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Hierarchical Fuzzy Rule-Base System for MultiAgent Route Choice

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1. Introduction

In view of both complexity and dynamicity of road networks and the sharp increase of vehicle number, accidents and traffic jam situations in all road networks have become wide spread all over the world. A solution for these problems is to develop and invest in traffic management using intelligent techniques from artificial intelligence and soft computing. An accurate management will improve traffic efficiency over time and space with dynamic interventions. This latter means the need of an auto detection of jam situations or incidents, so vehicles will be adapted according to the new road network situation. In this way, it appears the necessity of an intelligent route choice system helping drivers to attempt their destinations.

The route choice concerns the selection of better itinerary from a set of feasible itineraries between an origin and a destination in road network. The route choice process improves the fluency of road network, reduces the number of traffic congestion and allows a dynamic assignment of traffic flows (Bierlaire et al., 2008). It is clear that route choice models play a crucial role in many transport applications (for example, it is the core of traffic assignment models). Furthermore, a better understanding of route choice decision-making behaviour will make possible to explain the modification of traffic flow.

A large number of research efforts are dedicated to studying the route choice problem. In this way, one of the most realistic technique used until now for route choice is the fuzzy logic (Teodorovic & Kikuchi, 1990). This model is capable of incorporating subjectivity, ambiguity, and uncertainty from perceptions for an accurate traffic management. The results of route choice based on fuzzy model are better than those using discrete choice models (Ben-Akiva & Lerman, 1985) (Bekhor et al., 2002).

Nowadays, after many developments in information acquisition technologies, route choice becomes even more complicated when more traffic information is available in real-time to drivers. In addition to all the usual factors that affect travel decisions (such as travel time, travel distance), additional factors (such as type of road, traffic flow speed, weather conditions, and personal preferences) affect also the final choice. So, the itinerary selection process made by drivers, taking into account many factors, is most often very complicated. It is extremely hard to formulate a suitable mathematical model due to the subjectivity, uncertainty, and dynamicity of traffic flows and other factors. Thus, the development of

Fuzzy Rule-Base System (FRBS) seems justified in this situation through its capability to approximate a real continuous function with a good accuracy.
However, the application of FRBS is difficult according to the rule-explosion problem due to the large number of criteria. In order to deal with this problem, we propose in this chapter a route choice model based on hierarchical FRBS. This system is encapsulated into an intelligent vehicle agent defined into a hierarchical multiagent architecture of an advanced road network developed previously in order to deal with its complexity (Kammoun et al., 2008).
The paper is organized as follows: Next section presents an overview on the use of fuzzy logic in route choice problem. The third section describes the road network architecture, the hierarchical FRBS, and the itinerary selection model. The multiagent simulation part is detailed in the forth section. The fifth section presents experiments and discusses results. Finally, we conclude by summarizing our contribution and presenting some directions for future work.

2. Literature review

In this review, we focus our attention especially on route choice models which are based on fuzzy logic. In fact, the fuzzy logic appeared in 1965 by Zadeh introducing the concept of a fuzzy set (Zadeh, 1965). It is shown as a very promising mathematical approach characterized by subjectivity, ambiguity, uncertainty, and imprecision. The model based on this approach is robust to small variations and easy to design. Figure 1 shows the basic elements of a fuzzy logic system: fuzzifier, rules, inference, and defuzzifier.

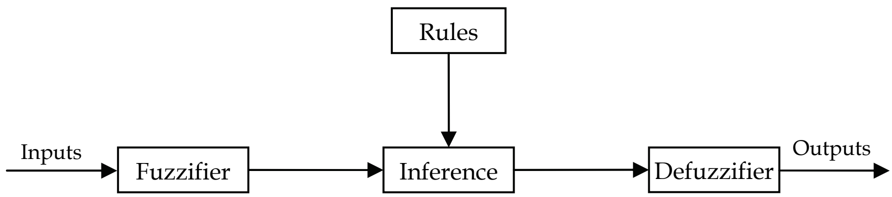


Fig. 1. Basic elements of fuzzy logic system

2.1 Previous works

The route choice problem has been dealt with several techniques using in the most cases the discrete choice models as logit and probit models (Ben-Akiva & Lerman, 1985) (Bekhor et al., 2002). However, these models can't consider subjectivity, ambiguity, and uncertainty from perceptions. Furthermore, they present an efficiency gap for addressing the complexity and the dynamicity of transportation systems.
In order to enhance these problems, research in soft computing field is still exploring the application of fuzzy set theory, using a set of "if-then" rules. This theory has been also used as a framework to solve other transportation problems as traffic assignment problem, accident analysis and prevention, traffic controller in roads intersection, and traffic light controller. For more details on transportation engineering based on fuzzy logic, see the state of art presented by Teodorovic (Teodorovic, 1999) which summarize important works in nineties.

Research in route choice problem based on fuzzy logic began by modelling a simple two-route choice problem in order to select the better route (itinerary) (Teodorovic & Kikuchi, 1990). The basis of this model is the use of fuzzy linguistic rules such as:

"*IF* perceived travel times on path A *IS* much longer than perceived travel time on path B, *THEN* fuzzy preference indices for A *IS* very strong".

