Simulation and Evaluation of Urban Bus Networks Using a Multiagent Approach

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Abstract

Evolution of public road transportation systems requires analysis and planning tools to improve service quality. A wide range of road transportation simulation tools exist with a variety of applications in planning, training and demonstration. However, few simulation models take into account traveler behaviors and vehicle operation specific to public transportation. We present in this paper a bus network simulation tools which include these specificities and allows to analyze and evaluate a bus network at diverse space and time scales. We adopt a multiagent approach to describe the global system operation as behaviors of numerous autonomous entities such as buses and travelers.

Key words: Public transportation simulation, Agent-oriented modeling, Multiagent system, Decision support system

1 Introduction

Users attitude towards transportation is in perpetual evolution for convenience, security and economical or environmental reasons. Public transportation systems, such as bus-networks, are a key design for people mobility. These systems, which are considered in this article, have to adapt to the demand in order to improve the service quality and the benefits. To develop new public transportation solutions it is very difficult or even impossible to use direct experimentation considering legal, financial, material or time constraints. Moreover, we cannot establish a global theoretical model for such systems due to

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their size and complexity. Thus, we adopt computer simulation as a solution for analysis and planning of public transportation systems.

A wide range of transportation simulation tools exist with a variety of applications from scientific research to planning, training and demonstration (1). In this domain, few works detail public transportation systems and they generaly deal with the demand estimation problem. In this paper we focus on public transportation networks and we put the emphasis on the system modeling and animation. We give a global and practical view on public transportation simulation, from the modeling to the analysis of simulation results.

In a bus-network system we can identify three main components: people behaviors, road traffic dynamics and specific bus-network operations. This last encapsulates the interactions between the buses, passengers and road traffic. Complexity of a bus-network system results from these interactions. In this paper we show that the multiagent approach is an interesting way to represent such systems and the interactions within them. This approach, derives basically from two observations. First, an urban public transport network is a naturally complex system which involves a set of distributed and interacting entities (2; 3; 4). Second, the global system behavior is made of several emergent phenomena that result from the behavior of individual entities and their interactions (5; 6; 7). For example, the real schedule of a bus is subject to users activity, road traffic and other buses. Multiagent approach allows to describe complex systems where numerous autonomous entities interact to produce global solutions or processes.

In this paper, we propose an original bus-network simulation handling three major constraints. First, the simulation must include the public transportation specificities. Second, it must allow to visualize the evolution of the different system components in simulated time (faster or slower than the real time). Finally, results of simulation must be analyzed at different time and space scales. As emphasized by Silva (8), few works propose to tackle these three objectives in a same simulation tool. These different constraints, which are considered in our approach, were determined from a project related to the design and evaluation of the bus network of Belfort city, situated in Eastern France.

This paper is organized as follows. After a presentation of our simulation objectives in Section 2, the architecture of the simulation model is presented in Section 3. Some details of implementation are drawn in section 4. Section 5 presents the application of simulation to real cases and analyze some experimental results. Then, a conclusion and some study's perspectives are drawn in Section 6.

2 Bus network : structure and simulation

In this section, we define first the main components of bus-networks, then, we explain the interest of bus-network simulation.

2.1 Bus network structure

Basically, the static structure of a bus network is composed of four elements: *itinerary*, *line*, *bus stop* and *bus station* (Figure 1(a)). An *itinerary* is one of the main elements of a bus network. It can be represented by an oriented path on the road network which serves several bus stops. The route between two stops is called an inter-stop. Itineraries are grouped into *lines* when their functionalities are similar or complementary. For instance, in Figure 1(a), the line A is composed of two itineraries which form a round trip. It is important to differentiate *bus stop* and b*us station*. A *bus stop* belongs to a single itinerary whereas a *bus station* gathers a set of close bus stops. The role of a *bus station* is to allow passenger connections. A temporal aspect is added to this static structure via timetables which describes the whole expected arrival or departure bus times on bus stops. It can be represented by several diagrams similar to the one in Figure 1(b). A timetable contains all buses missions for a day. A mission is composed of several journeys performed by a unique bus. Each journey corresponds to an itinerary covered by a bus at a given time. A mission often consists in alternatively covering the itineraries composing a round trip.

The presented structures describe the theoretical evolution of buses into the bus network. However, to plainly describe a bus network and give a relevant evaluation, it is necessary to take into account the travelers and the road traffic. Indeed, the global system evolution comes from behaviors and interactions between buses, travelers and road traffic. Thus, we adopt computer simulation as a solution for analysis and planning of bus networks.

2.2 Simulation statement

Simulation of a bus network has three main interests: observation, constraint verification and network evaluation (see Output level in Figure 2). The first one concerns the global observation of the network, from a visual point of view. It allows the designers, operators and public authorities to have a global vision of the network and its dynamics. In other words, the simulation allows to observe the network functioning and to discuss its global design. The second interest relies on the possibility to check local and global design constraints

