# Growing Artificial Transportation Systems: A Rule-Based Iterative Design Process

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***Abstract*—Artificial transportation systems (ATS) are an extension of traffic simulations that deal with transportation issues from the complex systems perspective in a systematic and synthetic way. A rule-based iterative ATS design process is presented in this paper, together with a prototype based on the multiagent platform—Swarm and the methods and results of computational experiments conducted on it. Both emergence-based observation and statistical analysis are used to evaluate those results. This paper demonstrates the ability of ATS to generate traffic phenomena from simple consensus rules and the possibility of designing a growing ATS with readily available multiagent tools.**

***Index Terms*—Agents, artificial transportation systems (ATS), computational experiments, emergence-based observation, rules.**

## I. Introduction

TRAFFIC simulation has been playing an increasingly important role in traffic planning, control, evaluation, etc. Artificial transportation systems (ATS) are an extension of microscopic traffic simulation that deal with modern transportation challenges from the perspective of complex systems.

Metropolitan transportation systems are considered to be complex systems in that they involve a large number of participants and influencing factors, among which, the relationships are nonlinear, dynamic, and hard to model precisely. Like other complex social systems, transportation systems are not suitable to employ reductionism or analytical modeling methods due to the involvement of social and behavioral aspects, but rather, they need to be modeled and analyzed using holism and in a systematic and synthetic manner. Based on those considerations, the concepts and methods of ATS were proposed by Wang and Tang [1], [2].

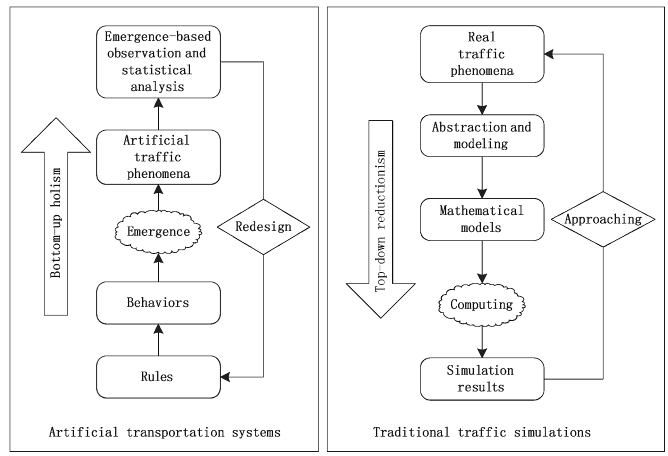


Fig. 1. Flow charts of design and computation for ATS and TTS.

The basic ideas of ATS are, first, to model the traffic elements as agents, whose models are built on simple objects and relationships, second, to generate traffic behavior from the interactions of a large number of traffic agents in a bottom-up manner, and finally to support the mathematical analysis and decision making of transportation issues. For these ideas to be applicable, an ATS platform that can generate various traffic behaviors needs to be established first. This platform can be used as an experiment field to conduct repeatable, controllable, and configurable experiments, which are called computational experiments. Computational experiments are ideal trials to evaluate regulations, strategies, and decisions for transportation issues. When connected to and running in parallel with real systems, this platform can also be used to support the management and control of real transportation systems. Furthermore, it can be used in the application of training traffic operators.

Both ATS and traditional traffic simulations (TTS) are computational methods of coping with transportation issues. However, they are different in the ways they compute. As we can see from Fig. 1, ATS employs a bottom-up holism. Experimenters first need to design a set of rules to describe the behaviors of the involved traffic elements, or agents, such as drivers, pedestrians, traffic signals, etc. Based on those rules, the agents act and interact with each other, from which artificial traffic phenomena emerge. Then, both emergence-based observation and statistical analysis can be used to evaluate the rules. According to the

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evaluation results, the experimenters can modify the rules to iteratively obtain better or desired traffic performance in some sense.

On the contrary, TTS employs top-down reductionism. Investigators first analyze real traffic phenomena of their interest and then devise, through abstraction and modeling, some mathematical models. Based on those models, simulations can be carried out by computers. Usually, one of the objectives of TTS is to reproduce real traffic phenomena, and the fidelity may even be viewed as a standard to assess TTS. However, this is not the case for ATS. Replicating or approaching reality is not the only, even not the main, objective of ATS [1]. The processes and results of computational experiments on ATS can be regarded as different possible versions of reality. By adopting this concept, we think of ATS as a handy tool to design new traffic rules and regulations for real transportation systems.

In this paper, we aim to provide an introductory case for the procedure of design and computation of ATS depicted in Fig. 1 and to test the ability of ATS to generate complex traffic behaviors, particularly traffic congestion, from simple consensus rules. The concept "rule set" was adopted to describe the different behavioral aspects of traffic agents. Nine rule sets were designed according to common traffic regulations and natural constraints. Based on those rule sets and the multiagent platform Swarm, we implemented a prototype for ATS by programming in Java language. The idea of Artificial Societies experiment design in [3]—gradually adding more rules to the experiments—was adopted herein to improve the prototype in an iterative way. Each version of the prototype corresponds to a specific combination of rule sets. In other words, the traffic agents in different versions have different behaviors. Six computational experiments were conducted with different versions and/or number of agents. Both emergence-based observation and statistical analysis were used to evaluate the results of computational experiments.

The rest of this paper is organized as follows. Related work is reviewed in Section II. In Section III, the agent-based model and the rules used on the Swarm-based prototype are described. The computational experiments conducted on the prototype are presented in Section IV. Analysis of the experimental results is done in Section V. Finally, in Section VI, conclusions are drawn, and future work is discussed.

## II. Related Work

ATS is an integrated and sustainable solution to metropolitan transportation issues from the complex systems standpoint. It was proposed based on the concepts and methods in artificial societies [3], [4] and the recent study on complex systems [5], [6]. ATS is also a further development of the transportation analysis simulation system [7], which is an activity-based microscopic traffic simulation software.