After this work, other works has been developed in order to improve the first one. In this way, Lotan and Koutsopoulos present a modelling framework for route choice under the presence of information, based on fuzzy logic and approximate reasoning (Lotan & Koutsopoulos, 1993). Later than, Lotan improves his framework with two stages: the first one presents the information integration and the second one presents the decision process (Lotan, 1998). In experimentation stage, both familiar and unfamiliar drivers have participated.

In order to deal with route choice behaviour, a fuzzy reasoning approach has been developed by Akiyama et al. (Akiyama et al., 1993). This approach has improved with a multi-stage fuzzy reasoning approach to solve the multi-route choice problem (Akiyama & Tsuboi, 1996). In fact, authors propose two approximate reasoning stages for driver decision making process. In the first one, travel time, degree of congestion, and risk of accidents are factors used to determine the utility of each feasible route. The second stage determines the frequency degree for each route, based on the difference between route utilities associated with the shortest path and the second shortest path, and the difference between route utilities associated with the second shortest path and the third shortest path. We note that only the case of three feasible routes has been considered. The fuzzy route choice model, taking into account imprecision and uncertainty, has been proved by Henn as a generalization of the standard logit model (Henn, 2000).

In this century, other works have been developed to deal with more complex route choice taking into account other factors. Ridwan has the first work that considers the spatial knowledge of individual travellers (Ridwan, 2004). He proposes a model of route choice, based on fuzzy travellers' preference relations, of which elements are fuzzy pairwise comparisons between feasible routes. In order to improve the route choice behaviour, Hawas proposes calibration methodology and knowledge base composition, using a combined approach of fuzzy logic and neural nets (Hawas, 2004). Four stages are developed to compute the final route utility based on both numerical and categorical inputs: prior-to choice stage, following-the-trip choice stage, reliability level stage, and route choice stage. Furthermore, Peeta and Yu propose a fuzzy model, using a hybrid probabilistic-possibilistic model, in order to quantify the latent attractiveness of alternative routes with regard to the qualitative variables (Peeta & Yu, 2004). Concerning the description of route choice behaviour, Arslan and Khysti propose a hybrid model using concepts from fuzzy logic and analytical hierarchy process AHP (Arslan & Khysti, 2005). The route selection in this work is provided by pairwise comparisons with respect to related criteria (travel time, congestion and safety). The fuzzy linguistic rules used in this model have the following structure:

"*IF* alternative A *IS* more desirable *AND* alternative B *IS* much more desirable, *THEN* preference of A over B *IS* weak importance".

Nowadays, in order to deal with the presence of many components in road networks, research direction in this area has improved by the integration of multiagent systems from artificial intelligence. In fact, after thirteen years, Teodorovic concludes that a number of emergent traffic phenomena cannot be analyzed successfully and explained using analytical models (Teodorovic, 2003). Then, it is necessary to develop models based on multiagent approach and especially on swarm intelligence. The interacting agents might be drivers, passengers, cars, etc. In this sense, Teodorovic propose a fuzzy ant system for transportation modelling. Furthermore, under the influence of real-time traffic information, Panwai and Dia model drivers as intelligent agents composed of various mental elements: beliefs, capabilities, commitments, behavioural rules, and commitment rules. The agent's knowledge relevant to route choice decision is constructed using the fuzzy-neural approach based on socioeconomic data (Panwai & Dia, 2006).

2.2 Towards the use of hierarchical fuzzy logic

In recent years, many developments in information acquisition technologies through Advanced Traveller Information Systems (ATIS) 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 in real-time. It is clear that for an accurate selection, route choice model have to consider all available information.

Regarding the increasing number of selection criteria used to select the better alternative, the application of fuzzy logic to route choice problem with a large number of inputs involve the problem of rule-explosion. For example, if a system requires n input variables each partitioned into m membership functions, the total number of rules required to model the system by using one single fuzzy inference system is m^n. In order to deal with this problem, some hierarchical fuzzy systems have been proposed (Lee et al., 2003) (Rattasiri & Halgamuge, 2003). With a hierarchical architecture, the number of rules increases linearly related to the number of inputs $(n-1).m^2$ rather than exponentially. We note that the hierarchical FRBS has been successfully used in several applications areas showing a real improvement in precision and interpretability (Kallel et al., 2005).

Furthermore, few models (Panwai & Dia, 2006) have been proposed to solve the complexity of a fuzzy-route choice problem by distribution and parallelisation under the multiagent approach (Wooldridge, 2002).

Until now, fuzzy-route choice is applied by evaluating only two or three alternatives with a few number of selection criteria. This encourage us to go on further and to develop a hierarchical FRBS, 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.

3. Description of the multiagent-fuzzy system

The whole system includes two parts: a multiagent system for both distributed and cooperative management, and a hierarchical fuzzy system for itineraries evaluation and better itinerary selection.

3.1 Multiagent approach for traffic management

The traffic management in urban or interurban road networks is an important task in any country, and especially in industrialized countries, by its implications in economy and quality of life. It is clear that an accurate traffic management will allow more efficient vehicle routing in order to improve traffic efficiency. Due to the interaction of many components in road networks, it is necessary to have a representative architecture and real-time model capable to provide better routing while avoiding congested and jam roads.