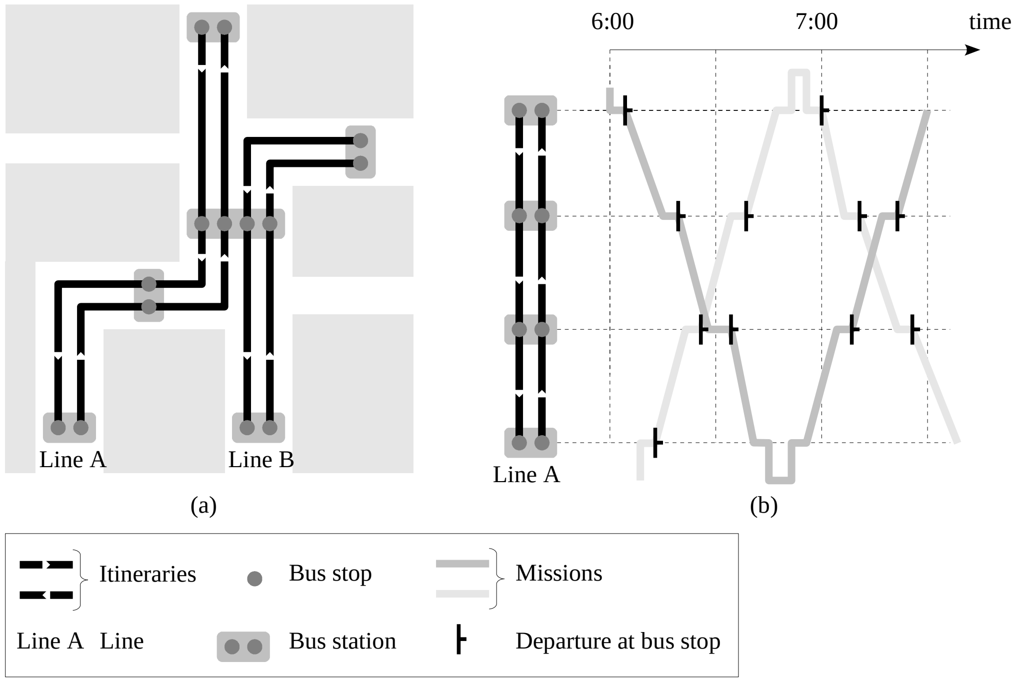


Fig. 1. Structure of a bus network: (a) Static structure (b) Timetables view.

such as passenger connections or timetable synchronization. Moreover, it allows to evaluate/control dynamic processes that are difficult to analyze from a static point of view. Finally, the third main advantage of the simulation is the evaluation of the network efficiency, considering different static and dynamic criteria through different scenarios. This evaluation is divided according to three points of view: *Travelers*, *Operator* and *Authorities* (9). For the travelers, the efficiency of a public transportation network is measured by the accessibility of the network, the trip duration and its cost. The interest of the operator, which is the company operating the network, is the global profits and the operational costs. Finally, the interest of the authorities is to balance the profits of the operator and the transportation service. Thus, our simulation tool must provide different measures allowing the evaluation of the network following these three points of view.

As the input of the simulation we dispose of some available data. They are the characteristics of the population and the description of transport structures presented in the previous section. From these initial data, the simulation must depict the evolution of the bus network. The global running of a bus network results from the behaviors of entities and their interactions. Three main entities are identified as essential elements involved in a bus network: Buses, Travelers and the Road traffic. Figure 2 represents the main components of the proposed simulation. The model is based on these three elements. To represent such distributed and interacting entities we adopt an agent oriented approach for the simulation of bus network.

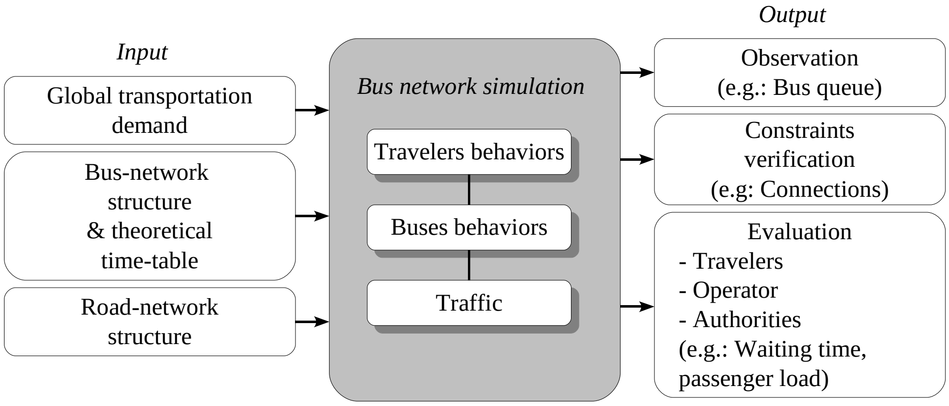


Fig. 2. Simulation components.

3 Agent-oriented modeling and simulation

We have shown in the previous section that bus networks are complex systems. This complexity is particularly due to the dynamic of the system resulting from the interaction between the different components. The multiagent approach is a well suited approach to design such complex systems. Indeed, this approach relies on the assumption that a system is composed of autonomous entities, called agents, that interact in order to deal with a global goal or some local tasks.

In the following part, some definitions about Multi-Agent Systems (MAS) are presented and the interest of using such approach for transport simulation is discussed.

3.1 Multiagent approach

If MAS is a growing research domain, there is no universally accepted definition of the term agent. Each MAS application domain gives its proper definition which exhibits a specific process or architecture. Nevertheless, some agent properties are generally accepted. Wooldridge (10) widely describes agents as computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives.

