated from ants' behavior in order to select the best itinerary based on both traffic quality and itinerary length; and the second is based on a hierarchical fuzzy model in order to improve the itinerary selection by adding other criteria influencing the selection stage.

B. Itinerary Evaluation based on Ant Colony Behavior

The proposed collaborative and adaptive itinerary evaluation method considers that each vehicle is an ant-agent evolving on the road network, having the initial road as a source and the final road as a destination. The vehicle guidance is based on a trade-off between road traffic qualities representing the pheromone quantity deposited by ants on the road, and the itinerary length. In terms of multiagent technology, the method consists of three parallel and distributed processes embedded in the following agents:

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 source and destination of the driver. 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 an itineraries set as follows [29]:

- From the current intersection, search the shortest itinerary

from each next possible road intersection to road destination, based on itinerary length;
- 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.

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

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

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 tradeoff 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. 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).

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

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).

$$q^{new}_{road} = q^{old}_{road} + \gamma(\hat{d}q - q^{old}_{road}) \quad (6)$$

with q^{old}_{road} is the old road quality, $\hat{d}q$ 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.

C. Route Evaluation based on Fuzzy Logic

Since the road traffic quality is not only the main factor for road traffic management, we propose to integrate the other factors such as travel time, weather conditions, work information, and other road network information (known as context) that can improve the route choice decision. These factors are known by its ambiguity and uncertainty of perceptions. The input of this stage is a set of the k best itineraries. So, the application of fuzzy logic is considered as an efficient framework to improve the proposed ranking of the first stage.

Regarding the increasing number of selection criteria used to select the best alternative, the application of fuzzy logic to route choice problem with a large number of inputs involve the problem of rule-explosion. In order to deal with this problem, some hierarchical fuzzy systems have been proposed [30] [31] [32]. In this case, the number of rules increases linearly related to the number of inputs $(n-1).m^2$ rather than exponentially.

We have chosen the following eight inputs that have an important influence of itinerary selection: work information, maximum allowed velocity in the itinerary, familiarity of the driver with the roads, usual driver velocity, travel time, and weather conditions. These selected factors are the most important criteria, more used, and accessible from the vehicle information system.

In a fuzzy hierarchical architecture, outputs from certain fuzzy controllers are used as inputs for the following fuzzy controllers. In this case, it is difficult to design this kind of system because the intermediate outputs do not have physical meaning. To deal with this problem, we chosen inputs combination that reduces limitations associated with the loss of physical meaning in intermediate outputs/inputs. So, inputs are regrouped by three categories according to the itinerary criteria, the driver criteria, and the environment criteria. All sub-fuzzy systems have two inputs and one output. Figure 2 illustrates the hierarchical fuzzy system for the itinerary evaluation.

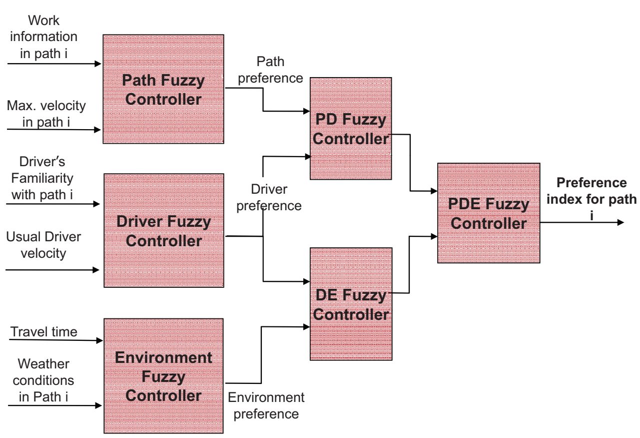

Fig. 2. Flowchart of the hierarchical fuzzy system for the itinerary evaluation

The selection of the best itinerary is now a trade-off between itinerary quality taking into account the itinerary length, and the context that is based on a set of factors having an important influence on itinerary selection.

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 [33]. In fact, this kind of simulation is very helpful to explain collective behavior 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 [34].

The following subsection presents the developed micro-simulation which is greatest strength to model congested road networks by means of queuing conditions. The micro-simulation tries to simulate the individuals' behavior 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 behaviors in one environment, and agent's interaction phenomenon. At each simulation step, each agent can receive a set of information describing the surrounding state in the environment [33].

For few years, we have noted the birth of some multi-agent 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 platform as a generic multi-agent platform [35]. Our choice is initially based on published comparison between well known multiagent platforms [36] [37].

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 [38], the MadKit platform can support thousands of vehicles agents which interact and perform tasks together by defining an agent with reactive intelligence [28].