Some concepts and methods adopted in ATS, such as agent-based modeling and emergence, have been applied in other research fields, including artificial life [8], natural evolution [9], the flocking behavior of birds (and other animals) [10], artificial societies [3], [4], the complexity of cooperation [11], and artificial stock markets [12].

To date, some work has been done to promote the development of ATS. Concepts and a theoretical framework for ATS are proposed in [1] and [2]. Basic approaches to ATS are studied in [13]. An implementation of ATS based on peer-to-peer computing is reported in [14] and [15], yet it mainly focuses on the aspect of computing. It is discussed in [16] how ATS stems from the study of complex systems and how ATS differs from TTSs. The concept of ATS is used in [17] to implement a framework for the specification and testing of intelligent traffic control systems.

Agent-based models have extensively been applied to transportation simulations in the literature. Nagel and Schreckenberg [18] are among the pioneers who apply the concept of agents in traffic simulation, although it is cellular automaton (CA) that is actually used. In this paper, they use four simple rules to model single-lane freeway traffic and generate a phase transition phenomenon that exists in real freeway traffic. Bazzan *et al.* [19] propose a two-layer agent model. In the tactical layer, Nagel and Schreckenberg's CA-based model is reimplemented, whereas in the strategic layer, a beliefs, desires, and intention formalism is used to model the social aspects of the travelers' route choice behavior. Burmeister *et al.* [20] propose an agent architecture for agent-based traffic simulations. The architecture consists of five top-level modules: 1) SENSORS; 2) MOTIVATION; 3) COGNITION; 4) COMMUNICATION; and 5) ACTUATORS. Schelhorn *et al.* [21] present an agent model—STREETS—to model and predict pedestrian movement in subregional urban districts. Dijkstra *et al.* [22] also report a multiagent CA model for pedestrian movement and decision making. However, their objective is to visualize pedestrian activities in an environment. A special issue of *Transportation Research Part C* is dedicated to agent technologies for traffic and transportation, with a few works on traffic simulation, including Dia's work [23] on drivers' route choice behavior, Hidas' work [24] on lane changing and merging behavior, the work of Rossetti *et al.* [25] on the influence of different types of traffic information on the drivers' behavior in a commuter travel scenario, and the work of Wahle *et al.* [26] on the impact of different types of information on the benefits of advanced traveler information systems in a two-route scenario. Cetin *et al.* [27] implement a large-scale agent-based traffic simulation based on a simple queue model and parallel computing. Balmer *et al.* [28] provide an overview of the scheme of multiagent traffic simulation, which covers mobility simulation, activity generation, mode/route choice, replanning, and computing issues. A case study that simulated one million agents for the morning traffic of all of Switzerland is also provided. Raney and Nagel [29] present a framework for large-scale multiagent traffic simulations by adopting the concepts of mental layer and physical layer proposed in [28] and using the simulation model as its mobility simulation. Miller *et al.* [30] report a project called integrated land use, transportation, and environment, which is an agent-based integrated model of urban land use and transportation. Lotzmann [31] presents an agent-based framework—TRASS—for traffic simulation with a three-layer agent model consisting of artificial intelligence, robotics, and physical layers. Panwai and Dia [32] report a number of reactive-agent-based car-following models using artificial neural networks, two of which are demonstrated to outperform some traditional car-following models. More agent-based work on transportation can be found in a recent review paper by Chen and Cheng [33], which includes a dedicated section on multiagent traffic modeling and simulation. In addition, there is some work on the activity approach to modeling travel demand in agent-based traffic simulations [34]–[36].

However, a very important characteristic of ATS—growing—has not been well studied or implemented. In this paper, we present an iterative design process that illustrates the growing ability of ATS. From fewer rules to more rules, under the supervision of the experimenter (or ATS designer), agent behavior and interactions among agents become increasingly complex, and therefore, collective traffic phenomena emerge with more holistic characteristics.

As previously stated, ATS is an investigation into transportation challenges from the perspective of complex systems. Bearing this idea in mind, this paper aims to implement an iterative design process of growing ATS, consequently to generate complex traffic behavior, particularly traffic congestion, by incorporating simple consensus rules.

## III. Agent-Based Model and Rules

Agent-based methodology is currently a major technique for modeling artificial societies and other complex systems [3], [37]. Although there is no consensus on the definition of agent, there are a few widely accepted characteristics of the agent [38]: autonomy, sociality, learning, proactivity, and mobility.

Agent-based modeling is also considered to play an important role in the design of ATS [1], [16]. The agent is well suited to conceptualize participants in transportation systems in that they have the foregoing agent characteristics as well.

The agent-based modeling of ATS consists of three aspects [38]: 1) traffic agents; 2) traffic environment; and 3) traffic rules. The traffic agents in ATS are normally participants that exhibit autonomous and intelligent properties. The traffic environment may include road networks, traffic detectors, signals, activity places like houses, factories, shops, etc., communication infrastructure like traffic radio/broadcast, weather, and so on. The traffic environment of a single agent also includes other agents around it. Then, the traffic agents and the traffic environment act and interact according to traffic rules.

The traffic rules usually take the form of mathematical models in TTS. Comparatively complicated models tend to be adopted in TTS to better approach real transportation systems. However, we hold a different view on the design of traffic rules in ATS. On one hand, it is easy for people to reach an agreement over simple matters, but it is not as easy with complicated matters. Thus, we are inclined to be agreeable with simple objects and relationships. On the other hand, the studies of artificial life [39] and complex adaptive systems [40] suggest that simple components may be sufficient for the emergence of complex systems behavior. Therefore, we use simple consensus rules to design agents in ATS in accordance with the principle of simple objects and relationships.