This definition allows to draw a set of key properties:

- An agent is an **autonomous** entity, i.e. it acts only on its self decisions.
- An agent is **situated** in an environment. It perceives the environment and performs action according to its goal and perception.
- An agent plays one or several roles inside the system, in order to reach its objectives.

From these properties a MAS is defined as a set of interacting agents. However, two types of MAS can be defined following the agent architecture which is used: *deliberative* (or cognitive) and *reactive* architecture. Deliberative agents have generally a symbolic representation of their environment and cooperate thanks to high level communication protocols (11). At the opposite, reactive agents do not have representation of their environment. They act following their perceptions, which are very limited. Reactive agents can cooperate and communicate through their interactions with the environment (called indirect communication). As a consequence, such reactive systems present some global intelligent behaviors that result from the numerous interactions between agents and their environment (e.g. self-organization and emergent phenomenon) (6). The model we propose for the simulation of a bus network relies essentially on the reactive approach. Buses and travelers are considered as simple entities evolving in a wide and complex system. However such entities have naturally cognitive skills that will be integrate as simple behaviors in a reactive-based architecture (see section 3.2).

Applying the multiagent approach to transport simulation presents several interests. First, there exists some techniques and platforms, as Madkit or Swarm (12; 13), to deal with the simulation of numerous entities. Second, agent modeling is a flexible approach to define autonomous behaviors. There is no constraint on the modelling level, i.e. an agent can describe one simple entity as a set of linked entities. For instance, in our model, the *Bus* agent represents the vehicle, its driver and a set of passengers. Finally, reactive MAS are good tools to observe and to study emergent phenomenon as they focus on the modelling of interactions between the entities (14). The emergence of traffic jams in urban networks can be easily modeled by this way (15). In our transportation model, where the dynamic is defined at the micro level by agents and their interactions, some complex phenomena can be obtained at a global level.

MAS have already been successfully used for simulating transportation systems. A first MAS purpose in transport simulation consist in simulate vehicles to study traffic dynamics (16; 17). An other direction of MAS in transportation simulation concern the study of learning and emmergence of coordination in the case of route-choice and modal-choice (18). In the proposed agent model we are interested in the first of these two perspectives.

3.2 Multiagent modeling of a bus network

Multiagent modeling requires to identify the relevant entities of the system and their interactions. In the considered urban environment, the basic components of our system are persons and vehicles. However, the potential number of these

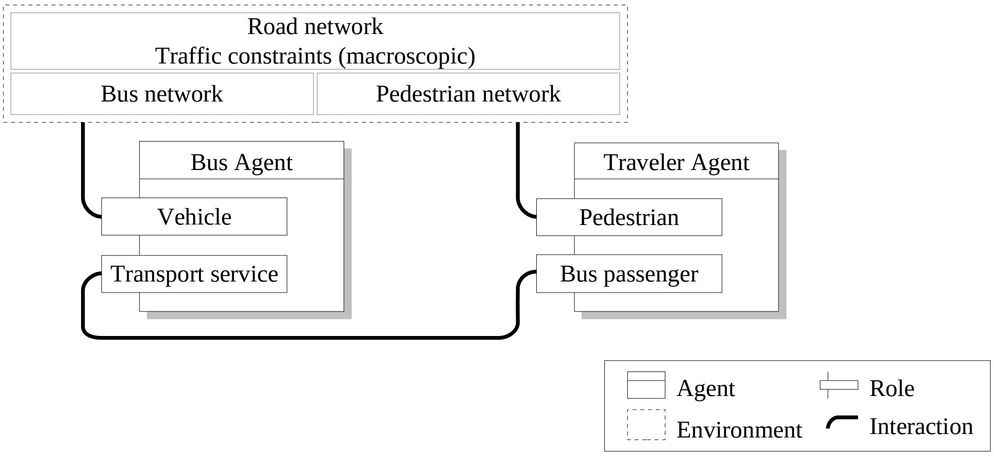


Fig. 3. Roles and interactions of agents.

entities is too important to "agentify" all of them. Thus, we choose to only model buses and travelers as situated agents, and model other entities in a macroscopic way as shown in Figure 3. This choice allows to focus on buses and travelers activities in order to analyze travel time and network operations.

The environment, where *Bus* agents and *Traveler* agents move, is the composition of *Road network*, *Bus network* and *Pedestrian network*. These three elements are strongly linked by several interfaces. For instance, bus-stops are shared by both *Bus network* and *Pedestrian network*. The environment has a prominent role in situated MAS (19; 20). In our case, the environment is not only a shared common space where agents are located, it exhibits dynamical properties as traffic constraints. The main role of the environment is to constraint perceptions and interactions of agents. Indeed, a *Bus* agent and a *Traveler* agent can interact only when they are located at the same bus stop. This constraint is provided by the environment. The two types of agents that move in this environment are now presented.

The *Bus* agent plays two roles at the same time: *Vehicle* and *Transport service*. The *Vehicle* role describes the moving of the bus within the road network. This role is constrained by the road traffic and other *Bus* agents. The second role, the *Transport service* one, represents the ability of a bus to transport persons, considering its capacity and the demands. The behavior of a *Bus* agent is depicted in Figure 4.(a) by a finite state automata. In practice, an instance of *Bus* agent corresponds to a mission as defined in section 2.1. The planning of the mission is pre-defined by the timetables, however, the progression of a *Bus* in the network is constrained by the road traffic and travelers as presented in section 3.3.