In previous years, road network is based on traditional stationary equipments, such as loop detector, microwave detector and so on, that can cover only specific road section. Thus, collect traffic information is done only at limited road sections. Then, we cannot achieve an accurate management with little information.

In advanced road network model, all vehicles have to be able to connect with advanced equipments. Vehicles are equipped with the Global Positioning System GPS to locate the current position, a Route Guidance System RGS interfaced with driver by an onboard system, the Geographic Information System GIS providing a digital map, and wireless connection equipment to collect real-time information from the traffic control system. We note that some traffic information (number of vehicles in each road, speed, direction, etc.) can be collected, at regular intervals of time, with GPS (Zito et al., 1995). 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 et al., 2008).

Using the natural geographic distribution of road networks, vehicles are regrouped by city and road. In order to deal with the complexity of road network and the large number of components, we propose hierarchical road network architecture based on multiagent approach (Kammoun et al., 2008). In our architecture, we assume that each road direction is supervised by an agent called Road Supervisor Agent RSA; the traffic control in each city is kept by an agent called City Agent CA; and each vehicle is considered as an agent called Intelligent Vehicle Agent IVA. Therefore, the use of both hierarchical and decentralized approaches is very interesting, and provides a flexible interaction between components and an adaptive behaviour according to the current traffic state. Figure 2 presents our hierarchical architecture for an advanced road network. The details of each agent are:

- City Agent CA: manages the connected city to obtain better road network exploitation. It maintains static information as roads characteristics and dynamic information as traffic information, road work information, weather information, etc., in each road in the city. By collaboration with RSA, CA receives, at each window time, information about each road. Furthermore, it cooperates with other CA managing other cities to collect real-time information, if a vehicle would reach another city;
- Road Supervisor Agent RSA: there are many RSA in one city. Each one supervises the state of traffic flow in the corresponding road, implements the control action of road, and achieves coordination control and integrated management by coordinating with the corresponding CA;
- Intelligent Vehicle Agent IVA: the vehicles are considered as reactive agents evolving in dynamic environment. In fact, using a multiagent reflexive reasoning, this agent is composed itself of three agents:

- Interface Agent: ensures the link between the driver's vehicle and the system. This agent communicates with GPS to receive its coordinates and informs the driver about the better path, the next road, and other information computed and collected by the decision making agent;
- Decision Making Agent: encapsulates the cooperative route choice algorithm. This agent selects the better alternative to reach vehicle's destination, while avoiding congested and jammed areas according to driver's preferences and history, under the influence of real-time traffic information collected by collaboration with CA and RSA. This algorithm is executed before each intersection (crossroad) to select the better next road for an adaptive routing;
- Effector Agent: Guide the driver to move the vehicle in order to reach destination (forward, turn left, turn right). It used in automatic driving or in simulation.

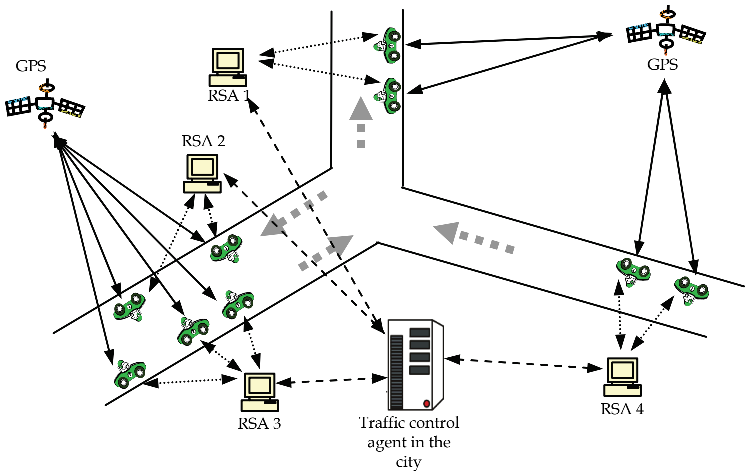


Fig. 2. Information flow in the modern road network

The sequence diagram shown in figure 3 illustrates the collaboration between agents to help driver. This sequence of actions is repeated in each intersection until reach destination. On the other hand, figure 4 illustrates the collaboration between RSA and CA in each window time to maintain real-time information.

3.2 Hierarchical FRBS for an itinerary evaluation

After a first attempt to develop a hierarchical FRBS for route choice problem, we present in this chapter an improvement of our previous works (Kammoun et al., 2007). We note that this work is the first dealing with a hierarchical FRBS for route choice problem. The aim of this system is to evaluate one itinerary (path, a set of roads) according to selection criteria, to available real-time information in feasible itineraries, and to driver's preferences.

We have chosen eight inputs that have an important influence for road evaluation. However, the architecture can support other selection criteria. The following factors are the most important criteria, more used, and accessible from the vehicle information system:

- Vehicle number: corresponds to the average of vehicle number throughout roads composing the itinerary. This value takes into account the number of lanes and the road length;
- Congested vehicles number: corresponds to the average of vehicle number in congestion situation;
- Path work information: corresponds to the average of work information in a set of roads;
- Maximum path speed: corresponds to the average of speed allowed in a set of roads;
- Path familiarity: corresponds to the familiarity degree of driver in a set of roads;
- Driver speed: represents the average of speed usual used by the driver;
- Time of day: represents the time of travel;
- Weather conditions: represents the average of weather conditions in a set of roads.