The detailed design of those three aspects is presented as follows.

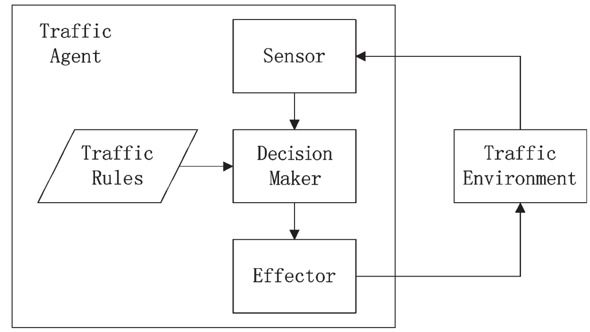



Fig. 2. Agent architecture.

### A. *Traffic Agents*

In this paper, the agents are driver–vehicle units, and no pedestrian is considered.

A well-developed ATS platform is supposed to include transportation subsystem, social and economic subsystem, logistical subsystem, and other urban systems to achieve an integrated solution to transportation issues [2]. However, this paper, as a prototype of ATS, only considers transportation subsystem and agent activities related to the social and economic subsystem.

The agents can either stay in an activity place or be on a trip from one place to another. The agents' moving behavior, destination, and dwelling time at the destination are all determined by rules that will be presented in Section III-C. It should be noted that the agents are modeled as reactive agents without learning ability.

The agent architecture adopted in this paper is depicted in Fig. 2. An agent perceives environmental information through a sensor module. This information, together with traffic rules, is fed into a decision maker. Then, the decision is put into action by an effector, and thus, the agent's maneuver is performed. The decision-making process is illustrated in Fig. 3.

### B. *Traffic Environment*

This paper is done with the multiagent platform Swarm [41], [42]. Swarm is a software platform for agent-based models, which was originally developed at the Santa Fe Institute, Santa Fe, NM. It includes a conceptual framework for modeling agents and many handy tools for human–computer interaction. Therefore, it is suitable for the multiagent simulation of complex systems. A comparison between Swarm and several other agent-based simulation platforms can be found in [43]. It is the pioneer of the framework and library platforms and has its own advantages, such as stable, small, easy to organize models with the concept of "swarm," etc. Java Swarm 2.1.1, which is a Java version of Swarm, was used as the platform to implement the design of this paper.

The traffic environment in this paper includes a road network, traffic signals, and three types of activity places: 1) dwelling; 2) working; and 3) entertaining places.

The simulation scope, which is called the City of ATS, is a 166-pixel-by-166-pixel square, as illustrated in Fig. 4. The layout of the road network and activity places in the City of ATS is actually an imitation of the map of Beijing, China. There

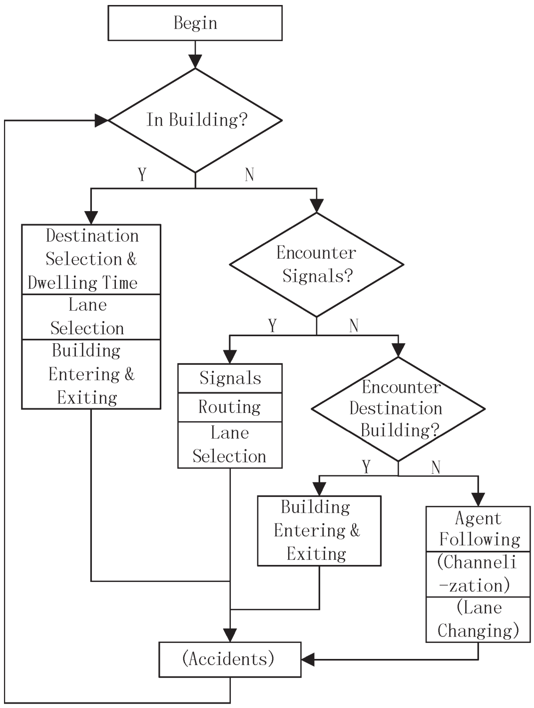



Fig. 3. Decision-making process. Traffic rules are in rectangles. The rules in parentheses are optional. The details of the rules are described in Section III-C.

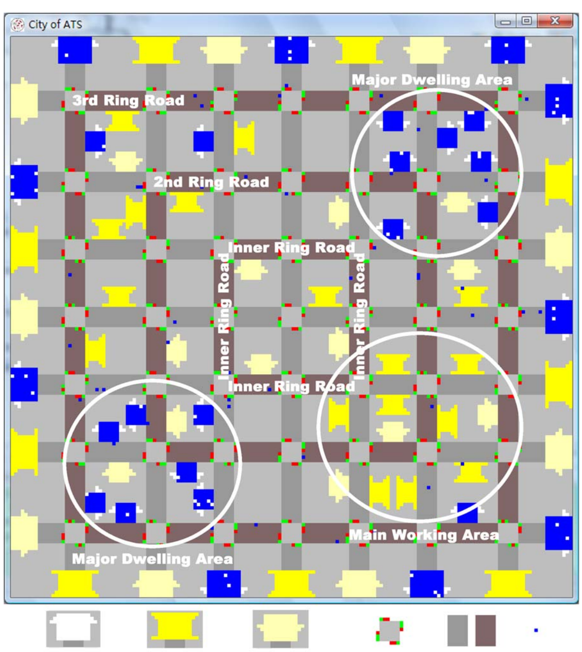



Fig. 4. Layout of the road network and activity places of Swarm-based ATS, with three ring roads, two major dwelling areas, and a main working area. The traffic elements in the virtual world, which are called "the City of ATS," include roads, activity places, intersections, traffic lights, and agents. Note that the places in blue or dark color in gray tone are filled with agents, which is also the case for Figs. 6 and 10.

are three ring roads, named the inner ring road, the second ring road, and the third ring road, respectively. All roads are two-way roads with three lanes in each direction. The width of the lane is one pixel. All the intersections are signalized. In addition, there are multiple activity places distributed in the city along roads or at borders. The size of each place determines its capacity. Note that, in Figs. 4, 6, and 10, the places in blue or dark color in gray tone are filled with agents. There are one main working area at the bottom right and two major dwelling areas at the bottom left and top right, respectively. (These areas are marked by circles in Fig. 4.) The maximum number of agents is determined by the capacity of all dwelling places. The agent size is one pixel by one pixel.