The *Traveler* agent plays alternatively the roles *Pedestrian* and *Bus passenger*. The *Pedestrian* role of a *Traveler* agent is played when *(i)* he goes to the first bus-stop, *(ii)* joins a new bus-stop for a connection and *(iii)* goes to the travel

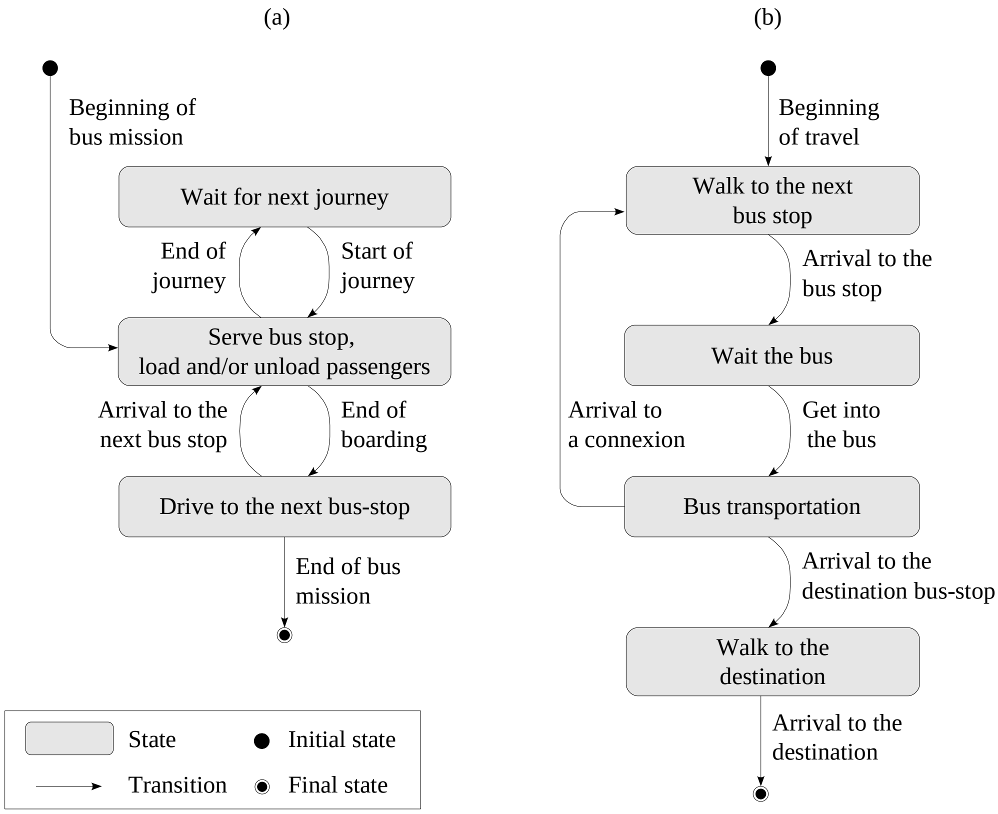


Fig. 4. Agents behaviors presented as finite state automata: (a) Bus agent (b) Traveler agent.

destination from the last bus-stop. The *Bus passenger* role of a *Traveler* takes place when the agent waits at a station with the intention to take a bus. This role persists until the traveler reaches the desired station. The behavior of a *Traveler* agent is given by Figure 4.(b). Each travel by bus corresponds to an instance of a *Traveler* agent. The route of a *Traveler* agent is pre-determined by an utility model, detailed in section 3.4, but it is important to note that the transport duration results from the buses' behaviors.

3.3 Traffic simulation

We have seen in the previous section that a *Bus* agent interacts with car traffic when it covers an inter-stop. It is, then, necessary to represent this traffic because it has a significant impact on the simulated system. Road traffic simulation has attracted much research (1). Simulation models can be classified in three categories (21; 22): microscopic, macroscopic and mesoscopic models.

- Microscopic model considers each moving vehicle within the road network. A vehicle has its own characteristics as its instantaneous speed, its size, its

driving style, etc. The movement of a vehicle results from these "vehicle scale" properties. In (21), the authors discern submicroscopic models and microscopic models. Submicroscopic simulation models bring an additional level of details by describing the functioning of vehicles' subunits and the interaction with their surroundings.
- Macroscopic models represent traffic by introducing aggregated variables like vehicles density or their mean speed. These variables characterize the traffic at the scale of road segment or network.
- Mesoscopic models derive from both microscopic and macroscopic models. The vehicles are discerned but their movements result from macroscopic variables.

Microscopic simulation models require more detailled input, and greater computational resources than macroscopic and mesoscopic ones (23). As we need to take into account the road traffic of a whole city and visualize the evolution of the bus network, we chose to develop an hybrid traffic simulation model. Vehicles, except the buses, are simulated with a macroscopic model whereas buses are simulated with a microscopic approach.

The data of our traffic simulation is obtained in two steps. From the global demand, we first determine the modal choice. Then, we compute the traffic flow from personal vehicles demand. Finally, the movement of Bus agents is determined by a volume-delay relation. The volume-delay function used is the one defined by the Bureau of Public Roads (24). The influence of traffic flow on agents are unilateral. We neglect the direct effect of buses on traffic since they have only a local action on road traffic and it is not our objective to analyze impact of buses operations on road traffic.