We note that in a hierarchical architecture, outputs from certain Fuzzy Inference System (FIS) are used as inputs for the following FIS. 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 choose inputs combination that reduces limitations associated with the loss of physical meaning in intermediate outputs/inputs. So, inputs are regrouped by four categories according to traffic criteria, road criteria, driver criteria, and environment criteria. All FRBSs have two inputs and one output. Figure 5 illustrates the set of eight FRBSs used to evaluate one itinerary.

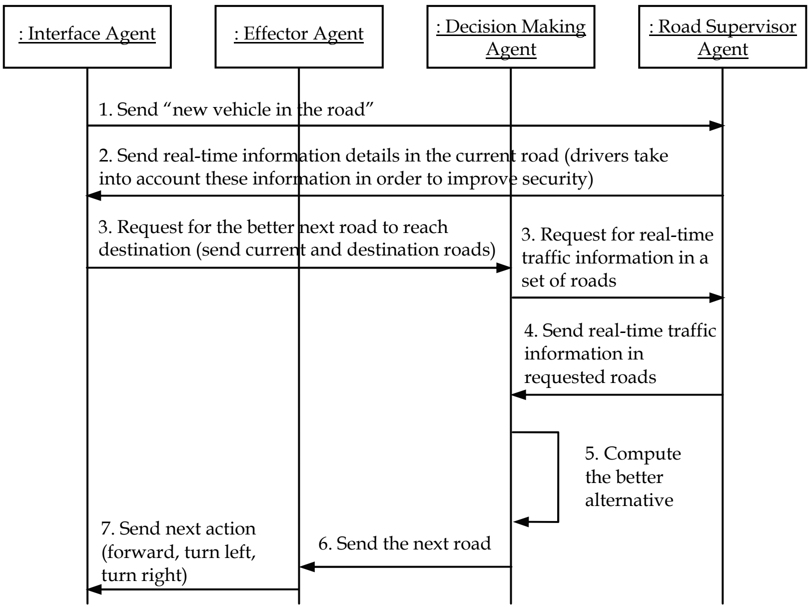


Fig. 3. Sequence diagram for next road selection

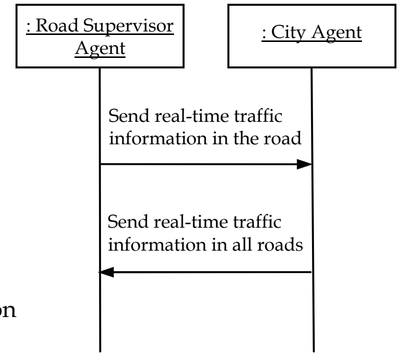


Fig. 4. Interaction between road supervisor and city agents

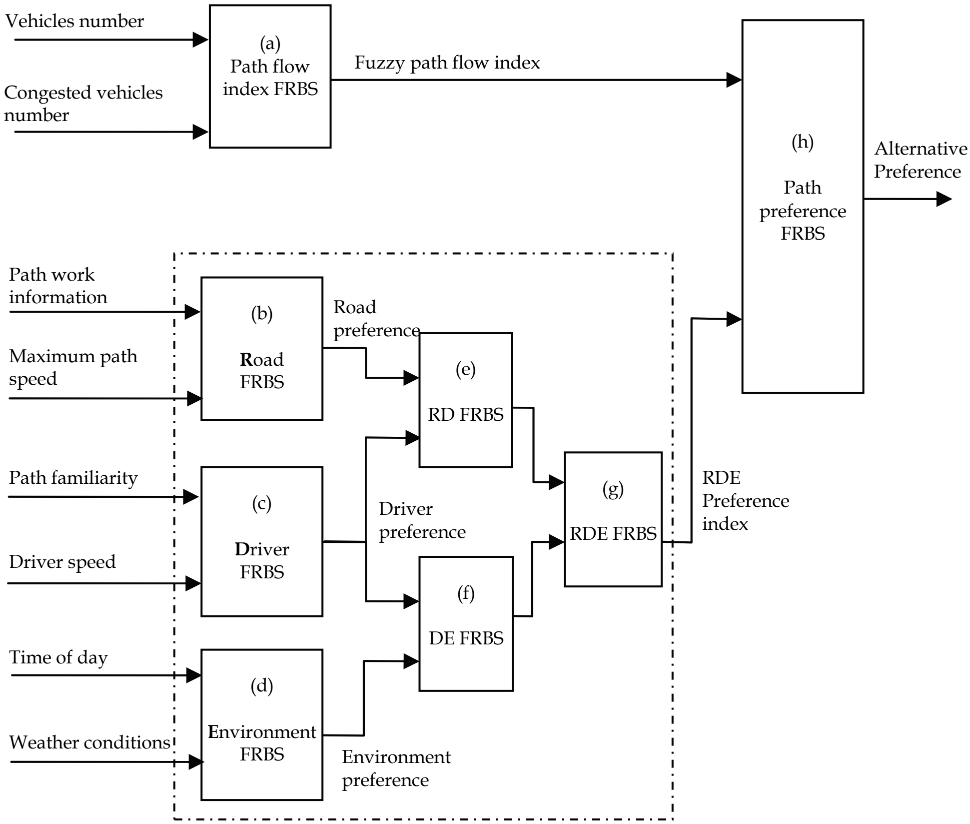


Fig. 5. Flowchart of the Hierarchical FRBS for an itinerary evaluation

3.2.1 Fuzzy data base

Classically, the crisp value corresponding to fuzzy variable is fuzzified into a set of couples (fuzzy set, membership degree) by matching the crisp value against the membership function of each fuzzy set of the fuzzy variable. In the following sub-section, we present inputs and output of each FRBS.

