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Modeling and Analyzing Transportation Systems Based on ACP Approach

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***Abstract*—The ACP (Artificial societies, Computational experiments and Parallel execution) approach has provided us an opportunity to look into new methods in addressing transportation problems from new perspectives. In this paper, we present our works and results of applying ACP approach in modeling and analyzing transportation system, especially carrying out computational experiments based on artificial transportation systems. Two aspects in the modeling process are analyzed. The first is growing artificial transportation system from bottom up using agent-based technologies. The second is modeling environment impacts in simple-is-consistent principle. Finally, two computational experiments are carried out on one specific ATS, Jinan ATS, and numerical results are presented to illustrate the applications of our method.**

***Index Terms*—ACP approach, artificial transportation systems (ATS), computational experiment, agent, simple-is-consistent**

I. Introduction

The urban congestion problem is increasingly becoming a major issue in social, economic, and environmental concerns around the world. According to a recent survey, the fifteen major cities in China are losing about one billion RMB Yuan (about $150,000,000) every day due to traffic congestions. The number of motor vehicles ownership in Beijing, the capital of China, has exceeded 4,510,000 by September 12, 2010. So many vehicles have caused particularly serious congestions in this city. For example, the average time of Beijing residents' commuter trip has reached 52 minutes, which is the longest among all cities in China [1].

The main difficulty of transportation modeling and analysis lies in the ability to reproduce an authentic transportation environment within the laboratory, as real world traffic scenarios are both too huge and too complex to be modeled [2]. Traffic simulation has been considered as one promising tool in this area. Theoretically, simulation software can be used widely in transportation modeling and analysis. However, it still faces many challenges and its application is restricted in very limited areas. Conclusively, there are two insurmountable obstacles in the modeling and analysis road using simulation software. The first is how to generate individual travel demand for each person. Most traffic simulation software uses aggregating methods and requires historical origin-destination (OD) data as input. It is not only very costly to collect OD data in wide area, but also very difficult, if not impossible, to transfer dynamic OD data into individual travel path. Second, almost all simulation software focuses on direct traffic-related activities alone and neglects other indirect facilities and activities, such as weather, legal and social involvements. As environments exert a profound influence over traffic, it is impossible to build an accurate suitable model for transportation R&D using traditional methods[3].

Although the limitations of traffic simulation software have been noticed soon after it was introduced into the transportation study, there was little can be done to deal with them for a long time. However, the status has changed evidently since the early of 2000s. First, the theory of traffic demand generation based on activity (TDGA) is becoming mature and has been applied in transportation planning in many developed countries[4-6]. In U.S., more than 40% of large metropolis plan organizations (MPOs) and 20% of the medium and small MPOs have adopted, or plan to adopt, TDGA models in their work[7]. Second, the theory of artificial life and artificial society has been proved to be a feasible approach in the research of the complexity of society and many achievements have been reached. For example, Epstein and Axtel established "the world of sugar" to simulate the human society[8], Los Alamos laboratory developed the epidemic simulation software based on individual behavior[9], Research Triangle Institute (RTI) used and extended an iterative proportional fitting method to generate a synthesized, geospatially explicit, human agent database that represents the US population in the 50 states and the District of Columbia[10]. All these achievements demonstrated that the integrative artificial society can be constructed from bottom up. Third, high performance computing is becoming more and more popular. Not only software and hardware of one computer have advanced rapidly, but also many networked computing technologies that can provide enormous computing capability utilizing the internet have been proposed. So that heavy demand on computing and storage can be satisfied.

