Transportation Research Part C 42 (2014) 147–167

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Adapt-Traf: An adaptive multiagent road traffic management system based on hybrid ant-hierarchical fuzzy model

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A R T I C L E   I N F O

Article history:
Received 1 May 2012
Received in revised form 29 December 2013
Accepted 5 March 2014

Keywords:
Traffic management
Adaptive vehicle route guidance
Multiagent systems
Ant colony
Hierarchical fuzzy system
Traffic simulation

A B S T R A C T

Usually, road networks are characterized by their great dynamics including different entities in interactions. This leads to more complex road traffic management. This paper proposes an adaptive multiagent system based on the ant colony behavior and the hierarchical fuzzy model. This system allows adjusting efficiently the road traffic according to the real-time changes in road networks by the integration of an adaptive vehicle route guidance system. The proposed system is implemented and simulated under a multiagent platform in order to discuss the improvement of the global road traffic quality in terms of time, fluidity and adaptivity.

1. Introduction

Nowadays, the Intelligent Transportation System (ITS) represents an important component of human life and economic challenges. It is in growth phase on behalf of the monitoring and the management of road traffic. The objectives of ITS are the vehicle route guidance (Schmitt and Jula, 2006; Bierlaire and Frejinger, 2008), the optimization of the road traffic flow (Hallam et al., 2004), the management of the road network capacity (Bertelle et al., 2003), the real-time traffic signal control (Kouvelas et al., 2011), the improvement of the traffic safety, the minimization of the energy consumption, and others.

Road traffic management consists on improving the traffic fluency on road networks, assigning dynamically the traffic flows, and reducing the number of traffic congestions states as well as their negative effects (i.e. delays, waiting time, drivers' stress, air and noise pollution, and blocking the emergency vehicles) (Bierlaire and Frejinger, 2008; Pan et al., 2008). A more effective and contextual management will improve transportation supply performances over time and space with real-time interventions. These intelligent methods applied to vehicle guidance system will facilitate the task of drivers.

On the one hand, due to the high dynamics of traffic flow and the increase of the travel time when the number of vehicles increases in the road networks, the route traffic management becomes more complex. So, the shortest itinerary based on

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http://dx.doi.org/10.1016/j.trc.2014.03.003
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route length (like offered by GPS navigators) cannot be the best itinerary nowadays. The navigator systems need to be adaptive by taking into account the real-time traffic flow of possible itineraries in order to provide itineraries with a lower travel times.

On the second hand, due to the topology of the road network and the possible interactions of many heterogeneous entities, the use of an intelligent distributed approach is interesting. In this way, the attention will be for the multiagent approach that handles complex systems modeling where numerous autonomous entities interact and collaborate in order to produce a global system behavior. This behavior is made by several emergent phenomena resulting from the behavior of individual entities and their interactions (Wooldridge, 2002; Bazzan et al., 2005).

On the third hand, in order to enhance the problem of subjectivity, ambiguity, and uncertainty from road perceptions, the application of fuzzy logic, was considered as an efficient decision making for transportation engineering (Teodorovic, 1999).

The current trend of research work in traffic and transportation is to investigate in intelligent approaches integrating soft computing techniques (Avineri, 2005), distributed and collaborative intelligence (Hallé and Chaib-Draa, 2005), bio-inspired intelligence (Teodorovic, 2008), hybrid approaches (Peeta and Yu, 2004; Lup and Srinivasan, 2007), and others. The challenge is to take advantage of each research trend and provide an innovative ITS.

This paper proposes a novel adaptive multiagent system for road traffic management instigated from swarm intelligence [specifically ant colony behavior which is well known for its good adaptivity and providing a reduction in computation times (Dorigo, 1992; Bertelle et al., 2003; Kallel et al., 2008a)] and based on a hierarchical fuzzy system used for itinerary evaluations by integrating important contextual factors influencing the route choice. The objective is to increase the quality of the entire road network, especially in case of congestions and jams, taking into account real-time traffic information and travel time of drivers to reach their destinations.

The paper is organized as follows: Section 2 presents an overview on related works on road traffic management. Then, Section 3 describes the proposed multiagent real-time road supervision model. Section 4 presents the hybrid model of the intelligent vehicle agent for the adaptive vehicle route guidance system. The simulation and results' discussion are presented in Section 5. Finally, the conclusion summarizes the presented work and points to some future research directions.

2. Related works

In recent years, researchers have shown great interest to use techniques and methodologies from artificial intelligence and soft computing. These methodologies have the ability to control the quantitative and qualitative measures more effectively than usual methods. They allow to intelligently solving complex problems related to the transportation systems (Avineri, 2005).

This section focus especially on latest road traffic management models which are based on fuzzy logic, multiagent approach, and swarm intelligence.

2.1. Road traffic management based on fuzzy logic

The fuzzy logic appeared in 1965 by Zadeh introducing the concept of fuzzy sets (Zadeh, 1965). It was shown as a very promising mathematical approach for dealing with subjectivity, ambiguity, uncertainty, and imprecision. The model based on this approach is robust to small variations and is easy for design and implementation. It was used as a framework to solve transportation problems such as traffic assignment problem, accident analysis and prevention, traffic control at roads intersection, and traffic light control (Teodorovic, 1999).

The research in this field began on 1990 by modeling a simple two-route choice problem in order to select the best one (Teodorovic and Kikuchi, 1990). The basis of this model is the use of fuzzy linguistic rules such as:

> "**IF** *perceived travel time along route A* <u>is much less than</u> *perceived travel time along route B*, **THEN** *fuzzy preference indice for A* <u>is</u> *very stronger than B*".

During the last decade, some developments in information acquisition technologies through advanced traveler information systems have been done. However, many contextual factors (such as departure time, travel distance, usual driving speed of the driver, weather information, personal preferences, roadwork information, and other information which could be available to the guidance systems in real-time) increase the uncertainty of the itinerary choice. The following Table 1 summarizes the main features of most important works on road traffic management based on fuzzy logic.

According to Table 1, the application of fuzzy logic is considered an efficient framework to solve transportation problems in order to enhance the problem of subjectivity, ambiguity, and uncertainty of perceptions.

It is clear that for an effective road traffic management, the traffic models have to consider the maximum available information. Until now, the developed models based on fuzzy logic are applied by evaluating only few possible alternatives considering limited number of criteria in order to be simple and avoid the problem of rule-explosion.

In this paper, the proposed model is to improve the effectiveness-simplicity trade-off by developing a hierarchical fuzzy model for itinerary evaluation handling greater number of criteria.

2.2. Multiagent road traffic management

The multiagent approach, appeared in the middle of the nineties, it was known by its ability to model complex systems where numerous autonomous entities interact to produce global solutions (Ferber, 1999; Wooldridge, 2002; Abraham et al., 2008).

Recently, a number of intelligent transportation systems based on multiagent approach come into being and have already been reported in the literature. Most of them are still under development or at experimental stages, but they clearly demonstrate the potential of implementing this technology in order to improve dynamic routing performances and traffic management by employing cooperative and distributed approach (Schleiffer, 2002; Bazzan et al., 2005; Chen and Cheng, 2010). Table 2 summarizes the main features of some works on multiagent road traffic management.

The selected related works show that multiagent approach is considered as a powerful computing paradigm to manage the complexity in dynamic distributed systems, such as road traffic control and management systems. The most of works focus on modeling and simulation, but some of them are deployed for real case. Few of them use multiagent platforms for simulation although they develop a multiagent architecture and multiagent simulation.

2.3. Road traffic management based on swarm intelligence

The swarm intelligence was well used to model complex traffic and transportation processes (Teodorovic, 2008). In fact, the self-organization of the social insects is based on relatively simple rules of individual insect's behavior. Among the different colony insects, the ant colony succeeds to find food by following the path with highest pheromone quantity deposited by other ants (Bonabeau et al., 1999). The pheromone signal represents the communication tool between individual ants. It contributes to the formation of collective intelligence of social ant colonies that can be considered as multiagent systems.

Although Ant Colony Optimization (ACO) (Dorigo et al., 1996) was well used to solve transportation problems, especially industrial problems such as Travelling Salesman Problem (TSP) and Vehicle Routing Problem (VRP), only few works based on swarm intelligence are developed to solve road traffic management problem. In fact, the problem cannot be solved using the classic versions: artificial ants are able only to generate successively shorter feasible tours by using information accumulated in the form of a pheromone trail deposited on the graph edges.