Lots of accurate models exist for the modal-choice (25) and the traffic assignment (26; 27; 28). However, we opt for a Multinomial-Logit model (MNL) combined to an all-or-nothing procedure. These two components have been choosen for their intelligibility, facility of parameter setting and computation speed.

In addition to this traffic model, the time spent by a *Bus* agent at bus-stops is computed with a model derived from observations of Rajbhandari et al. and Dueker et al. (29; 30). The model assumes that the main determinants of the dwell time are the number of person boarding and number of person alighting at the bus stop.

3.4 Modeling of traveler behaviors

To identify the bus passengers and establish their transport behavior we mainly use a modal-choice model. The objective of a modal-choice model is to

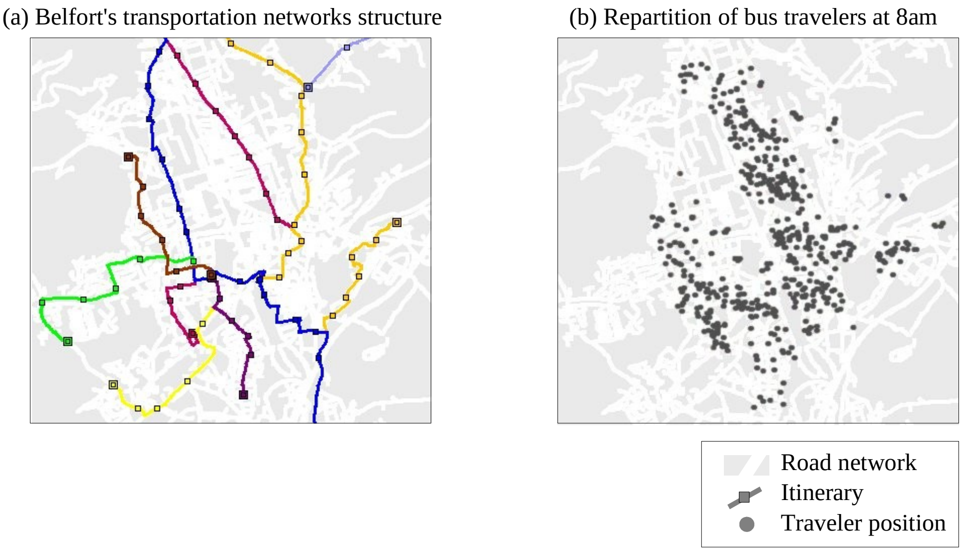


Fig. 5. Views from Simulation with repartition of bus-travelers at 8am.

assign demand to the different transportation supply. Typically, the input of the model is the global demand and the output correspond to the distribution of this demand over the transportation modes. Figure 5(a) is an example of the supply side of the model.

A transportation demand related to a person is defined as an origin, a destination and a departure or arrival date. The demands properties are generated from statistic data. Within a day, a person can make several transportation demands. For each demand, the user is faced to several alternatives of route, transportation mode or other choices. He makes his transportation choices considering his characteristics and the attributes of each potential alternative. To determine the demands related to the bus network, we focus on the mode choice. We describe this choice with a Multinomial-Logit Model (MNL) (31; 32; 33). This model assumes that each alternative is expressed by a value called utility, and includes a probabilistic dimension to the decision process.

The multinomial choice model defines the probability for a given individual n to choose transportation mode i within the choice set C_n by :

$$P\left(i|C_n\right) = \frac{e^{V_{i,n}}}{\sum\limits_{j \in C_n} e^{V_{j,n}}} \tag{1}$$

Where C_n are the transportation mode alternatives which include personal vehicle like *car*, *walk* or other non-motorized mode, and *bus*. $V_{i,n}$ is the utility function of the transportation mode i. We consider an expression of utility derived from (31) and (34).

$$V_{i,n} = \mu_{cost}\left(c_{i,n}\right) + \mu_{time}\left(d_{i,n}\right) \tag{2}$$

where :

$$d_{i,n} = \beta_{wait} t_{wait_{i,n}} + \beta_{walk} t_{walk_{i,n}} + \beta_{vehicle} t_{vehicle_{i,n}}$$

The utility function $V_{i,n}$ expresses that the perceived cost of a travel is composed of the financial or "out-of-pocket" cost of trip $c_{i,n}$ and the perceived duration of trip $d_{i,n}$ (35). The parameters μ_{cost} and μ_{time} allow to balance these two costs. Thus, the ratio μ_{time}/μ_{cost} represents the cost of time. The perceived duration of a trip considers the effective duration of waiting, walking and in-vehicle situation of the traveler (t_{wait}, t_{walk} and $t_{vehicle}$). These values are weighted to add a comfort dimension and denote that the three situations, namely walking, waiting and in-vehicle are increasingly comfortable.

