MultiAgent Approach for Simulation and Evaluation of Urban Bus Networks

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ABSTRACT

Evolution of public road transportation system requires analysis and planning tools to improve the service quality. A wide range of road transportation simulation tools exist with a variety of applications in planning, training and demonstration. However, few simulations take into account the specificities of public transportation. We present in this paper a bus network simulation which models 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 from behaviors of numerous autonomous entities such as buses and travellers. The developed simulation has been integrated into a decision support system for the design and the evaluation of bus networks. Some experimental results on a real case, showing the efficiency of the proposed model, are presented and discussed.

Categories and Subject Descriptors

I.6 [**Computing Methodologies**]: Simulation and Modeling; I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent systems*

Keywords

Agent-oriented Modeling, Multiagent System, Public Transportation Simulation

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 their size and complexity.

A wide range of transportation simulation tools exist with a variety of applications from scientific research to planning, training and demonstration [20]. In the dynamic simulation domain, research usually focus on personal means of transportation and do not take into account the specificities of public road transportation. For example, in bus-network the vehicles are constraint by a timetable. In this paper we propose to integrate these constraints and parameters in the modeling and simulation process.

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 model such systems and their interactions. This choice, 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, 9, 13]. Secondly, the global system behavior is made of several emergent phenomena that result from the behavior of individual entities and their interactions [10, 12, 19]. For example, the real schedule of a bus is subject to passagers, road traffic and other buses. MultiAgent approach allow to model 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 model 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 simulations must be analyzed at different time and space scales. As emphasized in [22], 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 town (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. Section

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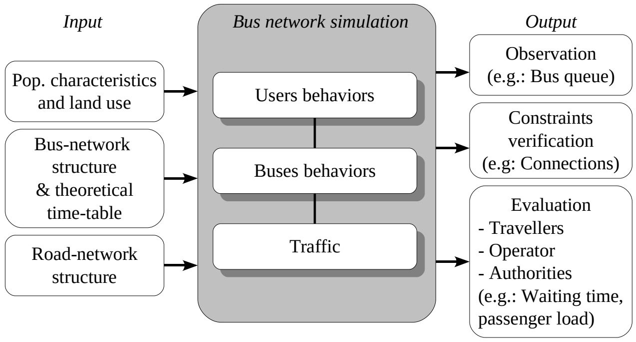

Figure 1: Simulation components.

4 presents its application to real cases and analyze some experimental results. Then, a conclusion and some study's perspectives are drawn in Section 5.

2. OBJECTIVES AND DEFINITIONS

2.1 Objectives of bus network simulation

Simulation of a bus network has three main interests: observation, constraint verification and network evaluation (see Output level in Figure 1). 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 of simulating such a network relies on the possibility to check local and global design constraints (e.g. passenger connections, 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.

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 next section. From these initial data, the simulation must model the evolution of the bus network.

The global running of a bus network results from the behaviors and the interactions of the entities. Three main entities are identified as essential elements involved in a bus network: Buses, Passengers and the Road traffic. Figure 1 represents the main components of the proposed simulation. The model is based on these three elements.

2.2 Bus network structure

Basically, the static structure of a bus network is composed of four elements: itinerary, line, bus stop and bus station (Figure 2(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 example, in Figure 2(a), the line L_1 is composed of the two itineraries L_1-Iti_1 and L_1-Iti_2 which form a round trip. It is important to differentiate: bus stop and bus 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.

A timetable 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 2(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 to alternatively cover 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 travellers and the road traffic. Indeed, the global system evolution come from behaviors and interactions between buses, travellers and road traffic. To model such distributed and interacting entities we adopt a agent oriented approach as described in the next section.