Table 3 summarizes the main features of relevant related works on traffic management based on swarm intelligence.

According to the literature, the swarm intelligence was applied to optimize traffic signals and bus networks. In other works, ants' colony was used to find the shortest path with generalized cost. Furthermore, during the two last years, mobile agents and agents based on ant behavior are integrated to deal with the adaptivity in dynamic environments. The main limitation is that these research works do not consider the dynamic real-time information during the travel.

In this way, this paper tries to confirm the powerful of the both ant behavior integrated into multiagent system and multiagent simulation platforms to deal with traffic management. Moreover, the hybridization of ITS based on swarm intelligence and multiagent simulation is not yet prominent.

2.4. Synthesis

Regarding the related works detailed in the previous subsections (Tables 1–3), the development of traffic management systems, based on latest improvements in artificial intelligence and soft computing, is in its progressive phase during the last decade. The forecast in this field is to deal mainly with the uncertainty and the dynamics of travel demand in order to provide better guidance management.

This leads us to think about investigating in a real-time design considering for example, the vehicle as an ant-agent while taking into account contextual influent factors for itinerary selection on the one hand, and for a collaborative and adaptive road traffic management of the entire road network on the other hand.

3. Multiagent real-time road supervision model

By modeling the separate tasks as intelligent agents, it will be possible to adapt the actions of vehicle's driver through the concept of agent cooperation in order to achieve a common goal. In this way, the multiagent modeling will be applied since it is better than standard one in terms of individual and collective behaviors (Klügl et al., 2002; Kammoun et al., 2008; Kefi et al., 2010).

Since that the traffic flow in the road network is the result of interaction between network performances and drivers' behavior, the proposed model takes into account that not all drivers follow the suggested road of the guidance system. It means that the driver behavior will affect the network performances.

3.1. Proposed deployment of the road network architecture

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

Table 1
Relevant related works on traffic management based on fuzzy logic.

Ref. work	Objective	Method features	Strength	Unhandled issues
Ridwan (2004)	Traffic assignment	– Choice function based on fuzzy preference relations – Consideration of the spatial knowledge of individual drivers	Fuzzy preference relations for travel decision	Small number of influence factors
Hawas (2004)	Route utility estimation	– Fuzzy system with 4 modules – Neuro-fuzzy data training with a hidden neurons in each fuzzy process	Adaptivity to the variation of perceptions from drivers	– Design of 4 fuzzy logic systems – No fuzzification training not exist
Peeta and Yu (2004)	Route choice model	– Hybrid probabilistic–possibilistic model to quantify the latent attractiveness of alternative routes	Good day-to-day prediction	Poor prediction in case of heterogeneous drivers behavior
Arslan and Khisty (2005)	Route choice model	– Hybrid model based on fuzzy logic and analytical hierarchy process – Fuzzy sets based on Weber psychology law	Preferences extracted from driver's psychology	– One simple road network test – Intuitively promising results
Panwai and Dia (2006)	Route choice model	– Fuzzy neural approach for modeling behavioral rules – Calibration of membership function	– Socio-economic, context, and information variables of individual behavior – Real microscopic traffic simulation (Australia)	– Small data collection – Low interpretability of results
Ghatee and Hashemi (2009)	Traffic assignment	– Algorithm based on quasi-Logit formulas	– Maximize the level of certainty – Minimize the perceived travel delays	– No results for real networks
Balaji and Srinivasan (2011)	Urban traffic management	– Multi-agent system based on type-2 fuzzy decision module	– Reduce the total delay of vehicles – Real traffic simulation (Singapore)	– No vehicle route guidance

Table 2
Relevant related works on multiagent road traffic management.

Ref. work	Objective	Method features	Strength	Unhandled issues
Hernández et al. (2002)	Traffic management	– Traffic management agents – Centralized /decentralized coordination	– Use knowledge-based reasoning techniques – Real traffic simulation (Barcelona)	– Only one type of agent
Dia (2002)	Route choice behavior	– Driver-vehicle agents – Coordination	– Real simulation under the influence of real-time traffic information	– Few number of agents based on BDI framework
Katwijk and Koningsbruggen (2002)	Traffic management	– Network agent, route agents, measure agents – Cooperation and coordination	– Coordination of traffic management instruments	– No simulations
Adler et al. (2005)	Traffic management and route guidance	– Driver agents, information service provider agents, system operator agents – Negotiation and cooperation	– Efficient route allocation across time and space – Negotiation model for pre-trip route assignment	– Five-node network for test
Srinivasan and Choy (2006)	Real-time traffic management	– Intersection controller agents – Cooperation	– Effective traffic signal control – Performance compared to two other techniques – Real traffic simulation (Singapore)	– Only one type of agents – No multiagent platform for simulation
Meignan et al. (2007)	Urban bus network management	– Traveler agents, bus agents – Cooperation	– Combines buses operation, traveler behaviors and road traffic model – real case study (Belfort)	– Traffic scenarios did not include particular events: accidents, traffic jams, or roadwork
Chen et al. (2009)	Traffic control and management	– Laser detector agents, loop detector agents, video camera detector agents, transportation management center agent, mobile agents – Cooperation	– Mobile agent technology – Deal with the uncertainty in a dynamic environment	– No comparison with previous works using stationary agents – No multiagent platform for simulation
Claes et al. (2011)	Vehicle routing	– Vehicle agents, infrastructure agent, antlike agents – Cooperation	– Anticipatory vehicle information to prevent the creation of unnecessary congestion – real case study (Leuven)	– Forecast information cost

Table 3
Relevant related works on traffic management based on swarm intelligence.

Ref. work	Objective	Method features	Strength	Unhandled issues
Bertelle et al. (2003)	Road traffic management	– Ant system for shortest path in weighted dynamic graph	– Neural networks for traffic flow regulation – Simulation using multiagent platform	– Simple road network for simulation
Yang et al. (2007)	Bus network optimization	– Optimization model based on coarse-grain parallel ant colony algorithm	– Update the increased pheromone based on the objective function – Reduce transfers and travel time – real case study (Dalian city, China)	– No consideration of real-time traffic management
Deng et al. (2010)	Dynamic traffic assignment	– Hybrid Particle Swarm Optimization (PSO) algorithm combined fluid neural network	– Search best path in stochastic traffic networks	– Simulation in road network with only 20 nodes
D'Acierno et al. (2012)	Asymmetric traffic assignment	– ACO-based algorithm to optimize the signal settings of each intersection – Improvement of (D'Acierno et al., 2006)	– Innovative ant behavior based on the pressure of ant stream – Real case study (3 cities in Italy)	– No real-time management
García-Nietoa et al. (2012)	Traffic light scheduling	– PSO algorithm to find successful cycle programs of traffic lights	– Real case study (2 cities in Spain)	

- sensors for counting the number of vehicles;
- cameras to detect the vehicular flows;
- Variable Message Sign (VMS) devices showing the road status;
- other equipments.

Using these road equipments, it is difficult to obtain traffic information in real-time for the entire road network. In fact, an effective management cannot be done with simple traffic information and without on board information. Moreover, the integration of traditional equipments in all roads, in each city, is expensive. The use of an advanced road network model for the road management system is hence necessary.

Accordingly, a satellite navigation system such as the Global Positioning System (GPS) (Zito et al., 1995) is well suited to collect the localization data, vehicle's speed, 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 (Gong et al., 2007; Bierlaire and Frejinger, 2008).

The proposed traffic management system assumes that all vehicles are equipped by GPS in order to compute the real-time traffic flow. The traffic control center is responsible on sending and receiving position data from vehicles. In case of unavailability of GPS data, especially in developing countries, the travel speeds (the traffic flow can be estimated, under some assumption, via travel speed) can be computed via the cellular data network such as GSM (Global System for Mobile communications) (Ramm and Schwieger, 2007). The GSM 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 speed exceeding the walking passenger's one and without considering persons mobile equipped in the same vehicle or more mobiles for each person. This technique provides the average speed 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 vehicle's dashboard or into a third generation mobile phone.

Fig. 1 illustrates the proposed advanced 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 based on hierarchical multiagent architecture detailed in the next subsection.