The states of agents and traffic signals are updated step by step. One discrete-time step represents 1 min in our computational experiments.

### *C. Traffic Rules*

The following nine rule sets were designated and deployed in the prototype:

1) agent following (AF);
2) building entering and exiting (BEE);
3) signals (S);
4) routing (R);
5) lane selection (LS);
6) destination selection and dwelling time (DSDT);
7) lane changing (LC);
8) channelization (C);
9) accidents (A).

These rule sets are divided into two categories. The first six are fundamental or essential, which assure the agents' activities and movement. The last three are optional, which can be added in to enhance the agents' mobility and traffic features. The rule sets are described as follows.

*1) AF:* This rule set determines how an agent moves on a single lane. An agent only moves along the direction of the road.

> At each step, if the immediate pixel in front of an agent on the road is neither a traffic light nor occupied by another agent, it moves forward by one pixel.

This rule implies that all agents move at the same speed.

*2) BEE:* This rule set determines when and how an agent enters or exits a building. Hereafter, building is a concise and general way to indicate activity places.

1) At each step, if an agent is one pixel to the entrance of its destination building and there is at least one vacancy inside, it enters, or if the capacity is reached, it waits at the entrance.
2) At each step, if an agent's planned dwelling time (derived from DSDT) in the building is reached or exceeded and the exit of the building is vacant, it exits, or if the exit of the building is occupied, it keeps staying in the building.

Exit is downstream to the entrance of the same building.

*3) S:* This rule set determines the traffic signal timings and the agent's reactions to signals. In this paper, no amber or all-red intervals are considered. All right-turn signals are always green.

1) The phases are switched in the following sequence: horizontal through, horizontal left turn, vertical through, and vertical left turn.
2) The initial phase is randomly set for each intersection.

3) At each step, if the immediate pixel in front of an agent is a traffic light, it follows the light.

*4) R:* This rule set determines which way an agent will go after the next intersection.

> If an agent's vertical distance to the destination at the next intersection is longer than its horizontal distance to destination, it selects the vertical road towards its destination; otherwise, it selects the horizontal road towards its destination.

The timing of such decisions depends on the options of the LC rule set. If LC is not allowed, then routing decisions are made whenever an agent exits a building or passes an intersection. If LC is allowed, then routing decisions are made whenever an agent enters an intersection. For channelized intersections, the decision is made before entering the channels. For other intersections, the decision is made immediately before the lights.

*5) LS:* This rule set determines which lane an agent enters when it exits a building or passes an intersection.

> If lane changing is not allowed, routing is done before lane selection. An agent selects the lane corresponding to the selected road from the Routing rule set. If the lane is not occupied, it enters; otherwise it waits. If lane changing is allowed and an agent exits a building, it enters the right-side lane. If lane changing is allowed and an agent passes an intersection, it first selects the middle lane; if the lane is occupied, it selects the right-side lane; if the lane is also occupied, it selects the left-side lane; if all the lanes are occupied, it waits.

*6) DSDT:* This rule set determines which building is the next destination when an agent leaves a building and for how long it will dwell in the next building. A uniformly distributed decimal fraction (hereinafter referred to as "probability") is generated for each agent that is leaving or entering a building. If the decimal is smaller than 0.95, then the agent is called a "high-probability" agent; otherwise, it is called a "low-probability" agent. For a given time, one of the three types of buildings is called a "high-probability" type, and the other two are called "low-probability" types.

> For a high-probability agent, if it is leaving a low-probability type building, a high-probability type building is randomly selected as destination; if it is leaving a high-probability type building, a new high-probability type building is randomly selected. For a low-probability agent, if it is leaving a building, a low-probability type building is randomly selected as destination.
>
> If an agent is entering a building, a random positive number that is smaller than T is assigned to it as its planned dwelling time. However, for a high-probability agent, if it is entering a high-probability type building, an extended dwelling time is added to the plan.

T is 100 in our experiments. The extended dwelling time is determined by assuring that the total planned dwelling time exceeds the current time section. There are three time sections a day, as follows:

Section 1: from 6 A.M. to 5 P.M. with working places being the high-probability type;

Section 2: from 5 P.M. to 9 P.M. with entertaining places being the high-probability type;

Section 3: from 9 P.M. to 6 A.M. with dwelling places being the high-probability type.

*7) LC:* This rule set determines when and how an agent changes lane. This is an optional rule set. If it is activated, then LC is allowed; otherwise, LC is prohibited.

> If the immediate pixel in front of an agent is occupied by another agent and, in a neighboring lane, the lateral pixel and its next downstream pixel are both vacant, the agent will change lane and move a pixel forward. If the agent is in the middle lane, the right side will be attempted first.

*8) C:* This rule set implements channelization near intersections. The length of channels is three pixels. This is an optional rule set. It effects only if the LC rule set is activated. If it is activated, then the routing rule set will be affected.

> If an agent is no more than two pixels to channels and is not in the lane related to the selected road from the Routing rule set, it waits for the chance to change lanes. If an agent is already in a channel, it can no longer change lanes.

*9) A:* This rule set determines how an accident happens. This rule set is optional.