a) Path flow index FRBS
   Inputs: - Vehicle number: low, medium, and high
   - Congested vehicles number: low, medium, and high
   Output: - Fuzzy path flow index: weak, medium, and strong
b) Road FRBS
   Inputs: - Path work information: No Path Work and Path Work
   - Maximum path speed: Slow, Medium, and High
   Output: - Road preference: weak, medium, and strong
c) Driver FRBS
   Inputs: - Path familiarity: unfamiliar, medium, and familiar
   - Driver speed: slow, medium, and high
   Output: - Driver preference: weak, medium, and strong
d) Environment FRBS
   Inputs: - Time of day: morning, midday, evening, and night
   - Weather conditions: bad, medium, and good
   Output: - Environment preference: weak, medium, and strong
e) RD FRBS
   Inputs: - Road preference: weak, medium, and strong
   - Driver preference: weak, medium, and strong
   Output: - RD preference: weak, medium, and strong
f) DE FRBS
   Inputs: - Driver preference: weak, medium, and strong
   - Environment preference: weak, medium, and strong
   Output: - DE preference: weak, medium, and strong
g) RDE FRBS
   Inputs: - RD preference: weak, medium, and strong
   - DE preference: weak, medium, and strong
   Output: - RDE preference: weak, medium, and strong
h) Path preference FRBS
   Inputs: - Fuzzy path flow index: weak, medium, and strong
   - RDE preference: weak, medium, and strong
   Output: - Alternative preference: weak, medium, and strong

Each of these inputs is defined by trapezoidal and triangular membership functions.

3.2.2 Fuzzy rule base

The fuzzy rule base is partitioned in sets of rules representing basic behaviours and weighting coefficients attached to the fuzzy rules. The rule base of each FRBS is built by combination of input and output variables. Each base is generated by experts in the transportation area. The total number of rules is 66 rules. As for fuzzy rules, FRBSs use ordinary rules of the type ‘IF *condition* THEN *action*’, where the *condition* part is a

conjunction or disjunction of such propositions, and the *action* part is an elementary fuzzy proposition of the form 'fuzzy-variable is fuzzy-set'.
We present in the following table (table 1) the fuzzy rule base of path preference FRBS. In this rule base, we provide greater importance to the fuzzy path flow index input. In fact, we assume that this input have more importance than path preference according to the road, driver, and environment.

Rule n.	Inputs		Output
	PFI	RDE Preference	
1	weak	weak	weak
2	weak	medium	weak
3	weak	strong	weak
4	medium	weak	weak
5	medium	medium	medium
6	medium	strong	medium
7	strong	weak	strong
8	strong	medium	strong
9	strong	strong	strong

Table 1. Fuzzy rule base of path preference FRBS

3.2.3 Fuzzy inference and defuzzification

In the inference process, Mamdani (max–min) inference method is used. In max–min process, firstly the minimum membership values of the used rules outputs are selected (i.e. the minimum membership value of each input sub-set), then maximum of the minimums are determined (i.e. the maximum membership value of each output sub-set is selected). This process is applied to all valid rules in each FRBS and a geometric shape is obtained. Then, the defuzzification process is applied to get the crisp value. Due to output importance for make decision in route choice problem, the Center of Gravity CoG method (also known as centroid method) is used for defuzzification. The implied fuzzy set is transformed to a crisp output, calculating the area in a particular output membership function, by equation 1.

$$\mu^{crisp} = \frac{\sum_i b_i \int \mu_{(i)}}{\sum_i \int \mu_{(i)}} \tag{1}$$

Where μ^{crisp} is the crisp output value, b_i is the center of each output membership function (called also the weight factor).

3.3 Itinerary selection

Starting with idea that better path is one of k shortest paths regarding only path length; we propose to select the k shortest paths as k feasible paths. The k shortest paths problem is a natural and long-studied generalization of the shortest path problem, in which not one but several paths in decreasing order of length are required (Eppstein, 1998). So, each itinerary from the set of *k* itineraries is evaluated with the hierarchical FRBS previously presented. The recommended itinerary is the one having the highest alternative preference (see figure 6). In order to do an adaptive routing according to the real-time information, this process is repeated before each intersection and after user request.