3.2. Hierarchical multiagent organizational architecture and agents' description

The hierarchical organizational architecture of road network is based on the AGRE (Agent-Group-Role-Environment) meta-model suggested by (Ferber et al., 2005). It is one of the proposed frameworks that define the organizational dimension of a multiagent system:

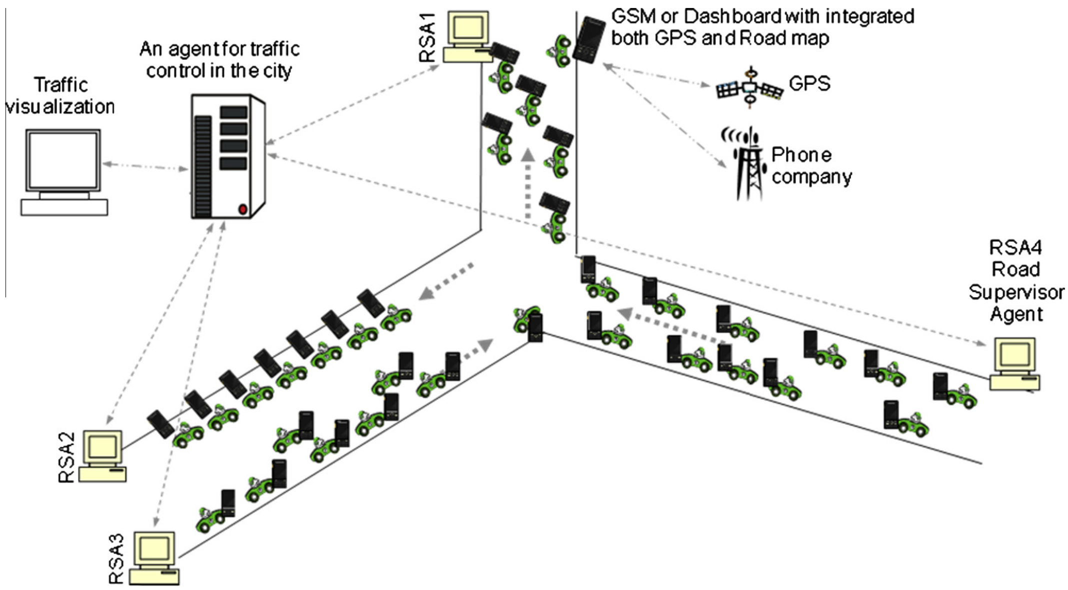

Fig. 1. Advanced road network architecture.

– *Agent* is specified as an active communicating entity which plays roles within groups.
– *Group* is considered as atomic sets of agent aggregation.
– *Role* is a representation of agent function, service or identification within a group.
– *Environment* is the physical area and its entities.

The organizational multiagent AGRE meta-model was selected since it is well appropriate to the transportation context. Furthermore, the necessity of dynamic traffic management including huge number of vehicles leads to use reactive agents more than cognitive agents. On the contrary of cognitive agents, reactive agents do not have representation of their environment. Reactive agents can cooperate and communicate by means of their interactions (direct communication) or through perception of environment (indirect communication). As consequence, the global intelligent behavior of reactive system is resulting from numerous interactions (Ferber, 1999).

According to the AGRE meta-model, the following sets were defined by adding the concept of subgroups in order to provide better organization of agents.

– Set of Agents = <*city*, *road*, *vehicle*>
– Set of Groups = <*city agents*, *road agents*, *vehicle agents*>
– Set of subgroups = <*road agents in the same city*, *vehicle agents in the same road*>
– Environment = <*roads*, *GIS*, *GPS*, *vehicles*, *drivers*, *server*, *communication equipments*>

The proposed model involves the following three agents.

• **City agent (CA)**

  – Agents: one agent for each city.
  – Roles: manages the road network in the city in order to obtain a better exploitation of the network; updates traffic quality of roads in the city.
  – Interactions: communicates and cooperates with other city agents according to the RSA request.
  – Group: member of city agents group.

• **Road supervisor agent (RSA)**

  – Agents: one agent for each road direction.
  – Roles: monitors the state of the traffic flow on the road; uses control actions for management; sends safety information for passengers.
  – Interactions: coordinates with CA and IVA regarding the road traffic quality, the weather information, and other information related to the road.
  – Group: static member of the road agents in the same city subgroup.

• **Intelligent Vehicle agent (IVA)**

  – Agents: one agent for each vehicle.
  – Roles: vehicle interface interacting with driver, itinerary decision maker providing best itinerary under real-time traffic information, vehicle actuator guiding driver to move the vehicle.
  – Interactions: coordinates with RSA to collect real-time traffic information, communicates both with a GPS to receive its coordinates and with a GIS to obtain a routing table.
  – Group: dynamic member of the vehicle agents in the same road subgroup. The vehicle agent can move from a subgroup to another when it changes the road.

Fig. 2 presents the hierarchical multiagent architecture including agents and groups as well as the acquaintance links between agents.

Regarding the collaboration between different agents, the following sequence diagram shown in Fig. 3 illustrates the sequence of actions repeated in each road intersection until reaching destination.

It is necessary to note that all agents have the same functioning cycle and exchange messages based on asynchronous point-to-point communication. Each agent lives according to a cycle bound to an iterative process of reception/deliberation/action detailed in (Kallel and Alimi, 2006). The reception represents the identification and the interpretation of all received messages in the mailbox. In addition, it reconstitutes them according to the agent internal beliefs. The deliberation expresses the whole internal process so that an agent accomplishes its action according to its internal rules while taking into account static and dynamic knowledge. The action describes the operation that an agent executes in order to be able to update its dynamic knowledge, to send a message to another agent, or to act in the environment. It is at this phase that each IVA executes their movement orders after the route choice decision making.

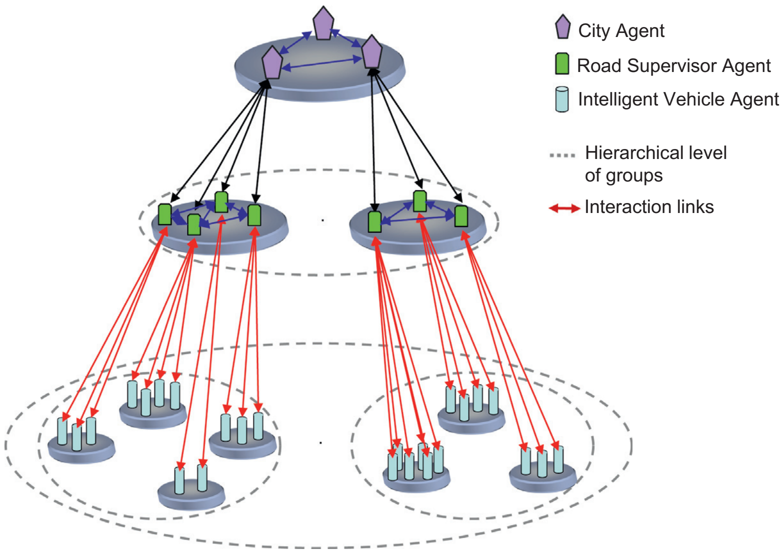

Fig. 2. Hierarchical organizational architecture of road network.

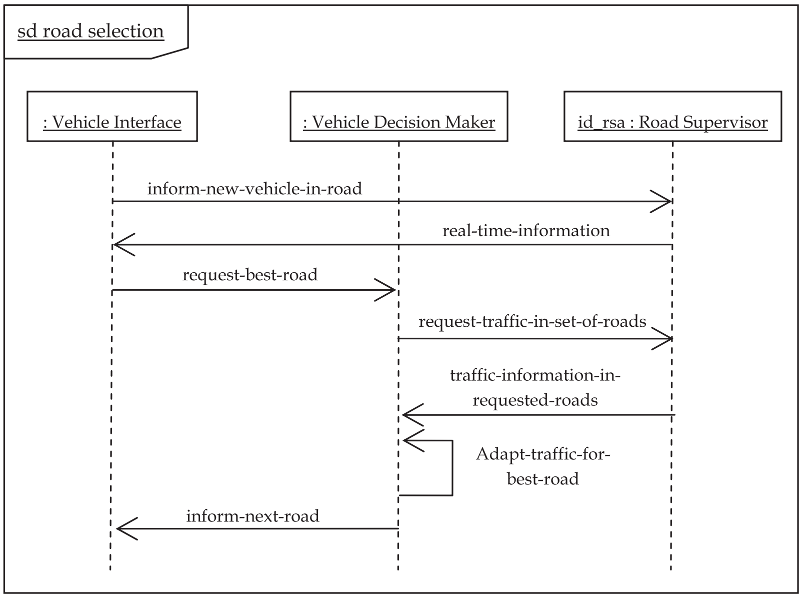

Fig. 3. AUML sequence diagram for next road selection.