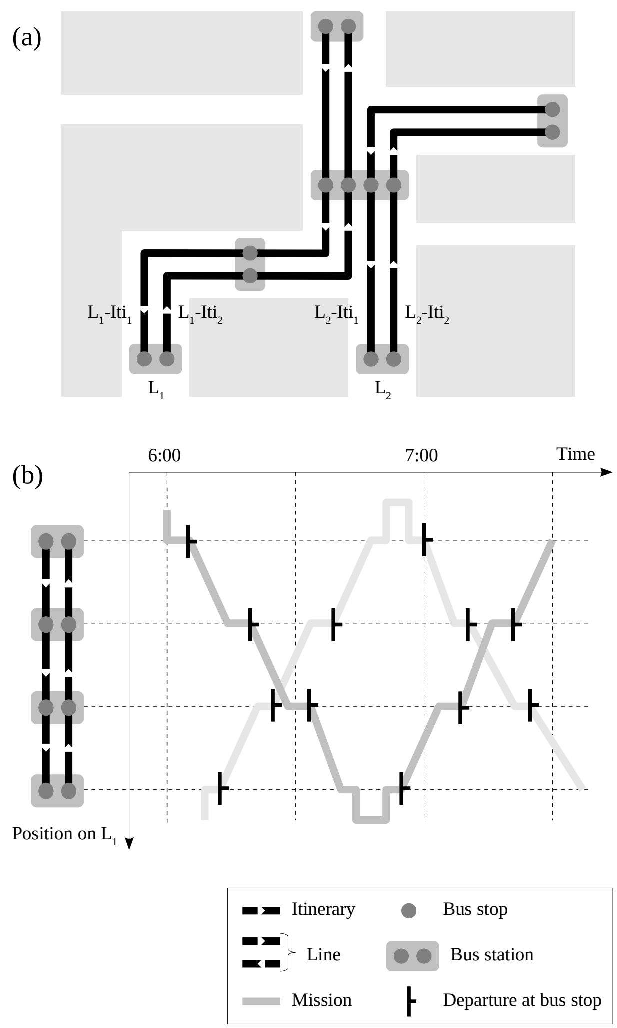

Figure 2: Structure of a bus network: (a) Static structure (b) Timetables view.

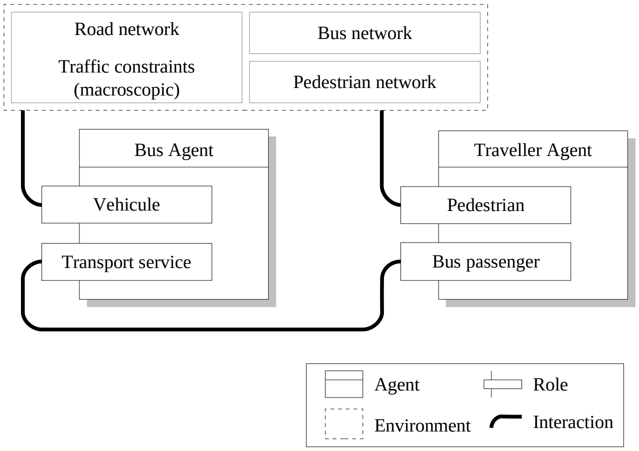

Figure 3: Roles and interactions of agents.

3. AGENT ORIENTED MODELING AND SIMULATION

3.1 Interest of a MultiAgent approach

The proposed simulation model of bus network relies on combining an aggregate model of road traffic and Individual Based Models (IBM) of some mobile entities. Buses and travellers are considered as autonomous entities evolving in a wide and complex system. Then, we adopt a situated multiagent approach to model these entities.

Applying the multiagent approach to transport simulation presents several interests. First, there exists some techniques and platforms, as Madkit or Swarm [8, 14], 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, a *Bus* agent can represent a bus, its driver and a set of passengers. Finally, reactive MAS are good tools to observe and to study emergent phenomenon, because they focus on the modelling of interactions between the entities [23]. The emergence of traffic jams in urban networks can be easily modeled by this way [18]. In our transportation model, where the dynamic is defined at the micro level by agents and their interactions, some global or macroscopic evaluations can be obtained.

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

The environment, where *Bus* agents and *Traveller* 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*. Environment has a prominent role in situated MAS [25, 26]. In our case, environment is not only a shared common space where agents are located, it exhibits dynamical properties as traffic constraints. The main role of environment is to constraint perceptions and interactions of agents. Indeed, a *Bus* agent and a *Traveller* 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.