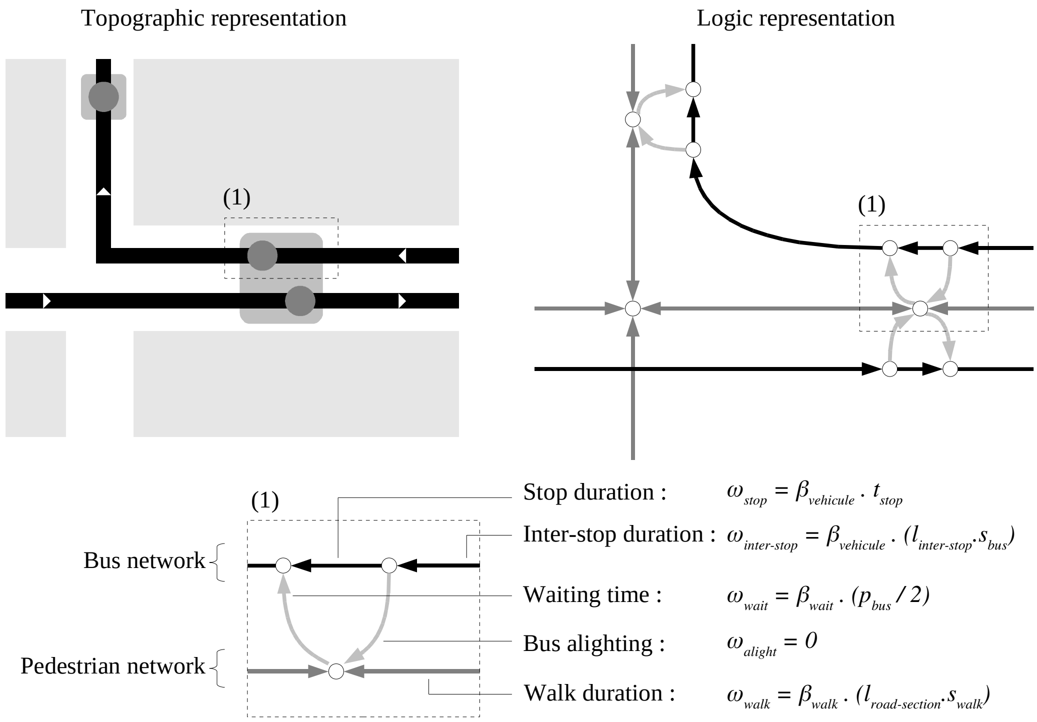
3.5 Computation of deterministic utility for mode choice

To estimate the probability of transportation modes for a demand n it is necessary to evaluate the utility of each mode. We consider three transportation modes : walk, car and bus.

For a walk trip, the financial cost $c_{walk,n}$ is null and the perceived duration is only composed of the perceived walk duration ($\beta_{walk} t_{walk_{walk,n}}$). To estimate the effective trip duration $t_{walk_{walk,n}}$ we consider the shortest path between origin and destination of the demand. This path is obtained with an A*-algorithm which minimize the length of trip on the pedestrian network (36).

In the case of a car trip we consider the shortest path between origin and destination. This path is obtained by an A*-algorithm applied on the road network. The financial cost of the trip $c_{car,n}$ is estimated from the product of the path length by an average fuel consumption. The perceived trip duration is only composed of the perceived car duration ($\beta_{vehicle} t_{vehicle_{car,n}}$). The effective trip duration $t_{vehicle_{car,n}}$ is estimated from the product of the path length by an average speed.

The utility of bus alternative is more complex than walk or car alternative because we consider in a bus trip the three situations: walking, waiting and in-vehicle. The financial cost of a bus trip is independent from the demand characteristics (origin, destination). We evaluate it by the average price of a bus ticket. To evaluate the perceived duration it is necessary to consider the three situations: walking, waiting and in-vehicle. We determine the better path in term of perceived duration with an A*-algorithm applied on a graph representation of both pedestrian and bus network (Fig. 6). The obtained path establishes the effective waiting duration $t_{wait_{bus,n}}$, effective walking duration



ω_{walk} : Perceived duration to cover a road section.
ω_{wait} : Perceived waiting duration to take a bus.
$\omega_{inter\text{-}stop}$: Perceived duration to cover the inter-stop in bus.
ω_{stop} : Perceived stop dwell time for a bus passenger.
ω_{alight} : Perceived duration to alight the bus.
s_{walk} : Average walking speed.
$l_{road\text{-}section}$: Length of a road-section.
p_{bus} : Average time between two buses.
s_{bus} : Average bus speed.
$l_{inter\text{-}stop}$: Length of an inter-stop.
t_{stop} : Average stop duration of a bus.

Fig. 6. Graph representation of mixed pedestrian and bus network.

$t_{walk_{bus,n}}$ and effective in-vehicle duration $t_{vehicle_{bus,n}}$. Note that the use of this graph representation allows multiple connections.

This model allows to instantiate the *Traveler* agents of our simulation and allows to determine their route within both pedestrian and bus networks. Then, the results of demand model for personal transportation mode are also used by the macroscopic traffic model.

4 Simulation software structure

Considering the previous specification of agents and environment, we have implemented a multiagent simulation. In this section, we first describe the simulation software, then, we present the implementation of the scheduler.