3.3. Main advantages of the proposed hierarchical multiagent model

As conclusion regarding the proposed model, it would seem wise to explain in which sense the approach is different from previous works. On the one hand, the tendency was for simple and efficient representation of road network by modeling the separate tasks as intelligent agents. In this case, it will be possible to adapt the actions of vehicle's driver through the concept of agent cooperation in order to achieve a common goal. The approach proposes a new hierarchical multiagent architecture where vehicles are regrouped by roads and cities since this is the natural geographic distribution of the road network. One advantage is that the architecture is well adapted to urban and interurban road networks.

On the other hand, the approach takes into account its deployment in real case; mainly in developing countries which collection of data from stationary equipments is not easy. For this reason, the information is collected from more developed global systems.

4. Adapt-Traf: a hybrid ant-hierarchical fuzzy model

This section deals with the deliberative agent of the proposed intelligent vehicle agent which proposes the best itinerary to the driver in order to reach its destination. The purpose is to increase the average speed of vehicles on the road network while selecting the best itinerary for each vehicle according to the real-time road traffic quality and other contextual factors related to the infrastructure, the environment, and the driver.

In order to deal with this goal, the proposed agent's architecture involves two stages (Fig. 4):

- The *first stage* is instigated from ants' behavior in order to propose the best itineraries based on both traffic quality and itinerary length. The vehicle is represented by an ant having a trip origin and a trip destination.
- The *second stage* is based on a hierarchical fuzzy logic model in order to improve the itinerary selection by adding other criteria influencing the selection stage.

4.1. Ant behavior for traffic management

The proposed deliberative agent process starts by an initialization of origin and destination of the driver. It consists to search the best itinerary at every intersection until reaching the destination. Indeed, the search of the best itinerary should be adaptive according to the high dynamics of the road network and to the traffic flow information in real-time (Kammoun et al., 2010). In terms of multiagent technology, the method consists of three parallel and distributed processes embedded in different agents as presented in Fig. 5.

Regarding the proposed algorithm, the used search method of the possible itineraries set is as follow:

- From the current intersection, the shortest itineraries from each next possible road intersection to destination are searched on the base of the itinerary length.
- Shortest itineraries that go back from the current intersection are removed.

It is important to note that the road traffic quality represents the real-time normalized average speed of vehicles in the road. It is a value between 0 (i.e. traffic jam) and 1 (i.e. free flow). The value is represented like the pheromone quantity deposited by many ants which traveled the same road. The traffic quality in a road is computed and updated after each time period regarding the travel times of vehicles which traveled this road during this time period. In this way, the traffic quality of an itinerary is the average of traffic qualities of roads belonging to the itinerary.

Similarly to the classical ant algorithm, the transition probability $P^{i}_{itinerary}$ in Fig. 5 is computed for each possible itinerary and depends on the itinerary quality and the itinerary length. $\alpha, \beta \in [0,1]$ represents respectively the relative importance of the itinerary quality and the relative importance of the itinerary length. An effective trade-off between them can improve the traffic flow. The transition probability is computed according to the traffic quality and lengths of a number of possible itineraries.

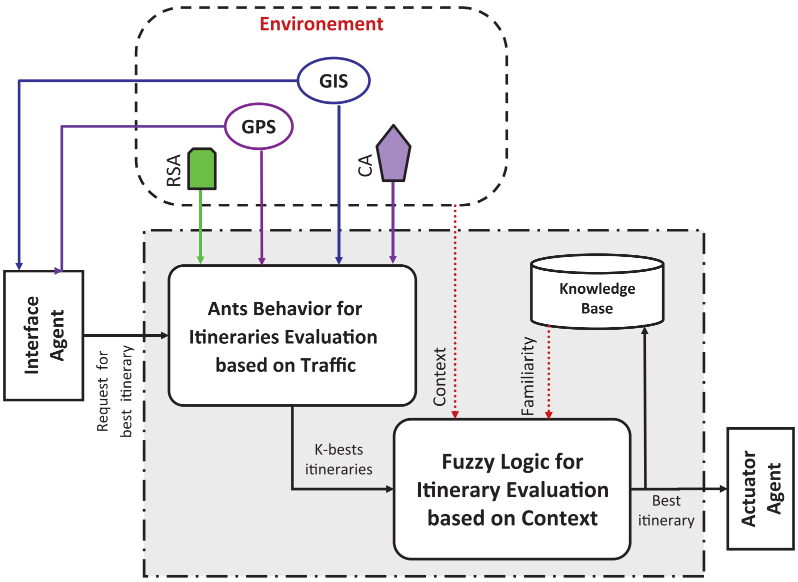

Fig. 4. Adapt-Traf architecture.

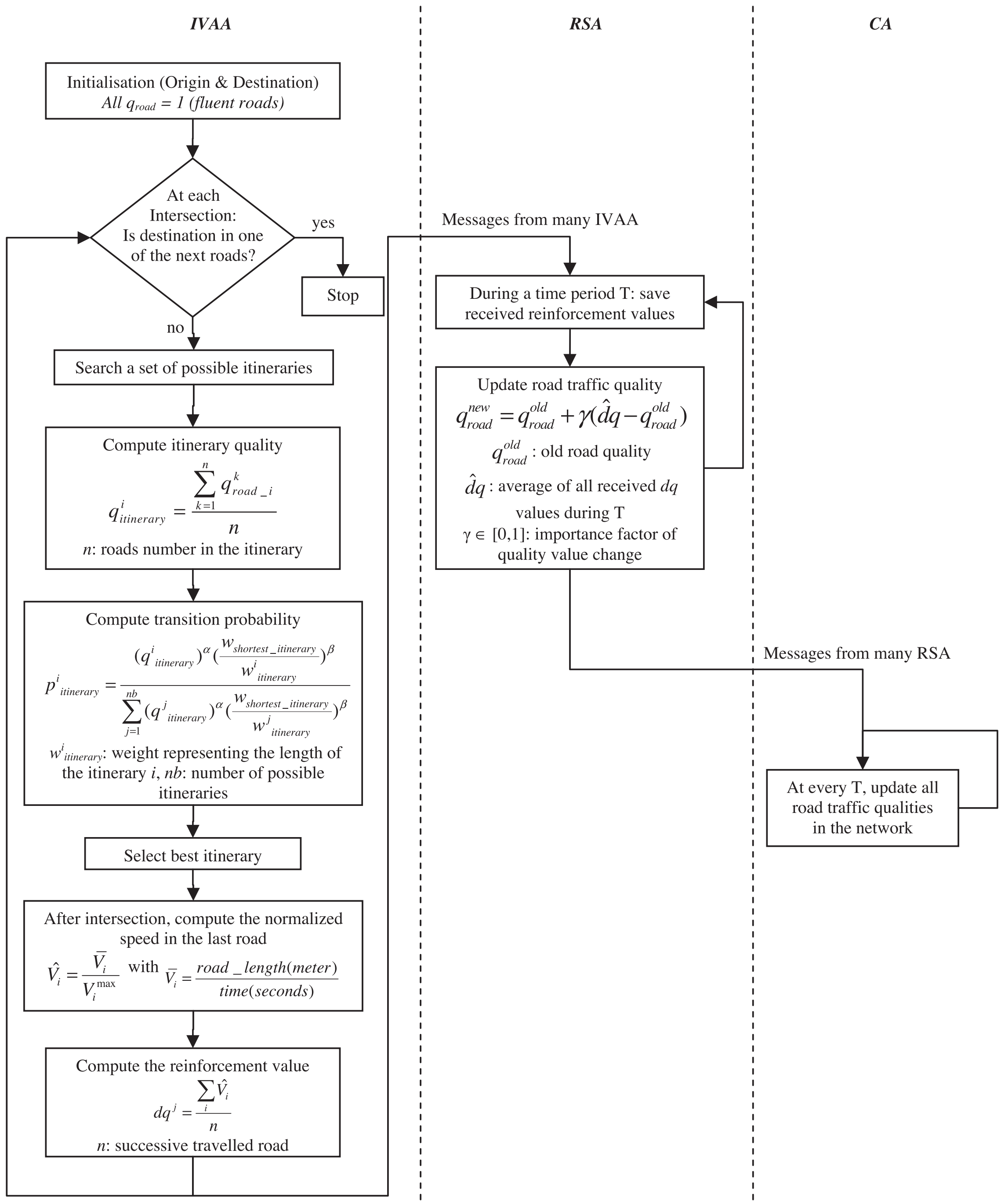

Fig. 5. Flowchart of the adaptive vehicle guidance method.