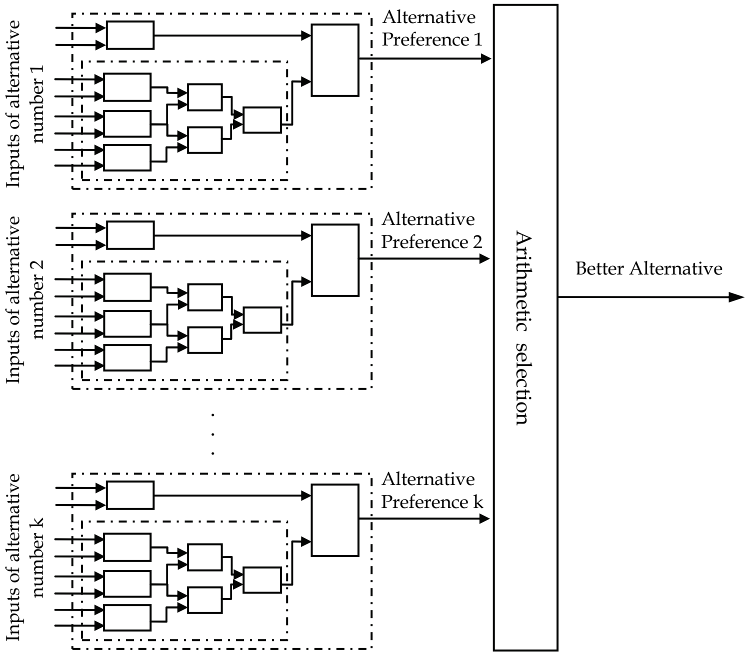


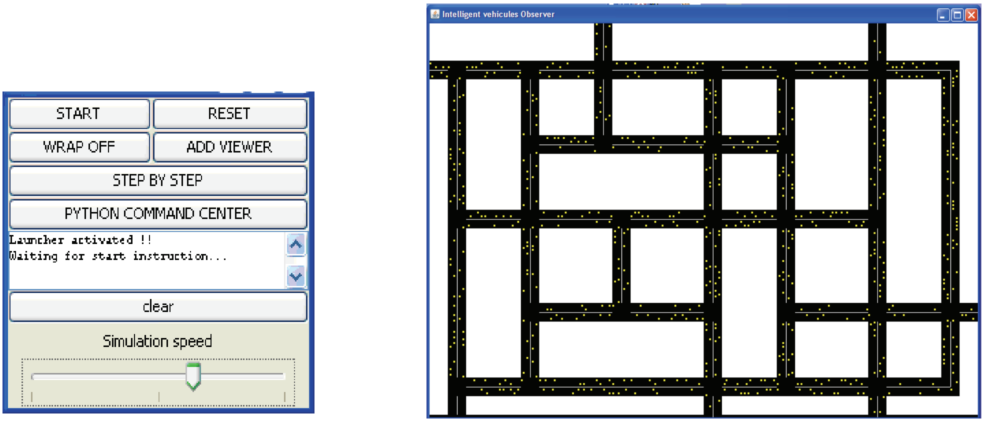
Fig. 6. Flowchart of the itinerary selection steps

4. Simulation and results' discussion

As we need to test our approach taking into account the variation of traffic information, and to visualize the evolution of the road network, we choose to develop a multiagent (MA) simulation model. In fact, it is very helpful in explaining collective behaviour as a result of individual actions. The MA 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 (Drogoul et al., 2003).

Since few years, we note the birth of some MA platforms. These platforms provide both a model for developing MA system and an environment for running distributed agent-based applications. To develop our simulator, we choose the MadKit platform as a generic MA platform (MultiAgent Development Kit) (Gutknecht & Ferber, 2001). Our choice is firstly based on comparison with other known MA platforms (Mulet et al., 2006) (Ricordel & Demazeau, 2000). Among its advantages, it is possible to make traffic services fully extensible and easily replaceable. MadKit allows a fast development of distributed agent system by providing standard services for communication and life cycle management

of the agents. This platform can support thousands of agents interact and perform tasks together by using a simple agent with reactive tasks. In addition, Madkit is a free platform with open source, and it can be programmatically extended using Java programming language. We use in the following multiagent simulation the version 4.1.2 of November 2005. The platform is stable since this date. We use also the TurtleKit tool (Michel et al., 2005) presented as a reactive agent execution tool that runs on the 'synchronous engine' of MadKit platform. This tool aims at providing to advanced users the simplicity of a Logo simulation model while proposing flexibility, modularity and extensibility.
In order to control simulations, we use a launcher agent having the role to set up, launch, and manage turtles (see figure 7a). At each simulation step, an agent receives a set of information describing the surrounding environment situations. Figure 7b presents an example of virtual maps, created by the observer agent from TurtleKit tool. Simulation environments contain roads with a fixed number of lanes and vehicles having each one both origin road and destination road.



(a) (b)

Fig. 7. The simulator (a) Launcher agent, (b) Example of simulation environment

Regarding the hierarchical FRBS, we use the Matlab Fuzzy Logic Toolbox. In this case, a connection between Java and Matlab should be done. We use the JMatLink library that provides some native method for connection (Müller & Waller, 1999). JMatLink includes methods and objects that allow Java to initialize a workspace, write data members of any format to the workspace, read from the work space, and execute command line functions.
In the other hand, for the *k* shortest paths algorithm, we use an implemented algorithm with Java provided by JGraphT[1]. It is a free Java graph library that provides mathematical graph-theory objects and algorithms. The *k* shortest paths algorithm used is similar to Bellman-Ford except that at each iteration, instead of storing only the best path, the

[1] http://www.jgrapht.org

algorithm stores the *k* best paths from origin vertex to destination vertex in an increasing order of length.