1) At each step, there is a 1% probability that an accident between an agent and its neighbor may happen on the inner ring road or inside roads.

   Note that the foregoing probability is set to be 1%, which is normally higher than that in reality, just to observe an accident and its consequence within a short period of time.
2) If an accident happens, both involved agents stop where they are.
3) If an accident already occurred, no more accidents will happen.

It is worth noting that there are some subjective simplifications and choices in the designation of the foregoing rules, including the identical speed of all agents, the omission of amber and all-red phases, etc. In addition, note that some details about the rules, for example, the values of some parameters, which are needed for coding, are omitted. We found in our research that those are not critical for the purpose of this paper to implement an iterative design process of ATS and to generate emergent traffic behavior from simple consensus rules but should be considered in future research in terms of approaching reality.

## IV. Computational Experiments

Computational experiments, as opposed to field experiments, are repeatable, controllable, and configurable experiments conducted on a computer-based artificial system. In the concept of ATS, computational experiments, together with artificial systems, are ideal trials to validate goals and objectives or to evaluate strategies and decisions for transportation issues [2].

Emergence is central to the study of complex systems. Goldstein [44] defined emergence as "the arising of novel and coherent structures, patterns, and properties during the process of self-organization in complex systems." It is often used to describe the unplanned collective behavior of complex systems that emerges from the interaction of simple agents. Whereas it is essentially an experimental, observational, and explanatory concept, it plays a key role in the analysis of ATS [1].

The rule sets presented in the previous section can be combined in different configurations to construct different versions of the prototype. Computational experiments can be conducted on each version. We adopted the method of experiment design in [3], from fewer rules to more rules, and followed the idea of feedback and redesign for ATS depicted in Fig. 1 to design computational experiments in this paper. That is, with a combination of rules that assure the agents' basic ability of movement as an initial version, by gradually appending more rules that add more features to the prototype, we implemented four versions of the prototype and performed computational experiments on each one. Then, emergence-based observation was used as the main method to describe and explain the emergent traffic behaviors, which focus on congestions and the inefficiency of specific road sections or the entire road network, which resulted from the inability of movement or the decision making of agents.

In addition to the qualitative analysis with emergence-based observation, quantitative experimental results were evaluated using statistical analysis as well. To this end, two performance indices were defined. Specifically, space occupancy, which is defined as

$$\text{space occupancy of a road} = \frac{\text{number of agents on the road}}{\text{capacity of the road}}$$

was used to evaluate the congestion level of a specific road. The average trip time, which is defined as

$$\text{average trip time} = \frac{\text{total finished trip time}}{\text{total number of finished trips}}$$

was used to measure the efficiency of the entire road network.

The validation of this paper at the current stage is not a major concern. As stated in Section I, the aim of this paper is to generate complex traffic behavior from simple consensus rules by iteratively constructing a prototype of ATS. However, qualitative validation is expected and useful. This can be considered in two aspects. First, the traffic rules designed in the previous section make sense and are reasonable for research purposes. Consequently, the emergent traffic phenomena from these rules sound reasonable, at least in the experiment scenario. Second, if any emergent traffic behavior bears a similarity to real traffic conditions, then it can be considered a validation for the prototype. The emergent traffic congestions observed at rush hour in the computational experiments can be viewed as a validation of this kind, which will be reported in the following sections.

### A. No LC

Rule sets AF, BEE, S, R, LS, and DSDT were deployed in the prototype. In this version of "the City of ATS," no agent changes lanes, and they move like a platoon. A total of 1412 agents, which is the largest number of agents that can be held in all the dwelling places in the map, were put in the city. Note that the prototype starts from midnight (time in "the City of ATS"), and all agents are initially in the dwelling places, which is also the case for all the other experiments.

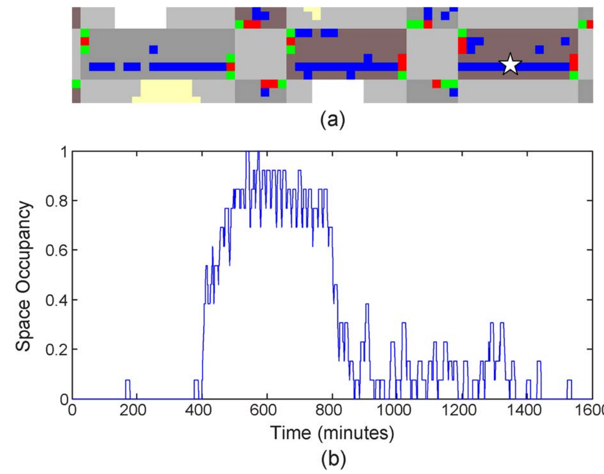



Fig. 5. (a) Emergent congestion at the morning rush hour, with a star marking the observed road. (b) Space occupancy of the observed road. (The space occupancy is adjusted such that only the agents and capacity of the middle lane are considered to highlight the single-lane congestion.)

A screenshot of several local road sections where congestion happens in the rush hour is illustrated in Fig. 5(a). We can see that long queues form at rush hour. The curve in Fig. 5(b), which shows the space occupancy of the observed road [marked by a star in Fig. 5(a)] over time, agrees with this observation. The space occupancy is over 0.7 between 500 and 800 min, which indicates a heavy congestion. The space occupancy herein is slightly different from that defined in an earlier part of this section in that only the agents and the capacity of the middle lane of the observed road are considered to highlight the single-lane congestion specifically in this experiment.

In this experiment, road resource is not well utilized due to the very long queues that only occupy a single lane. As a matter of fact, the congestion results from the lack of freedom in the agents' driving decision. The agents have no choice other than following their leading agents or driving ahead. In the next experiment, the freedom of driving will be enhanced by enabling LC to see if the efficiency of the road network will be increased.