Regarding the update of road traffic quality q^{new}_{road}, it is related to the reinforcement value dq computed according to the recent travel times of vehicles traveling the road and to $\gamma \in [0,1]$ which represents the importance factor of quality value changes. It can eliminate the effect of fast and slow vehicles. So, it is determined according to the different types of roads (highway, number of lanes, etc.). All these formulas are presented in Fig. 5.

Two best road selection methods are developed:

- *Heuristic method*: selects the itinerary having the highest transition probability.
- *Probabilistic method*: select the first itinerary whose accumulated normalized value of transition probability is greater than a random value.

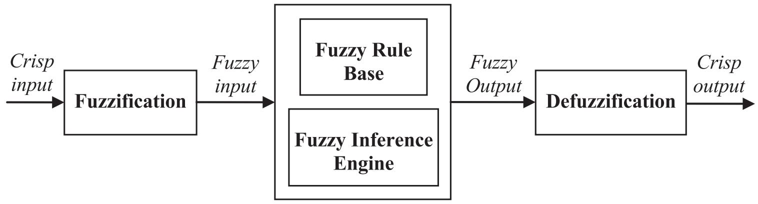

Fig. 6. Fuzzy controller.

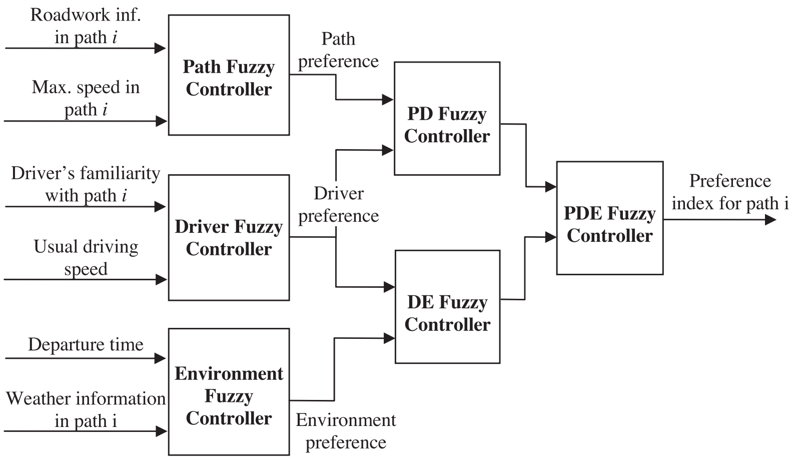

Fig. 7. Hierarchical fuzzy model for one itinerary evaluation.

The concept of the probabilistic method is to deal with congestions in rush hour. In fact, the quality of roads during this situation will decrease quickly when many vehicles select the same road having the highest road probability. In this way, the probabilistic method recommends other good itineraries, which imply a lower decrease of the road traffic quality in the whole network.

4.2. Hierarchical fuzzy system for itinerary evaluation

Since the road traffic quality is not only the main factor for road traffic management, other contextual factors was integrated such as departure time, weather information, roadwork information, and other road network information that can improve the route choice decision. It is extremely hard to formulate a suitable mathematical model due to the ambiguity, uncertainty, and dynamicity of these factors. Thus, the development of Fuzzy controller seems justified in this situation through its capability to approximate a real continuous function with a good accuracy. The fuzzy controller consists of an input stage, a processing stage, and an output stage (Fig. 6). As presented in Fig. 4, the input of the fuzzy stage is a set of the k best itineraries proposed by the first stage. The output of this stage is the recommended road selected as the best of the given best roads.

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 (Lee et al., 2003; Rattasiri and Halgamuge, 2003). In this case, the number of rules increases linearly related to the number of inputs rather than exponentially.

$$nbr\_rules = (n-1) \cdot m^2$$

where n is the number of inputs and m is the number of fuzzy sets in each input.

Within a hierarchical fuzzy model, Fig. 7 presents the six fuzzy inputs which have an important influence in one itinerary evaluation: roadwork information, maximum allowed speed in the itinerary, familiarity of the driver with the roads, usual driving speed, departure time, and weather information. Fig. 8 illustrates their fuzzy sets.

In some fuzzy hierarchical architectures, outputs are considered as inputs of the following fuzzy layer (Lee et al., 2003). Nevertheless, the intermediate outputs do not have physical meaning. To deal with this problem, the inputs combination was chosen to reduce limitations associated with the loss of physical meaning in intermediate outputs/inputs. So, inputs are associated by pairs according to the itinerary criteria, the driver criteria, and the environment criteria (Kammoun et al., 2011). All sub-fuzzy systems have two inputs and one output.

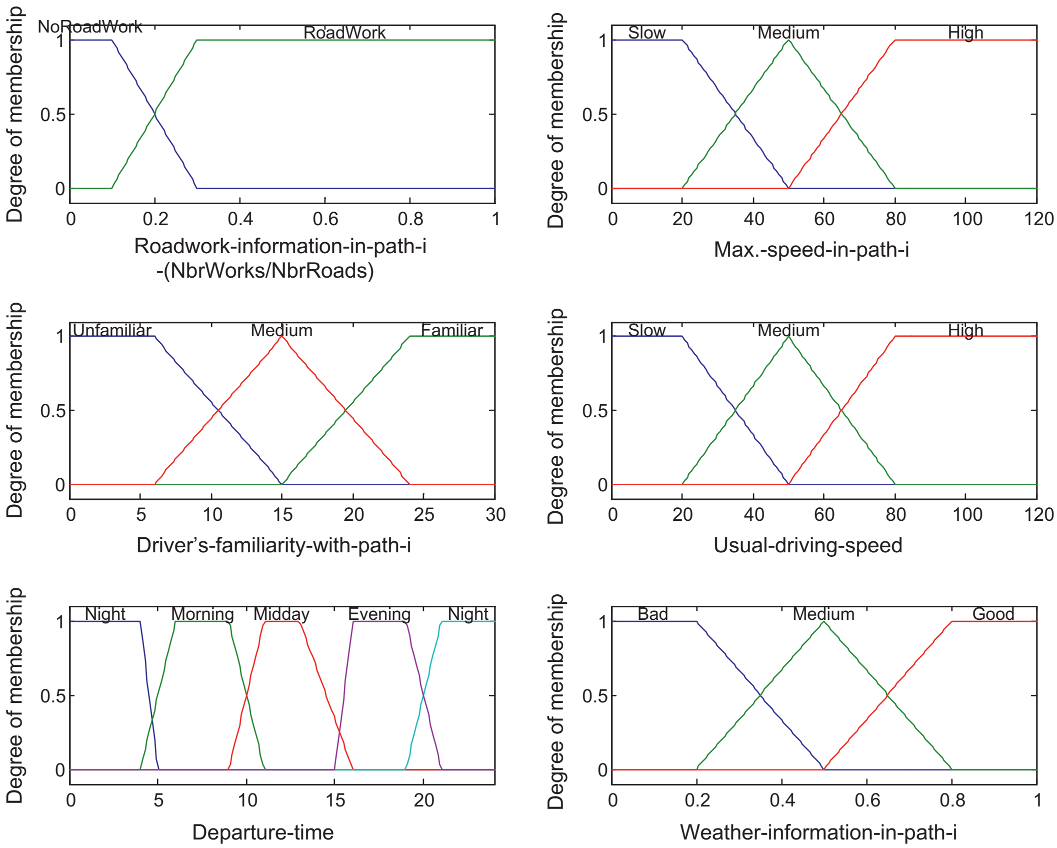

Fig. 8. Inputs membership functions.

Thus, the selection of the best itinerary is a trade-off between itinerary quality taking into account the itinerary length, and the context based on factors having important influence in the itinerary selection.

5. Simulation, results, and discussion

Since the road traffic management requires clear comprehension of the flows and it is very expensive to carry out the real plan, the traffic simulation is the best achievable option to make predictions in a scientifically proven way, to test, and to evaluate several use cases (Pursula, 1999). Thus, to simulate the proposed model, the multiagent simulation approach is proven to be interesting. This kind of simulation is very helpful to explain a collective behavior as a result of individual actions (Drogoul et al., 2003).