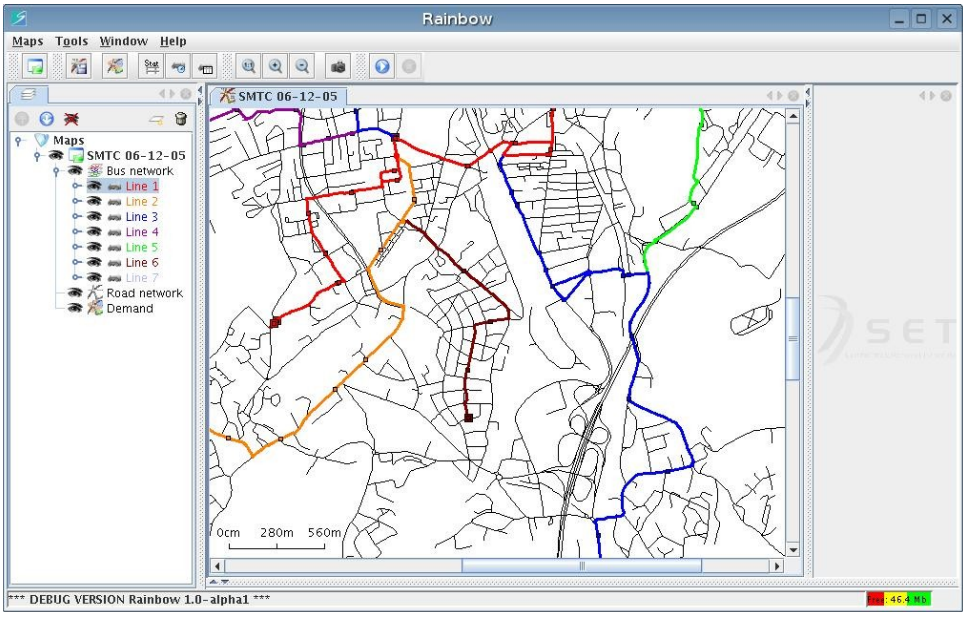


Fig. 7. Screen shot of the decision support system.

4.1 An overview of the simulation software

The proposed simulation model has been entirely implemented in a decision support software dedicated to the design and the evaluation of bus networks (Figure. 7). This system is implemented in Java language and is linked to a relational database which involves a Geographical Information System (GIS) data and transport structures data. The main features of the system are:

- Visualization and edition of a bus network that take into account the road network constraints.
- Static evaluation of a bus network through several measures: bus line length, inter-stop length, covering population by bus-stop, etc.
- Simulation of buses activity for observation and evaluation of operations occurring during a day.

Calibration and validation of the simulation have been performed from the analysis of passenger counter data of the current Belfort city bus network. These data correspond to the counting of passenger boardings and alightings for each bus along a day. Then, the simulation has been applied for the design and evaluation of a new bus-network solution of Belfort city.

4.2 Implementation of the scheduler

While developping a multiagent simulator, management of time remains a critical issue. We have defined in previous sections the behaviors of agents, we detail in this section the process of agent evolution through the simulated time.

In our simulation the time is managed in a discrete and synchronous way. The simulation process activates all agents for a fixed period Δt, then, after this first step, each agent must exhibit the same simulated date to begin the next step. This process is necessary to give a consistent observation of the system evolution. This approach is appropriate if the step duration Δt has no significant influence on the simulation results. Indeed, through a simulation step the agents have an asynchronous evolution and this might create time inconsistency when they interact. For instance, when a *Traveler* agent and a *Bus* agent move near a bus-stop. If the simulation step allows the bus to serve the bus-stop and the traveler to arrive to the bus-stop, the traveler loading depends on the relative time execution of the two agents. Thus, to exclude time inconsistency we synchronize interactions by scheduling some events.

A wide range of the works dealing with distributed computer simulation are interested in the problem of synchronization (37; 38). In our case, the goal of the synchronization mechanism is to ensure that each agent interacts in well-known order. This requirement is referred as the local causality constraint as formulated in (39). To solve it, we use a conservative approach, i.e. our algorithm avoids the local causality constraint violation. In practice, when an agent needs to perform a synchronous interaction, it is suspended until it is "safe" to process this interaction. In our previous example, the execution of the *Bus* agent and the *Traveler* agent is suspended when the agents arrive at the bus-stop. The two agents stay suspended while all other agents have a smaller internal date. Finally, the *Bus* agent and the *Traveler* agent are activated in the correct order to undertake the interaction.

5 Experimentation

The simulation model has been applied for the design and evaluation of a new bus-network solution of Belfort city. The target area represents approximately 50 square kilometer and about $50,000$ citizen are covered by the bus-network. The last includes 8 bus-lines which represent 35 kilometer of covered roads as shown in Figure 5(a). For this study, input data comes from a domestic travel inquiry (40). This survey provides the global transportation demand as a temporal O-D matrix. In this case study, a significant number of measures

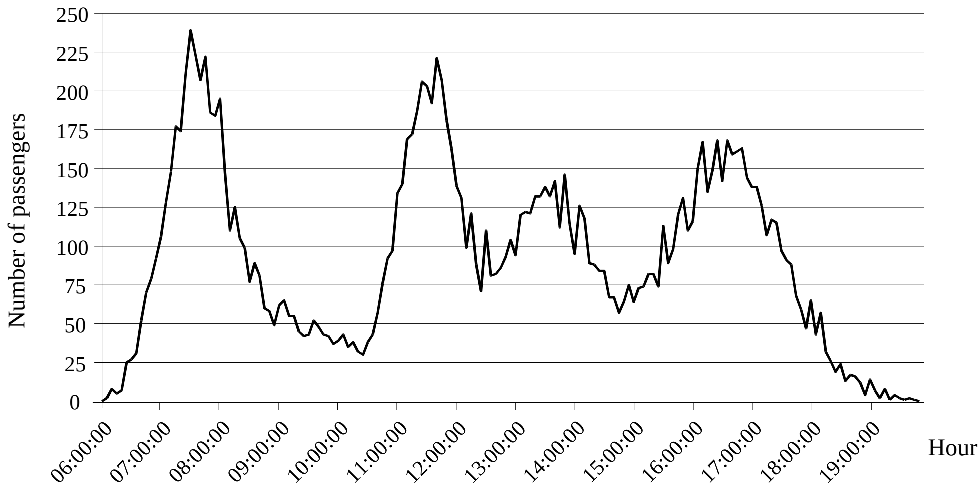


Fig. 8. Simulation results for Belfort bus network, measure of the load of passenger.

has been produced by the simulation tool. In this section, we focus on two representative results: measure of passenger load and measure of bus passenger waiting time.