### B. No Channelization With LC

In addition to the rules deployed in Experiment A, the LC rule set was added into the prototype. Again, 1412 agents were put in the city.

We can observe that the agents' mobility is significantly increased as they can change lanes. The traffic capacity of the road network is increased accordingly. Long queues can most of the time quickly dissipate in the experiment. The road network is utilized in a more efficient way in this experiment than in Experiment A. We did not observe many agents waiting in queues for a long time as in Experiment A until the following situation arose. In this situation, the only severe congestion in the experiment happens, as we can see in Fig. 6(a), because some destination places are full of agents and still many agents want to enter. The space occupancy of the same observed road

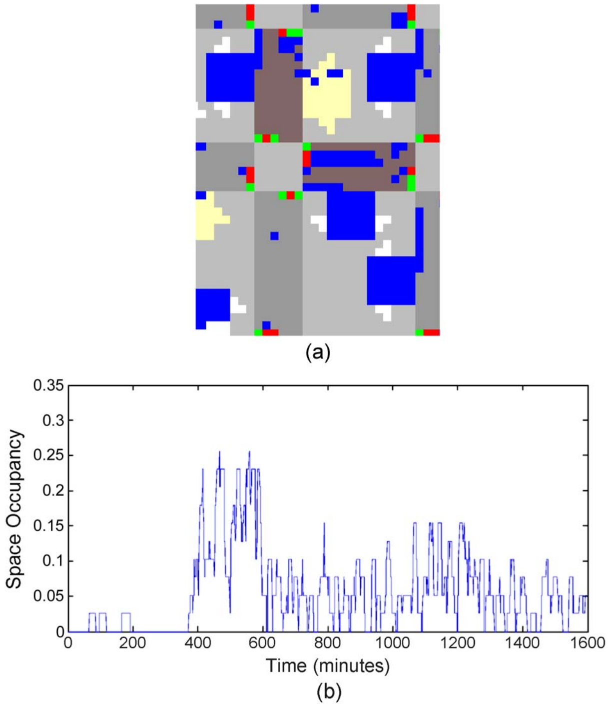



Fig. 6. (a) Emergent congestion that happens after the capacity of a number of dwelling places is reached. (b) Space occupancy of the same observed road as in Fig. 5(a).

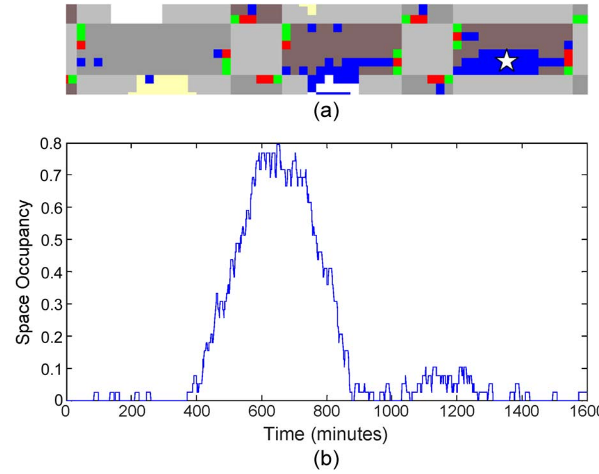



Fig. 7. (a) Emergent congestion that looks like the congestion in reality during the morning rush hour, with a star marking the observed road. (b) Space occupancy of the observed road.

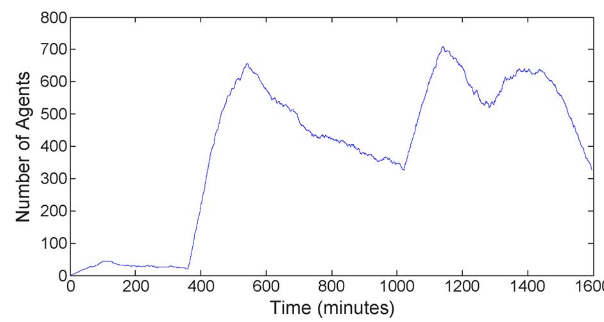



Fig. 8. Number of the agents on the road.

as in Experiment A shown in Fig. 6(b) also indicates that there is no apparent congestion at rush hour.

### C. Activities of Agents With LC and Channelization

In this version, the C rule set was added to the prototype of the previous experiment, which means agents have to complete LC before they enter channels. A total of 1012 agents were put in the city. Note that 400 less agents were involved in this case to avoid a kind of severe congestion, which will specifically be discussed in Experiment E.

In this experiment, it was observed that the efficiency of the road network is lower than that in Experiment B. In the rush hour, agents often have to wait in queues for a longer time than that in Experiment B to clear intersections. It indicates that the deployment of the C rule set decreases the efficiency of the road network.

Fig. 7(a) shows the congestion in this case that happens on the same road sections as in Experiment A. Actually, the road sections connect the major dwelling area at the bottom left with the main working area at the bottom right. We can also observe the same kind of congestion on the road sections that connect the other major dwelling area at the top right to the main working area. The space occupancy curve shown in Fig. 7(b) indicates that the congestion is considerably heavy.

Fig. 8 shows the number of agents on the road over time in this experiment. Three peaks can be observed, which, from left to right, correspond to the morning rush hour (360–720 min, i.e., 6–10 A.M.), the afternoon rush hour (1020–1260 min, i.e., 5–9 P.M.), and the period when agents go to dwelling places from entertaining places in the evening (1260–1500 min, i.e., 9 P.M. to 1 A.M. of the next day), respectively.

### D. Accidents

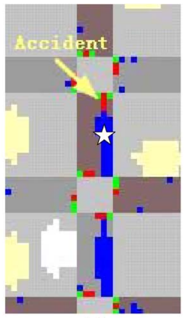
The accidents rule set was added in this version of prototype. Again, a total of 1012 agents were put in the city. An accident happened randomly between two adjacent (leading and following) agents on the inner ring road. Fig. 9(a) illustrates the congestion caused by the accident.