The following simulation tries to model congested road networks by means of queuing conditions and to simulate the driver behavior over time and traffic flow on the road network in order to show the influences of congestions in the traffic density. It reflects, even relatively, small changes in the physical environment such as topology, lanes narrowing, or the change between signalized and unsignalized intersections.

5.1. 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 (Drogoul et al., 2003).

During the last decade, some multiagent platforms were developed. They provide both a model for developing multiagent systems and an environment for running distributed agent-based applications. In order to develop our simulator, MadKit[1] platform was chosen as a generic multiagent platform (Gutknecht and Ferber, 2001). The choice was initially based on published comparison between well known multiagent platforms (Ricordel and Demazeau, 2000; Mulet et al., 2006).

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

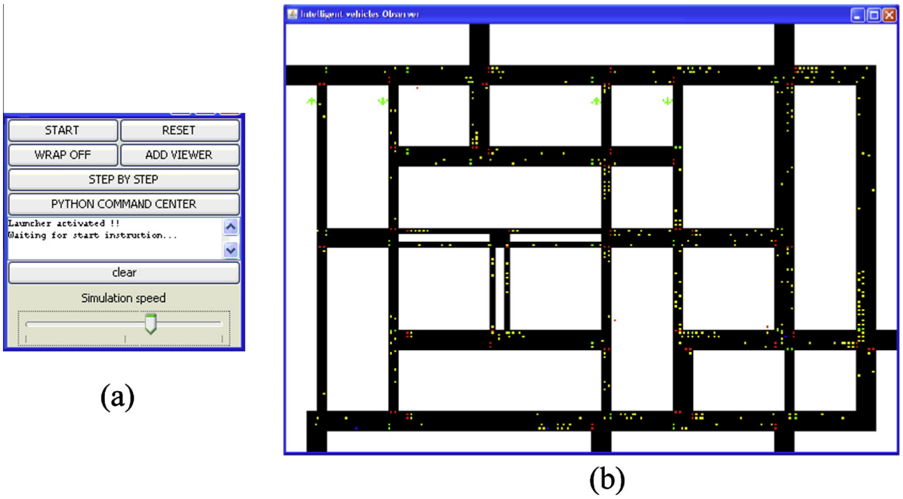

Fig. 9. The simulator: (a) launcher agent and (b) example of simulated road network in the observer agent.

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 (Michel et al., 2005), 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, a launcher agent was defined with the role of setting up, launching, and managing the simulation (see Fig. 9a).

Since the inexistence of an available road network benchmark with a set of origin–destination travels by time, a virtual urban road network map was designed (see Fig. 9b), as an instance of the observer agent of TurtleKit tool. The simulated network has 14 roads with 1 direction and 2 lanes, and 35 roads with 2 directions among them, 3 roads with 1 lane and 32 roads with 2 lanes; and 34 intersections equipped with traffic light signals. Each road is defined by a maximum speed value. The allowed speed for some roads in the center of the network (the interior of the network) is 16 m/s (meter/second) and other roads are considered as relatively high speed roads with 20 m/s (i.e. 72 km/h). In the simulation environment, the traffic signals have a static green period and change color every 20 s. The vehicle route guidance algorithm is running with alpha = 1, beta = 1, and gamma = 0.7. It means that we consider the same importance of the road traffic quality and the road length as explained above.

Each road network can be represented by a directed graph $G(V, E)$ where the set of nodes $V = \{1, 2, 3, \ldots, n\}$ represents the intersections in the network and the set of links $E = \{1, 2, 3, \ldots, m\}$ represents road segments joining node pairs. Fig. 10 illustrates an example of road network that will be used in the following simulations, with $n = 34$ intersections and $m = 84$ unidirectional roads.

Regarding the Origin–Destination matrix during the whole day, the estimation methods of Origin–Destination demand flows (using statistical methods like Monte Carlo and Latin Hypercube methods) cannot be applied since the simulation concerns a virtual road network. In this paper, the standard normal (Gaussian) distribution was used ($\mu = 0$ and $\sigma^2 = 1$).

$$(f(x) = \frac{1}{\sigma\sqrt{2\pi}} e - \frac{(x-\mu)^2}{2\sigma^2}$$

During the rush hour, the variance σ is increased in order to add more vehicles in the network during this period.

5.2. Results and discussion

Series of simulation are performed when varying the travel demand level, origins and destinations, departure time, congestion/jam position, and the context. The results of the proposed probabilistic method were compared to the results of static method based on the itinerary length using the algorithm of Dijkstra (1959); to the predicted itinerary travel time using a linear model in which the coefficients vary as smooth functions of the departure time (Zhang and Rice, 2003); and to the heuristic proposed method.

Around 30 000 vehicles (travel demands) were added randomly during a day (24 h) in the road network, presenting in the most appropriate way the usual rush hours of the day (3 times per day as presented in Fig. 11).

In the following, the first subsection presents the results of traffic management based on the first stage of itinerary selection. Later, the second subsection presents the influence of the hierarchical fuzzy system taking into account the global hybrid architecture (two stages). For validation, all results' curves represent the average of 5 simulation results using different Origin–Destination matrix based on the standard normal distribution.

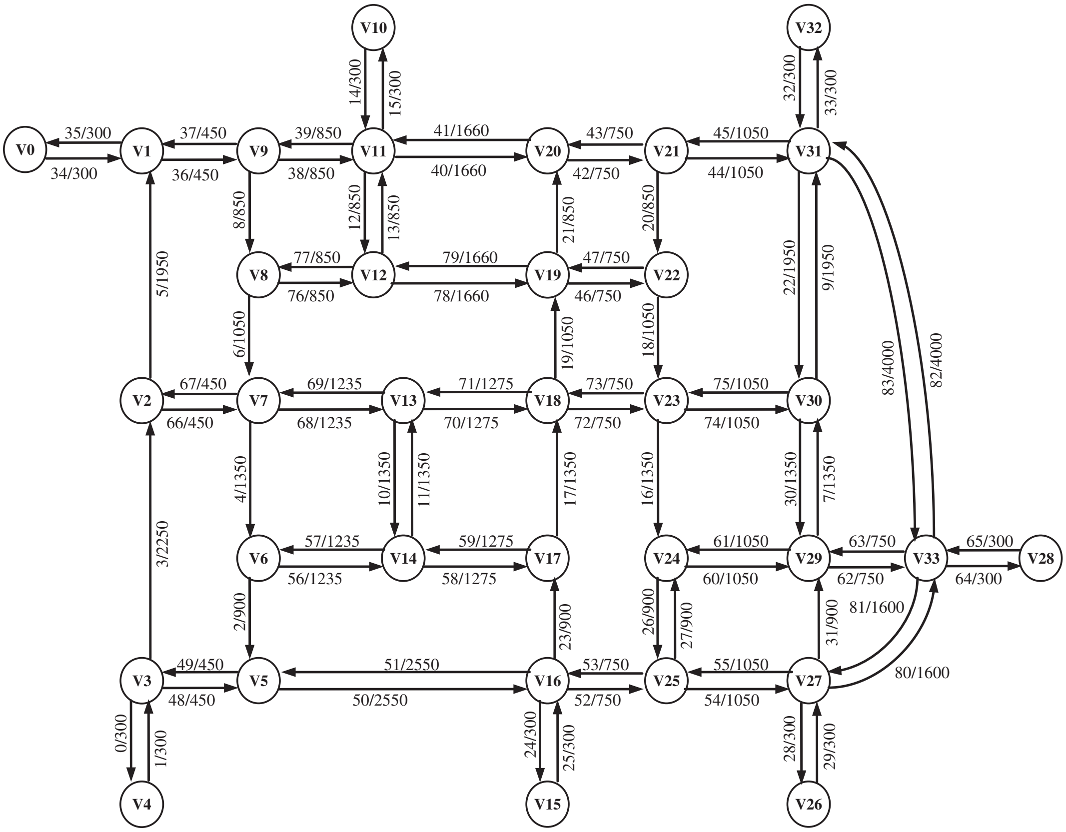

Fig. 10. Illustration of the road network as a directed weighted graph.