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

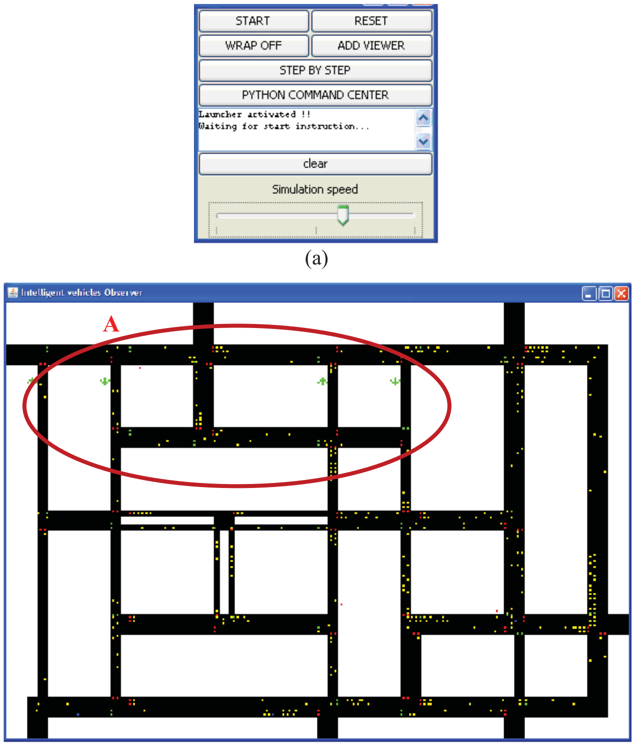

Fig. 3. The simulator: (a) Launcher agent, (b) Example of simulated road network in the observer agent

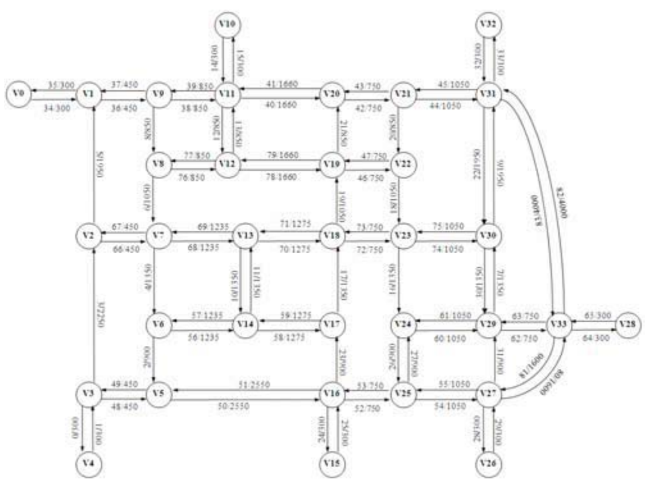

Fig. 4. Illustration of the road network as a directed weighted graph

B. Results and discussion

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

The first subsection will present the advantage of the first stage of itinerary selection based on ant behavior. The second subsection will present the influence of the hierarchical fuzzy system taking into account the context in order to improve the itinerary selection.

1) Vehicle guidance based on Ant Colony behavior: As regards to the quality of traffic flow in the road network with normal random variation, Fig. 5 shows the advantage of the proposed adaptive itinerary evaluation 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.

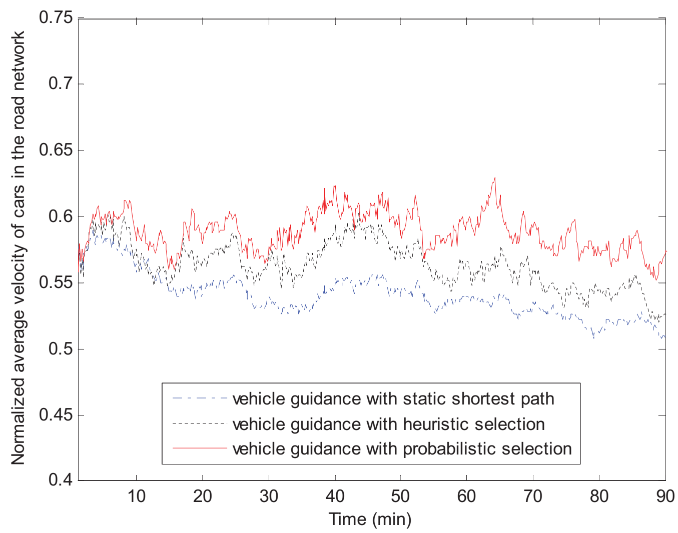

Fig. 5. Variation of the road traffic quality in the road network

2) Management Improvement based on Hierarchical Fuzzy System: Around 30000 vehicles with different couple origin-destination roads have been simulated twice, using the same road network presented in figure 4: the first simulation was based on the first stage only, and the second simulation was based on the global hybrid architecture (two stages).

In order to test the influence of congestion and to verify the efficiency of our method to minimize jam states, we add a high number of cars in the same time in nearest roads. For example, when forcing congestion from 16th till 23th minute, by adding 300 vehicles in area A (of Fig. 3b) and modifying some fuzzy inputs, Fig. 6 and Fig. 7 bear out the adaptability of the entire network in terms of road traffic quality and the number of circulating vehicles in the network.

Let focus on the adaptability of the proposed adaptive road traffic management for one vehicle; table III details the itinerary proposed to the same vehicle using different methods of selection into the same road traffic simulation conditions with congestions in different roads. The table confirms the global results illustrated by Fig. 6 and explains the improvement of the proposed method in terms of average velocity and travel time with the same distance, compared to static selection.