We represent the road network, shown in figure 7, by a directed weighted graph *G=(V, E)* where *V* is a set of vertices indicating intersections (crossroads) and *E* is a set of directed edges $e=(v_i, v_j)$ indicating roads (see figure 8). Each road direction between two adjacent vertices is represented by one directed edge. The weight of each edge is the road length. Given two vertices *s* and *t*, the *k* shortest paths algorithm provides *k* paths from s to *t* in increasing order of length. To better understand the broad outline of the system, we propose a class diagram, as the static structure, illustrated by figure 9.

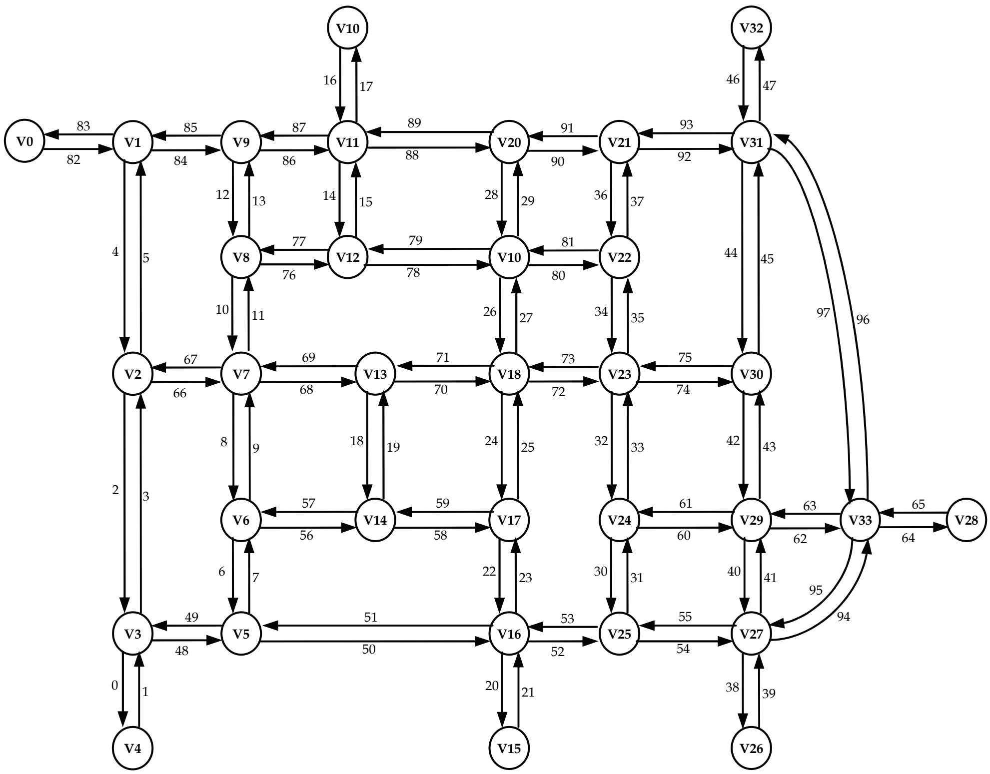


Fig. 8. An example of road network presented as directed weighted graph

Series of simulations are performed, with the environment of simulation presented in figures 7 and 8 (98 roads with 2 lanes and 34 intersections), using different couples (road origin, road destination) with random velocity. During simulation, we add randomly other vehicles having random origin and destination roads (using Random class of Java with uniform distribution). Furthermore, some congested and jammed area in intersection can occur. In order to represent the reality, some vehicles have a low probability to become jammed vehicles. A vehicle stops when perceiving halted ones and it continues moving in a free path. In carrying out the *k* shortest paths algorithm, we eliminate paths having some loops (i.e. visit of an intersection more than one time).

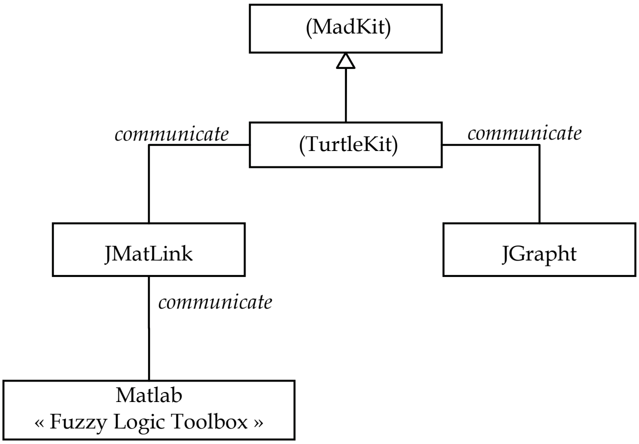
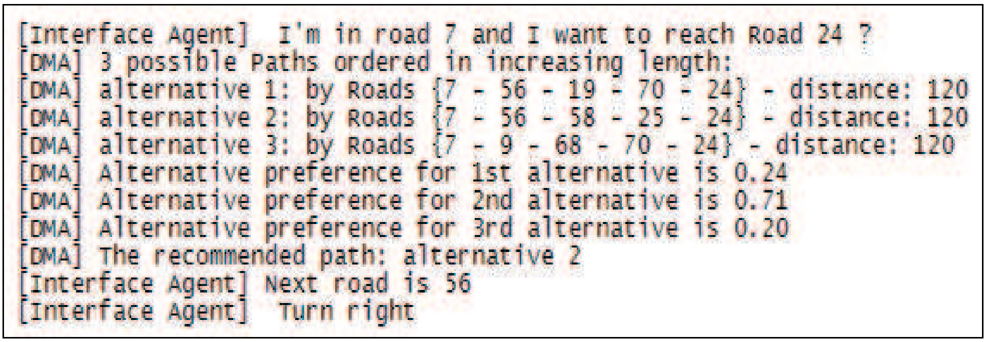