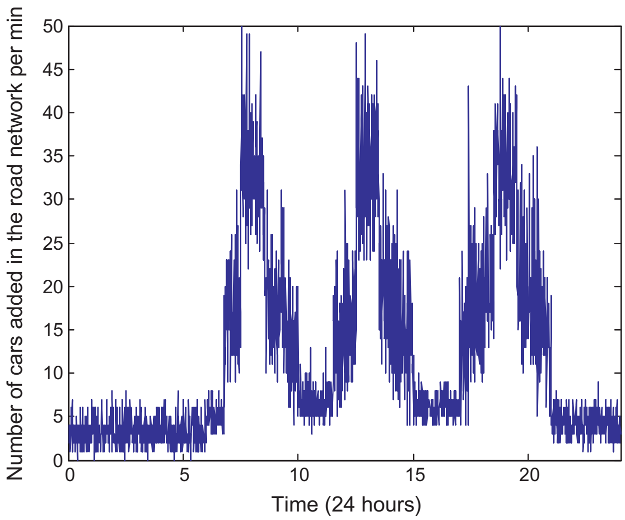

Fig. 11. Number of cars included in the road network during the day presenting the congested periods.

5.2.1. Vehicle route guidance based on ant colony behavior

As regards to the quality of traffic flow in the road network with normal random variation, Fig. 12 shows the advantage of the proposed ant behavior method using the heuristic selection strategy, in the raise of the average speed in the entire road network during 24 h, compared to the proposed method using the probabilistic selection strategy, to the predicted itinerary travel time method, and to the shortest path method.

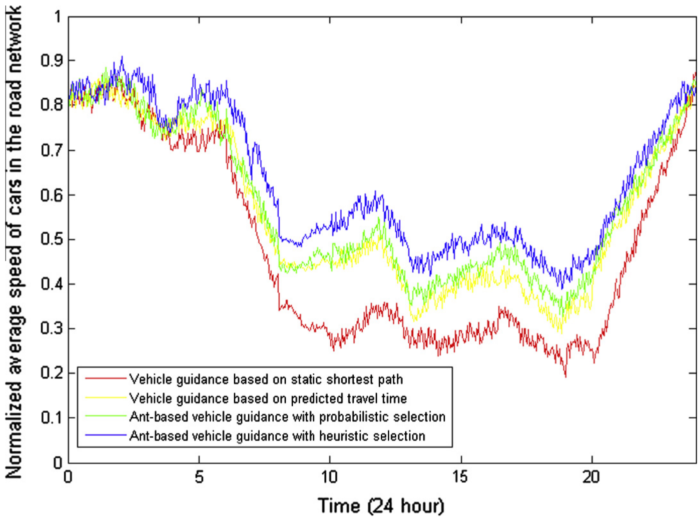

Fig. 12. Variation of the road traffic quality during the day.

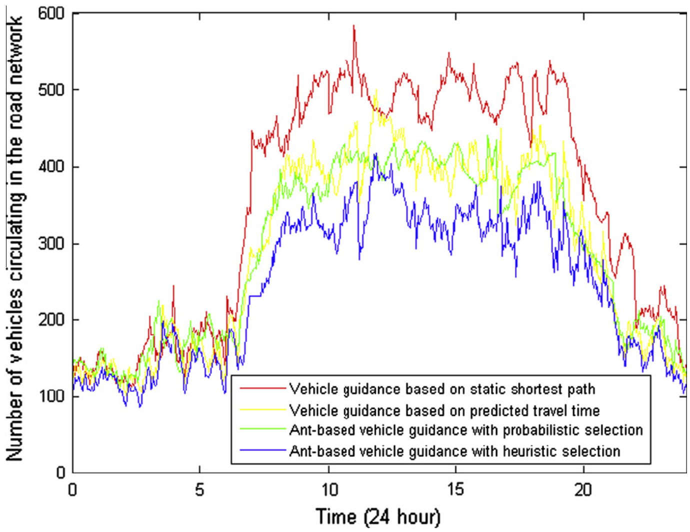

Fig. 13. Number of vehicles circulating in the road network during the day.

Fig. 13 illustrates that a highest number of vehicles reached their destinations early, compared to the other methods. These simulations suppose that all drivers accept the proposed itinerary given by the Intelligent Vehicle Agent (*IVA*).

In order to test the efficiency of the proposed method and its reactivity to minimize jam situations, simulations were made including 3 rush (peak) hours traffic congestion (morning, lunch time, evening). The number of cars was increased in these three rush hours time period in nearest roads in order to simulate the travel from/to home/industrial area. Figs. 12 and 13 bear out the adaptivity of the entire network in terms of road traffic quality and number of circulating vehicles, when injecting a high number of vehicles, in the same area, which have different origin–destinations.

Let focus on the adaptivity of the proposed vehicle guidance method following only one vehicle: Table 4 details the itinerary proposed to one selected vehicle using different methods of selection itinerary into the same road traffic simulation conditions. We notice that the three possible paths have the same distance, but the corresponding travel times are different and depend on the itinerary selection method; Table 5 presents the same simulation with rush hour traffic congestion in a set of roads.

The computed distances are the sum of length of each sequence road links. In fact, these tables confirm the global results illustrated by Fig. 13 and reveal the improvement of the proposed ant methods in terms of average speed and travel time compared to the static selection method, even with the same distance.

Regarding 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

Table 4
Itinerary selection of one vehicle without rush hour traffic congestion.

Intersections	Static method	Ant-based vehicle guidance with heuristic selection	Ant-based vehicle guidance with Probabilistic selection
From origin road 36 to destination road 62			
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[a]
4	–	**46**-18-74-30-62[a]	**42**-20-18-74-30-62[a]
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 speed (m/s)	11.06	12.27	12.17
Travel time (s)	683	616	621
Distance (m)	7560	7560	7560

Bold numbers indicates the next proposed road of the vehicule.
[a] Indicates a change in the proposed itinerary.

Table 5
Itinerary selection of one vehicle with congested roads with rush hour traffic congestion.

Intersections	Jammed roads	Static method	Ant-based vehicle guidance with heuristic selection	Ant-based vehicle guidance with probabilistic selection
From origin road 36 to destination road 62				
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[a]	**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[a]
4	68, 11, 71, 46, 20	–	**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[a]
6	14, 38, 13, 41	–	**52**-54-31-62[a]	**83**-63-62[a]
7	6, 66, 68	–	**54**-31-62	**63**-62
8	–	–	**31**-62	–
Average speed (m/s)		7.86	10.99	11.60
Travel time (s)		961	855	781
Distance (m)		7560	9400	9060

Bold numbers indicates the next proposed road of the vehicule.
[a] Indicates a change of the proposed itinerary.

Table 6
Fuzzy rule base of path preference.

Rule no.	Inputs		Output path preference
	Road work information	Max. speed in path	
1	noRoadWork		Strong
2	roadWork	High	Medium
3	roadWork	Medium	Weak
4	roadWork	Slow	Weak

on distributing vehicles on different good 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. The road network simulations were occurred 100 times for statistical validation. These simulations confirm that the probabilistic selection is better than the heuristic selection since its good adaptivity.

5.2.2. Management improvement based on hierarchical fuzzy logic

The simulation results in this section include the influence of the six external factors described above: roadwork information, maximum allowed speed in the itinerary, familiarity of the driver with the roads, usual driving speed, departure time, and weather information. Results are obtained using the Matlab Fuzzy Logic Toolbox for fuzzy control and the JMatLink library (Müller and Waller, 1999) for connection with the multiagent simulation platform (MadKit).

The hierarchical fuzzy system works hierarchically by pairs as described in the Section 4.2. The inference process of the fuzzy controllers is the Mamdani (max–min) inference method. Table 6 presents the fuzzy rule base of the path fuzzy controller, based on ordinary rules of the type 'IF condition THEN action'. Fig. 14 presents the inference and defuzzification stages of the path fuzzy controllers in the case of 15% road works percentage and maximum speed in the path is 60 km/h.