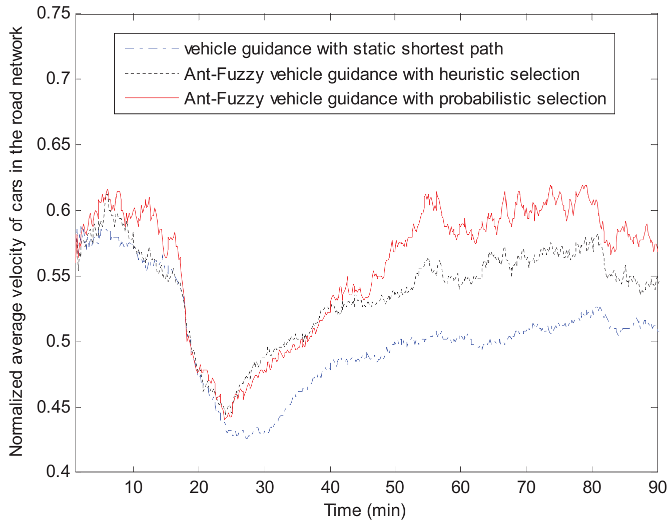

Fig. 6. Variation of the average velocity in the road network with some congestion roads

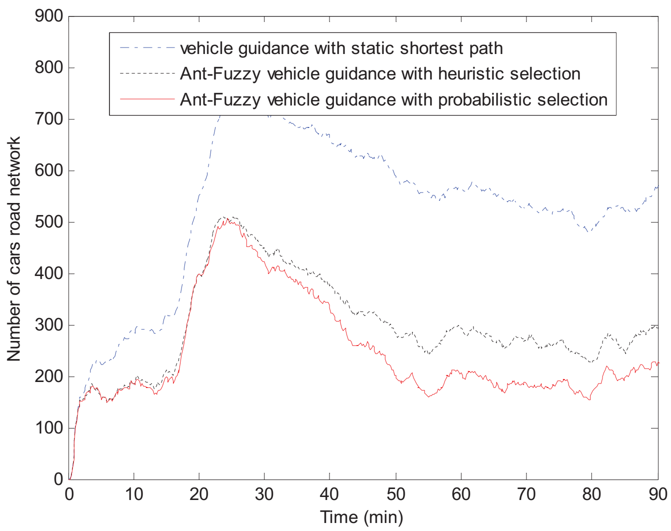

Fig. 7. Number of vehicles circulating in the road network with congestions in some roads

After statistical validation of simulation, we can conclude that the probabilistic selection is better than the heuristic selection since its good adaptability.

We remark that 31% of proposed itinerary was changed after the running the second stage. This modification implied an improvement of the normalized average velocity of cars in the whole road network from 0.563 to 0.579. This confirms the important influence of the selected factors (context) and the effectiveness of the hierarchical fuzzy system in order to improve traffic management.

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

TABLE III
TRAFFIC ITINERARY SELECTION OF ONE VEHICLE WITH CONGESTED ROADS

From road 52 to road 38					
Inter-sections	Cong. Roads	Static method	Heuritic selection	Prob. selection	Prob. Select. with fuzzy
1	21,40, 43,50, 48	53-23-17 -19-21- 41-39-38	**53**-51-49 -3-5-36- 38	**54**-31-7- 9-45-43- 41-39-38	53-23-17- 19-21-41- 39-38
2	9,44, 32,45, 42	-	**23**-59-11 -69-67-5 -36-38(*)	**31**-7-9- 45-43-41 -39-38	**51**-49-3-5- 36-38 (*)
3	30,31, 60,63	-	59-11-69 -67-5-36 -38	7-75-73- 19-21-41 -39-38(*)	49-3-5- 36-38
4	18,72, 42,45	-	11-69-67 -5-36-38	75-73-19 -21-41- 39-38	3-5-36- 38
5	21,40, 43,76, 41,14	-	69-67-5- 36-38	73-19-21 -41-39- 38	5-36-38
6	6,69, 66,5, 34,37	-	67-5-36- 38	19-79-13 -39-38(*)	36-38
7	11,68, 5,34, 37	-	5-36-38	79-13-39 -38	-
8	-	-	-	13-39-38	-
9	-	-	-	39-38	-
AV(m/s)		7.35	9.11	10.23	10.91
TT(s)		1007	917	929	769
D(m)		7410	8360	9510	8400

(*) indicates a change in the previous proposed itinerary
(*) AV: Average velocity ; TT: Travel Time ; D: Distance

V. CONCLUSION AND PERSPECTIVES

In this paper, we present an adaptive vehicle guidance system based on hybrid ant-hierarchical fuzzy method. This system allows adjusting intelligently and promptly the road traffic in the network according to the real-time changes. Multiagent simulation results confirm that the proposed algorithm with probabilistic itinerary selection offer a better road traffic quality of the entire road network without a great loss on individual travel time.

On the one hand, the proposed method consists in maximizing the capacity of the network by minimizing travel times while taking into account the current road traffic information; 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.

As perspective, 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 have in mind to evaluate the adaptability degree of our agents by means of the system proposed in [39].

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