Congestion is caused by the accident and is spreading towards upstream roads, as we can see in Fig. 9(a). Fig. 9(b) shows the space occupancy over time of the observed road under two circumstances—no accident and accident. Obviously, there is no congestion on this road if there is no accident. However, after the accident happens, the space occupancy of the road quickly rises to 0.6, which indicates a moderate congestion. Then, the accident is cleared. After that, it takes quite a while—two times longer than that the congestion accumulates—for the congestion to dissipate and for the traffic on the road to return to normal.

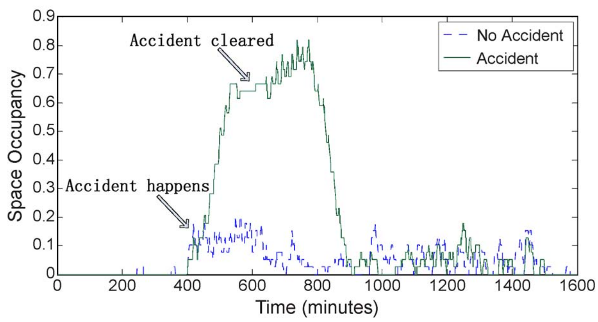
### E. Deadlocked Congestion

In this experiment, the rule sets deployed were the same as that in Experiment C. However, 400 more agents were put in the city in this case than in Experiment C. That is, a total of 1412 agents were involved.

In this case, we observed a kind of severe congestion emerging from the local interactions of many agents on two adjacent

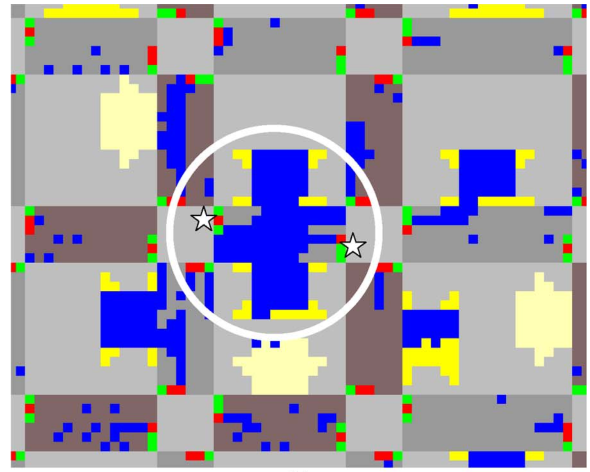



(a)

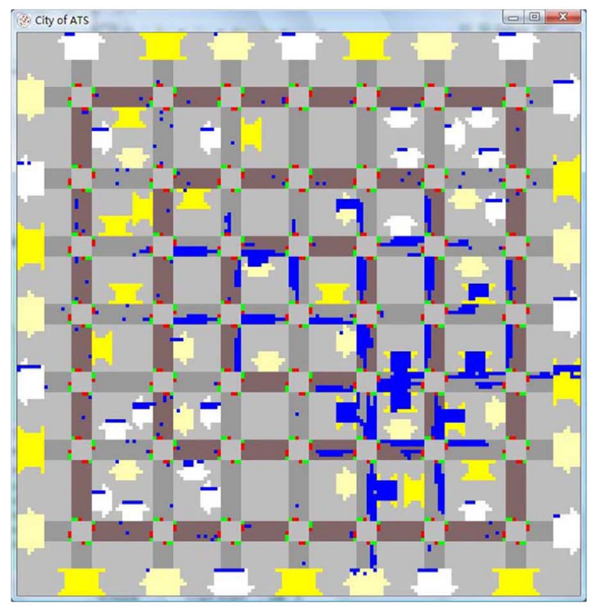



(b)

Fig. 9. (a) Congestion caused by an accident, with a star marking the observed road. (b) Space occupancy of the observed road.



(a)




(b)

Fig. 10. (a) Deadlocked congestion in the bold circle, with stars marking the intersections where agents try to make a U-turn. (b) Traffic gridlock resulted from the deadlocked congestion.

roads in opposite directions, as we can see in Fig. 10(a). The agents on the roads of both directions want to make a U-turn at the intersections to go to the working places on the opposite side of the street. But the long queues on both roads prevent the agents on the other side from doing so. In a word, a deadlock is reached on both sides of the street. Thus, a kind of congestion, which we call deadlocked congestion, happens. If the agents at the head of the queues trapped in a deadlocked congestion insist on making a U-turn, then the congestion cannot dissipate by itself, which, unfortunately, was the case in the experiment.

Even worse, local deadlocked congestion can result in traffic gridlock in the entire road network if no measures are taken. Fig. 10(b) illustrates the traffic gridlock caused by the deadlocked congestion in the experiment. Most of the agents in the city are trapped and unable to move at all.

To avoid the deadlocked congestion, we adjusted the signals marked by stars in Fig. 10(a) in favor of the left-turn phase. Specifically, we changed the configuration of green times of the through phase and the left-turn phase from 5:3 to 4:4. Then, we run the prototype again. No deadlocked congestion happened this time.

### *F. Comparison on the Efficiency of Road Network*

We also performed several additional experiments to quantitatively compare the efficiency of the entire road network in Experiments A, B, and C. The performance index average trip time defined in the first part of this section was used to measure the efficiency. To make the comparison context consistent, we put 1012 agents in Experiments A and B again, as in Experiment C. The comparison result is depicted in Fig. 11.