5.1 Passenger load of the bus-network

The load of the bus-network corresponds to the number of passengers in buses at a given date. The simulation allows to observe the geographical and temporal distribution of this measure in order to adjust, for example, the number of buses. This measure is obtained by counting, at each simulation step, the *Traveler* agents which are in *Bus transportation* state. The *Traveler* agents that walk or wait a bus are not taken into account. Figure 8 plots the simulated distribution of the bus-network load of passenger for a day. This measure results in about $15,000$ bus trips. We can discern the peak periods at 7, 12 and 17 o'clock which are commonly observed in urban traffic.

These measures allow to locate overload of bus and unused buses. Then, for a specific itinerary and a specific hour the number of buses can be adapted to avoid load problems.

5.2 Passenger waiting time

The previous load of passengers measure allows to give a first evaluation of the bus network considering the operator point of view. The passenger waiting time, discussed in this section, is a relevant measure to analyze bus network from a passenger's satisfaction point of view. The total waiting time for a

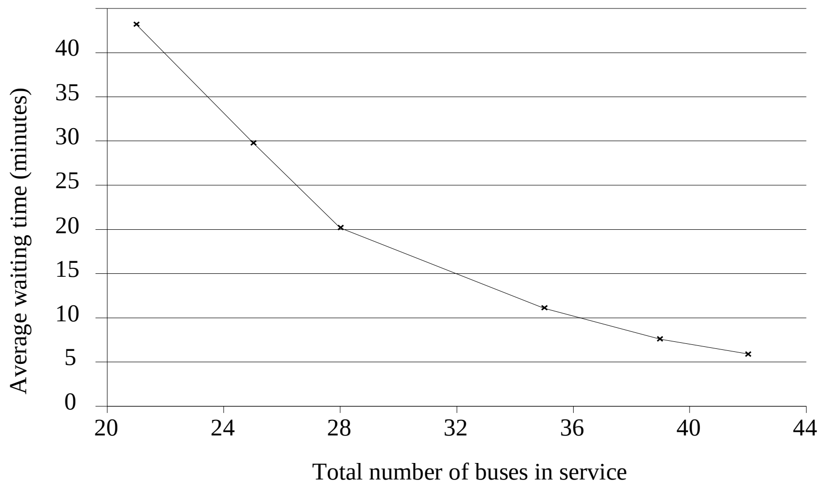


Fig. 9. Simulation results for Belfort bus network, measure of passenger waiting time.

bus trip corresponds to the sum of *(i)* the waiting time at the origin station and *(ii)* the waiting time at connections. In our simulation each agent keeps the simulating date of each state change. Thus, after a trip, a *Traveler* agent can calculate its waiting time. Figure 9 shows the average waiting time for different number of active buses on the network. Below a certain number of buses, a correct transportation service cannot be guaranteed. In the case of the studied bus network, if the objective is to obtain an average waiting time of 10 minutes, then the minimum number of buses must be 36. These values confirm the ones expected by the operators of Belfort bus-network.

Schedules of buses, and consequently travelers waiting time, result in emergent phenomena as bus queues. This phenomenon occurs when two close buses serve the same itinerary. The bus that follows the head one has less passengers than the other, because this last one serves the bus-stops just before it. Then, the following bus spends less time at bus stops and catches the first one up. This situation is commonly observed in reality and the simulation tool can prevent it.

The simulation allows several other measures on bus network efficiency like the bus saturation and the lack of passenger on bus-stops. Modeling buses and travelers as agents makes easy these kind of measures. Thus, most of evaluations to improve bus networks efficiency can be implemented through the proposed multiagent simulation tool.

6 Conclusion

In this paper, a multiagent simulation of bus networks has been presented. The model combines buses operation, traveler behaviors and a road traffic model. We shown that an agent-based approach allows to design such autonomous, dynamic and interacting entities. Moreover, this approach gives a solution to integrate an individual-centered view of buses and passengers within a macroscopic model of traffic. This model has been applied and validated on a real case study. Authorities, which manage the bus network of Belfort town (France), used the different functionalities and measures of our simulation tool to design new transportation solutions.

The main perspective of this work is to evaluate transit network policies (41). They are usefull to regulate bus networks when some particular events happen during missions (e.g. accidents, traffic jam, etc.). Modeling and measuring the efficiency of these strategies is an interesting challenge.

Forthcoming works will consider other modes of public transport, and then the extension of the traffic model to a multi-scale one. It concerns the integration of a mesoscopic model of vehicles in traffic. This objective must provide more realistic bus movements and integrate traffic scenarios as accidents or roadworks.

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