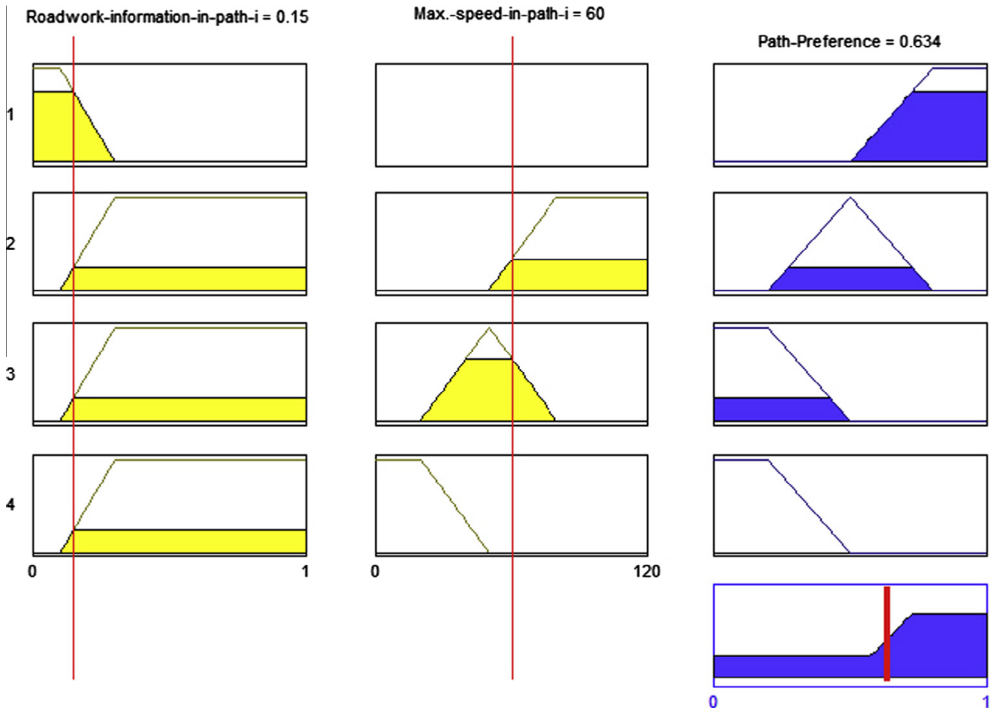

Fig. 14. Rules evaluation and defuzzification of the path fuzzy controller.

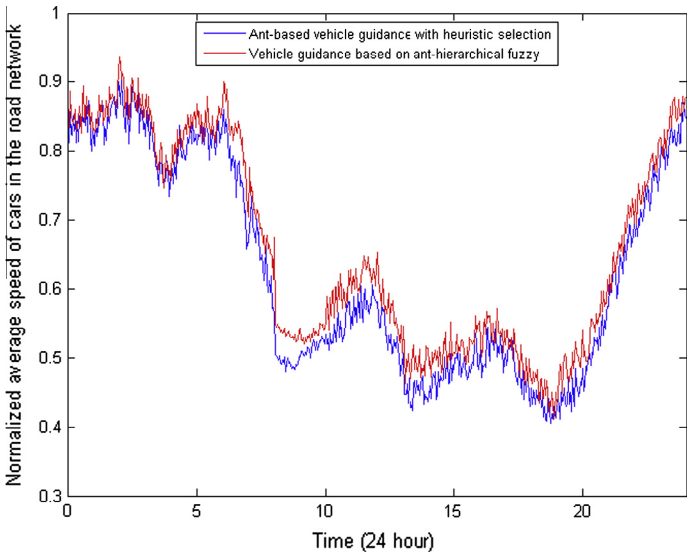

Fig. 15. Variation of the average speed in the road network with rush hour traffic congestion.

As results by the hierarchical fuzzy stage, 31% of proposed itineraries are changed compare to the proposed itineraries from the ant stage. This adjustment involves 2.1% improvement of the normalized average speed of cars in the entire road network, using the same sets of normal random variations in the injected vehicles. The result confirms the important influence of the selected contextual factors and the effectiveness of the hierarchical fuzzy system in order to improve traffic management. Fig. 15 compares the curve of the ant-based vehicle guidance with the curve of the traffic quality using the hybrid ant-hierarchical fuzzy algorithm (Adapt-Traf). Similarly to the previous simulations, all drivers accept the proposed itinerary given by the Intelligent Vehicle Agent (*IVA*).

Regarding the adaptivity of the proposed *Adapt-Traf* system, Table 7 details the itinerary selected by the same vehicle using proposed methods. The table confirms the importance of the proposed external factors (related to the road, environment, and driver) as illustrated by Fig. 15.

Table 7
Itinerary selection of one vehicle with rush hour traffic congestion.

Intersections	Cong. roads	Static method	Ant-based vehicle guidance with probabilistic selection	*Adapt-Traf* with probabilistic selection
From origin road 52 to destination road 38				
1	21,40,43,50, 48	53-23-17-19-21-41-39-38	**54**-31-7-9-45-43-41-39-38	**53**-23-17-19-21-41-39-38
2	9,44,32,45,42	–	**31**-7-9-45-43-41-39-38	**51**-49-3-5-36-38[a]
3	30,31,60,63	–	**7**-75-73-19-21-41-39-38[a]	**49**-3-5-36-38
4	18,72,42,45	–	**75**-73-19-21-41-39-38	**3**-5-36-38
5	21,40,43	–	**73**-19-21-41-39-38	**5**-36-38
	76,41,14	–		
6	6,69,66,5,34,37	–	**19**-79-13-39-38[a]	36-38
7	11,68,5,34,37	–	**79**-13-39-38	–
8	–	–	**13**-39-38	–
9	–	–	**39**-38	–
Average speed (m/s)		7.35	10.23	10.91
Travel time (s)		1007	929	769
Distance (m)		7410	9510	8400

Bold numbers indicates the next proposed road of the vehicule.
[a] Indicates a change of the proposed itinerary.

Table 8
Normalized average speed of cars during 24 h.

Percentage of drivers using the route guidance system (%)	*Adapt-Traf* with probabilistic selection	Deflorio's method
25	0.484	0.427
50	0.513	0.445
100	0.579	0.498

5.2.3. Adapt-Traf vs. Deflorio's system

This section draws comparison of the proposed *Adapt-Traf* with the reactive dynamic route guidance strategy proposed by Deflorio (2003). This paper was selected since it adopts a decentralized structure for routing strategy. The Deflorio's method was applied to the same example of road network and using the same lists of Origin–Destination-Time. Table 8 details the normalized average speed during the day using each approach. The average speed increases about 8% using the proposed *Adapt-Traf* in comparison to the Deflorio's method.

Table 8 also shows the variation of the percentage of drivers accepting the proposed itinerary given by the Intelligent Vehicle Agent (*IVA*). The remaining drivers select randomly one of the 3 shortest itineraries. The results confirm that when all drivers use the proposed route guidance system, the average speed in the entire road network is better.

6. Conclusion and perspectives

In this paper, a hierarchical organizational multiagent architecture was presented as well as a description of agents' behavior. The adaptive vehicle route guidance system integrated in the intelligent vehicle agent was developed based on hybrid ant-hierarchical fuzzy method. This allows adjusting intelligently and promptly the road traffic in the network according to the real-time changes. The itinerary selection is based on both traffic quality and itinerary length in the first stage and on a set of the most important contextual factors regarding the driver, the environment, and the path integrated in a hierarchical fuzzy system.

On the one hand, the proposed algorithm consists in improving the traffic flow (i.e. the road network can support more vehicles without decreasing the average speed of vehicles) while taking into account the real-time road traffic information; and on the other hand, in reducing the number of traffic congestion situations by avoiding the massive use of the same road at the same time (i.e. providing the suggestion of itineraries with a lower travel times).

Several multiagent simulations for road traffic network have been achieved while using 'TurtleKit' tool under the generic multiagent platform 'MadKit'. The coordination mechanism was tested on the basis of various virtual road networks and randomly generated congested area. Simulation results confirm that the proposed road traffic management system offers a better road traffic quality on the entire road network without a great loss on individual travel time.

As perspective, we intend in the near future to include adaptive light traffic signals with dynamic green/red period (instead of static period) in order to improve the management of the road network. Furthermore, we have in mind to evaluate the adaptivity degree of our agents by means of the system proposed in (Kallel et al., 2008b), to develop a consistent, complete and compact sets of fuzzy rules (Casillas et al., 2009), and to integrate an automatic design of the proposed hierarchical design taking into account recent innovations in the field of intelligent systems (Chen et al., 2007; Grosan and Abraham, 2011).

Acknowledgments

This work was supported, in part, by the General Direction of Scientific Research (DGRST) in Tunisia (ARUB program) and by the Spanish Ministry of Science and Innovation (grant no. TIN2011-28488).

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