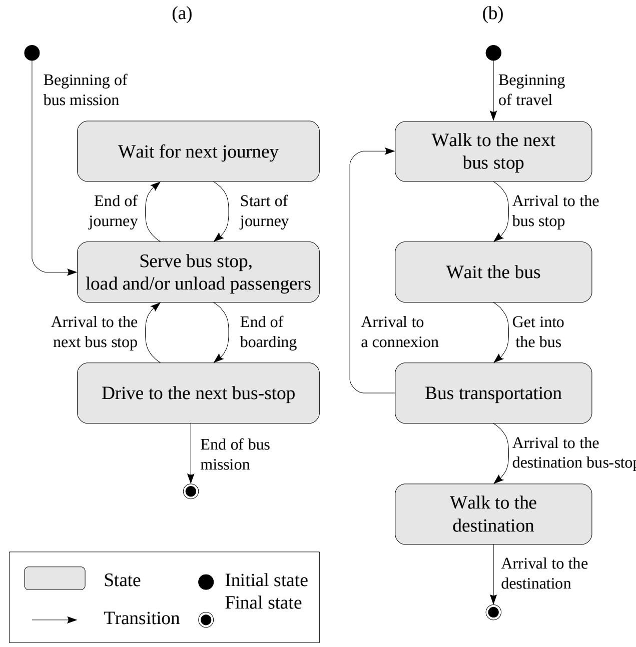

Figure 4: Agents behaviors presented as finite state automata: (a) Bus agent (b) Traveller agent.

The *Bus* agent play 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 detailed in Figure 4.(a). In practice, an instance of *Bus* agent corresponds to a mission (as defined in section 2.2). 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 travellers (see section 3.3).

The *Traveller* agent plays the roles of *Pedestrian* and *Bus passenger* alternatively. The *Pedestrian* role is played when *(i)* the traveller goes to the first station, *(ii)* join a new station for a connection and *(iii)* goes to the travel destination from the last station. The *Bus passenger* role of a *Traveller* takes place when the agent waits at a station with the intention to take a bus. This role persists until the traveller reaches the desired station. The behavior of a *Traveller* agent is detailed in Figure 4.(b). Each bus travel corresponds to an instance of a *Traveller* agent. The route of a *Traveller* agent is pre-determined by a choice model (see section 3.4) but 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 model this traffic because it has a significant impact on the simulated system. Road traffic simulation has attracted much research [20]. Simulation models can be classified in three categories [15, 16]: 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 [15], 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 [5]. 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.

For the macroscopic model of traffic, the flow of each road segment for a determined period derives from a travel-demand model which is presented in section 3.4. Then, the *Bus* agents are constrained by these flows when they move. 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. Moreover, when it is necessary, the *Bus* agents can interact directly to relate local moving constraints.

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. [11, 21]. 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 travellers objectives

To identify the bus passengers and establish their transport behavior we use a demand model. The objective of a demand model is to determine needs of transportation from population characteristics. Typically, the inputs of the model are land uses, household demographics and other socio-economic factors. The outputs correspond to all trips of the considered population during a fixed period of time. In our model, we estimate the transportation demands from statistic survey, then, we determine the route and transportation mode of each demand.

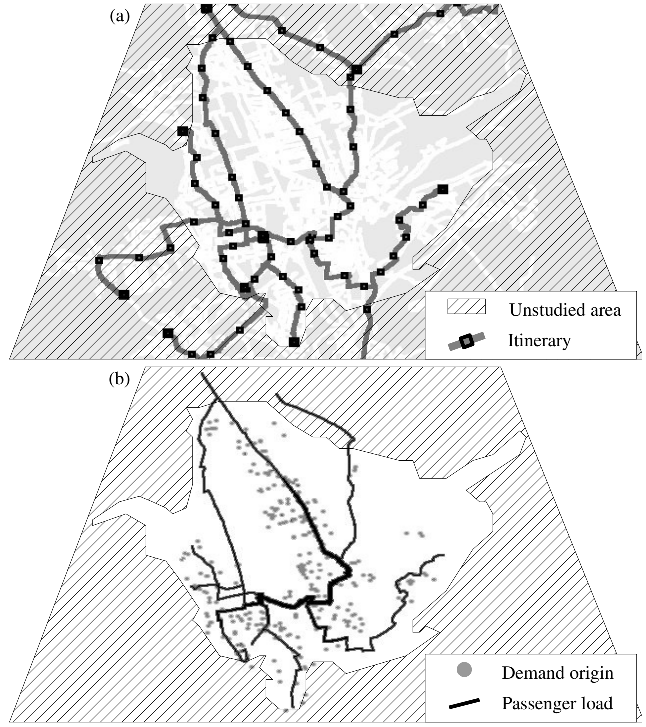

Figure 5: Views from Simulation: (a) Bus network structure (b) Repartition of the demand and passenger load at 8am.