Fig. 9. Class diagram

In order to present some collaboration between agents, figure 10 illustrates a sample of communication messages between interface agent and decision making agent. In this sample, although possible paths have the same length, the driver chooses the second path according to the alternative preference computed with the hierarchical FRBS. This decision is occurred following a congestion in intersection represented by vertex number 13.



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[Interface Agent]  I'm in road 7 and I want to reach Road 24 ?
[DMA] 3 possible Paths ordered in increasing length:
[DMA] alternative 1: by Roads {7 - 56 - 19 - 70 - 24} - distance: 120
[DMA] alternative 2: by Roads {7 - 56 - 58 - 25 - 24} - distance: 120
[DMA] alternative 3: by Roads {7 - 9 - 68 - 70 - 24} - distance: 120
[DMA] Alternative preference for 1st alternative is 0.24
[DMA] Alternative preference for 2nd alternative is 0.71
[DMA] Alternative preference for 3rd alternative is 0.20
[DMA] The recommended path: alternative 2
[Interface Agent] Next road is 56
[Interface Agent]  Turn right
```

Fig. 10. Sample of agents' communication

A comparison has been done between the shortest itinerary (according to the length) and the itinerary selected after applying hierarchical FRBS. Figure 11 presents the number of times when the route choice is the first shortest path, or the second shortest path, etc. 20000 vehicles with different couple origin-destination roads have been simulated with different k value (k=3, k=5, k=7) using the road network presented in figure 8.

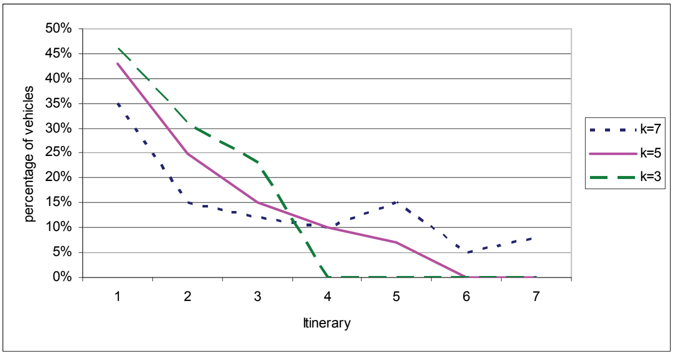

Fig. 11. Influence of parameter *k* on vehicles distribution

In order to view the modification of selected itinerary during the travel, another comparison has been done between the pre-selected itinerary and the real one. We remark that at about 38%, the itinerary has been changed during travel according to the real-time update of traffic information due to the reselection at each intersection. This confirms the adaptability of our hierarchical fuzzy multiagent system compared with its first version (Kammoun et al., 2007) (Kallel et al., 2008).

We remark also that:

- Interactions between different agents accomplished in a series of running simulations show the influence of an early detection of congestion and jam cases.
- More *k* is greater more the route selection is better.
- As regards the technical features, java programming language has some limitations to associate a thread to each agent. So, the management of a great number of concurrent threads is not efficient. The generic multiagent platform chosen can solve the problem. In fact, Madkit proposes a synchronous engine which can manage a big number (hundreds or even thousands) of agents in one thread. In spite of IVA agent is a MAS itself and the decision making agent of each IVA run the *k* shortest path algorithm, Madkit can support simulation in larger scenarios with a large number of agents.

Then, the results show the effectiveness of the hierarchical FRBS in the case of many selection criteria and the effectiveness of multiagent modelling and simulation in order to improve traffic management.

5. Conclusion and future work

In this paper, we present a hierarchical fuzzy rule-base system for route choice problem in order to evaluate one possible itinerary based on real-time information, driver's preferences, and other selection criteria. A cooperative route choice has been developed; it is based on an organisational multiagent architecture of the road network. Finally, several multiagent simulations with a virtual road network have been achieved in order to test the efficiency of the proposed hybrid method. These simulations are realized using 'TurtleKit' tool under the generic multiagent platform 'MadKit'. This chapter attests once more how multiagent modelling and simulation are among best achievable options used to solve complex

problem on road network. Furthermore, this chapter presents the feasibility of hierarchical fuzzy rule-base system to deal with a large number of selection criteria in order to improve the accuracy of route choice for a better management of road network.
As perspectives, we intend in the near future to apply learning method, such as the advanced one detailed in (Kallel et al., 2006), in order to optimize the rule base and tune the membership functions of the data base. Furthermore, real-time path learning for vehicle path planning can be added.

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