We are only concerned with the relative positions of the curves in the interval of (near) steady state. As we can see in

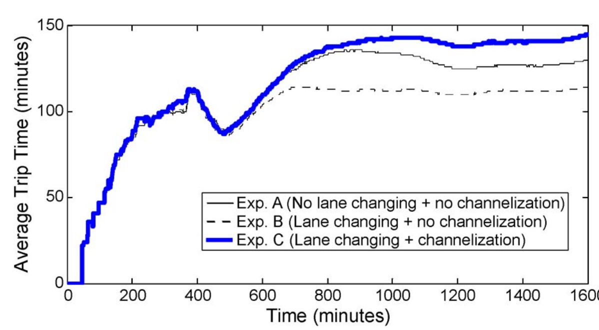



Fig. 11. Average trip time over time of three versions of prototype, each with 1012 agents.

Fig. 11, the three curves have clear steady relative positions after 1000 min. That is, the version of prototype in Experiment B featuring LC and no channelization is the most efficient, and the version of prototype in Experiment C featuring LC and channelization is the least efficient, with the version of prototype in Experiment A featuring no LC and no channelization in the middle.

## V. Discussions

In the previous section, the methods and results of six computational experiments were reported. Both emergence-based observation and statistical analysis were used to evaluate the experimental results. Five kinds of congestion, none of which was planned in the design phase, emerged from the interactions of the simple agents modeled by those simple rules expressed in Section II.

In Experiment A, the congestion features long moving queues and inefficient utilization of lanes. This kind of congestion mainly results from no LC. Since agents cannot change lanes, severe congestion can happen on certain lanes even when the corresponding roads are far from congested [see Fig. 5(a)]. Accordingly, road resource is not utilized efficiently. It implies that, to construct an efficient ATS, rules may not be too simple. The flexibility of rules directly affects the efficiency of ATS.

In Experiment B, the congestion happens upstream of full buildings. If no agent exits a full building, then the agents packed outside the congestion do not move. This kind of congestion happens because the agents insist on entering those full buildings, which is determined by the building-entering-and-exiting rules.

In Experiment C, the congestion happens on the shortest paths that connect the major dwelling areas and the main working area. Such congestion happens mainly because too many agents drive on the same road in the same direction during a period of time. This is much like the congestion due to the flow going to work in reality and thus can be viewed as a qualitative validation of this paper.

In Experiment D, the congestion results from an accident and can spread upstream very quickly. This kind of congestion happens because agents cannot change route in response to real-time situations. It suggests that if an accident happens in channels, then the consequence may be very harmful. It would cause severe congestion within a short period of time on the road that otherwise is easy to pass. Moreover, quite a while is needed for the congestion to dissipate and for the road traffic to return to normal after the accident is cleared [see Fig. 9(b)]. The ATS can be used to train personnel on how accidents would influence the traffic with the aid of the accident feature.

In Experiment E, the deadlocked congestion happens on a two-way road. Such a congestion cannot dissipate by itself also because agents cannot change route in response to real-time situations. Evidently, a deadlocked congestion is rather harmful to network capacity. It deserves to be dealt with in a timely manner before it could cause severe congestion in a large area of the entire road network [see Fig. 10(b)]. The emergence of such congestion relates to many factors. The experimental result suggests that it can be avoided by reducing the agent number or adjusting the traffic signals.

Through Experiment F, we want to argue that statistical analysis and evaluation can also be carried out in ATS to support the quantitative analysis of transportation strategies and solutions. The result of this specific experiment shows that under the configuration of rules in this paper, the LC of agents can substantially increase the efficiency of the entire road network. However, channelization on input roads of intersections can decrease the efficiency even more. The reason is that the agents waiting to change lanes by the end of channels block other agents to enter the empty channels, which dramatically degrade the efficiency of the road network. This is an emergent property that has to be investigated in an integrated fashion, as was done in this paper.

From the foregoing experiments, we can conclude that the operational efficiency of a road network is affected by a number of factors, including the number of agents, the freedom of the agents' movement, the traffic signals, and the accident management. Through computational experiments, the ATS can be an effective tool for transportation engineers and managers to generate and analyze traffic phenomena and to evaluate and validate traffic rules in both qualitative and quantitative ways.

## VI. Conclusion

Transportation systems need to be treated in a systemic and synthetic manner due to their properties related to complex systems. ATS is deemed to be a promising effort towards this direction. However, much more work needs to be done to advance the research on ATS. The key issues in the development of ATS include modeling, experimenting, decision making, and computing. This paper is only a beginning step in the direction of solving the first two issues.

In this paper, a prototype of ATS based on Swarm was implemented, and six computational experiments were conducted, which provides an introductory case for the procedure of design and computation of ATS. The experimental results demonstrate the ability of the prototype to generate traffic behaviors, particularly traffic congestion, from simple consensus rules and to analyze traffic phenomena and evaluate traffic rules in both qualitative and quantitative ways.

Future work can expand by growing in two dimensions. One is depth. That is, based on this simple prototype, conducting more computational experiments and revising traffic rules, if necessary, to investigate emergent traffic behaviors and related interesting issues in a deeper way, such as what are the key factors in the emergence of deadlocked congestion, how or in what ways we can avoid or alleviate such congestion, etc.

The other is breadth. It means expanding features of the prototype of ATS. Such expansion would bring about expansibility issues and scalability issues. To meet these challenges, the development on more powerful programming platforms and computing platforms is appealing. Work in this direction includes the following: 1) extending rule sets to express more behaviors of travelers, such as finer agent-following behavior involving various speeds, different destination-choosing strategies, different routing strategies, and different activity patterns; 2) integrating more measures of traffic management and control, such as variable message signs, adaptive traffic signal control, and traffic radio of route guidance information; 3) integrating more influencing factors of other urban systems, such as weather, social and economic information, and legal and regulation information; and 4) carrying out more comprehensive computational experiments to support applications such as traffic forecasting and performance evaluation of traffic measurements.

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