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 (The Figure 5(b) shows such demands at 8am). 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 model this choice with a Multinomial-Logit Model (MNL) [1, 3, 17]. This choice model assumes that each alternative is expressed by a value called utility, and include 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 [1] and [6].

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

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

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 $d_{i,n}$ [24]. 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.

This model allows to instantiate the *Traveller* agents of our simulation and determine their route within both pedestrian and bus networks. Then, the results of demand model for personal transportation mode are used by the macroscopic traffic model presented in section 3.3.

4. EXPERIMENTATION

Considering the previous specification of agents and environment, we have implemented a multiagent simulation. In this section, a case study referring to the bus network of Belfort town (France) is presented. This study illustrates the proposed model and different evaluations of a bus network.

The simulation has been entirely implemented in a decision support software for the conception and the evaluation of bus networks. This application uses Java language and is linked to a relational database which involves Geographical Information System (GIS) data and transport structures data. The main objectives of the application 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 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. 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 come from a domestic travel enquiry [7]. This survey provides information about population characteristics and activity patterns. In this case study, a significant number of measures has been produced by the simulation tool. In the next two sections, we focus on two representative results: measure of passenger load and measure of bus passenger waiting time.

4.1 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

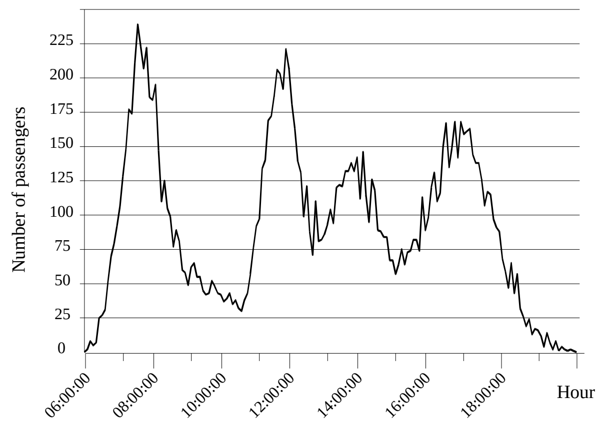

Figure 6: Simulation results for Belfort bus network, measure of the load of passenger.

of this measure in order to adjust, for example, the number of buses. This measure is obtained by counting, at each simulation step, the *Traveller* agents which are in *Bus transportation* state. The *Traveller* agents that walk or wait a bus are not taken into account. Figure 6 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 obtained in urban traffic analysis. Figure 5(b) represents the geographical distribution of passenger load at 8am and the associated demands origin. The stroke thickness denote the usage of the bus-network.

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

4.2 Passenger waiting time

The previous measure of load of passenger 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 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 *Traveller* agent can calculate its waiting time. Figure 7 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 a average waiting time of 10 minutes, then the minimum number of buses must be 36.

Simulated planning of a traveller, and consequently its waiting time, result in emergent phenomenons as bus queues. This configuration 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 phenomenon is commonly observed in reality and the simulation tool can prevent it.

The simulation allows several other measures on bus net-

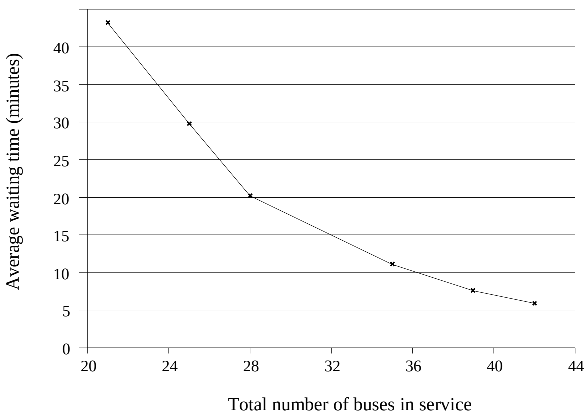

Figure 7: Simulation results for Belfort bus network, measure of passenger waiting time.

work efficiency like the bus saturation and the lack of passenger on bus-stops. Modeling buses and travellers 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.

5. CONCLUSION

In this paper, a multiagent simulation of bus networks has been presented. The model combines buses operation, traveller behaviors and a road traffic model. The agent-based approach allows to model 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), use the different functionalities and measures of the simulation tool to design new transportation solutions.

The main perspective of this work is to evaluate Intelligent Transportation Systems (ITS) [4]. 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 (e.g. accidents, roadworks).

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