The ACP (Artificial societies, Computational experiments, and Parallel execution) approach was originally proposed in [3,12], as a coordinate research and systematic effort with those emerging methods and techniques, for the purpose of modeling,

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analysis, and control of complex systems. Basically, this approach consists of three steps: modeling and representation with *A*rtificial societies; analysis and evaluation by *C*omputational experiments; and control and management through *P*arallel execution of real and artificial systems. The complex systems considered in the ACP approach usually have the following two essential characteristics [12, 13]:

- *Inseparability*. Intrinsically, with limited resources, the global behaviors of a complex system cannot be determined or explained by independent analysis of its component parts. Instead, the system as a whole determines how its parts behave.
- *Unpredictability*. Intrinsically, with limited resources, the global behaviors of a complex system cannot be determined or explained in advance at a large scope.

Clearly, real-world transportation systems, such as large scale urban traffic systems, exhibit the two characteristics considered in the ACP approach. However, the motivation for employing the ACP here is mainly due to the lack of timeliness, flexibility and effectiveness of the current simulation systems in transportation.

The focus of this paper is to present our works and results of applying ACP approach in modeling and analysis transportation system, especially establishing artificial transportation systems. The rest of this paper is organized as the following: Section II introduces the process of growing artificial transportation systems from bottom up and lists some basic rules in the implementation; Section III proposes the method to model environment impact and demonstrates the process by modeling transportation scenarios in adverse weathers; Section IV verifies our method by illustrating one case study we carried out in Jinan, China; Section V draws conclusions with some remarks on future works and directions.

II. Growing Artificial Transportation Systems from Bottom up

Transportation systems are becoming increasingly complex, nearly incorporating all aspects of our society. As more and more facilities and activities are involved in transportation, the connections between transportation system and urban environment are also getting closer and closer. All these make the top-down reductionism method of traditional simulation very ineffective and there are still no effective method to model and analyze transportation systems. However, since one is inclined to be agreeable with simple objects or relationships, it is useful to build agent models based on agreeable simple objects or relationships, then develop a bottom-up approach to "grow" artificial systems and "observe" their behaviors through interactions of simple but autonomous agents according to specified rules in given environments. In this context, ACP approach is proposed to grow holism artificial traffic systems (ATS) from bottom up [14-16]. Here the main idea is to obtain a deeper insight of traffic flow generation and evolution by modeling individual vehicles and local traffic behavior using basic rules and observing the complex phenomena that emerge from interactions between individuals. In the process of growing ACP-based ATS from bottom up, agent programming and object-oriented techniques are extensively used for social and behavioral modeling [17,18].

Based on the concepts and methods of artificial society and complex system, ATS differ from other computer traffic simulation programs mainly in two aspects. First, the objective of traditional traffic simulation is to represent or approach the true state of actual traffic systems, while the primary goal of ATS is to "grow" live traffic processes in a bottom-up fashion and provide alternative versions of actual traffic activities. In sociologist Theodor Adorno's words, ATS reveals traffic properties based on the belief that "only through what it is not will it discloses itself as it is". Second, ATS must deal with a wide range of information and activities. Most of the current traffic simulation focuses on direct traffic-related activities, while ATS generates their traffic processes from many indirect facilities and activities, such as the weather, and legal and social involvements. Some details about the first aspect will be explained in the following part of this section, while the second aspect will be the focus of the next section. Both of the introductions are very brief, for more details, readers can refer to [11]-[17].

Because individual's behaviors take the place of OD matrix as input data in ATS, the first step in building ATS is to generate reasonable population for specified area. We implemented one separate module, artificial population module (APM), and modeled each person as one agent in this module. APM provides mechanisms to assign attributes to an agent as well as how these attributes change over time. In the design process of APM, plenty of theories and models in sociology and anthropology area are adopted. For example, the population structures in APM are divided into three types, namely, increasing type, decreasing type and static type, which are widely used by sociologists in their research work.

Generally, travel is not undertaken for its own sake but rather to participate in an activity at a location that is separated from one's current location. After constructing activity plans for each member of a population, travel demand can be derived from the fact that consecutive activities at different locations need to be connected by travel. While one agent is carrying out its 24-hour activity plan, its autonomy is mainly reflected in its decision process, which is heavily influenced by its own habit and experience. All these features formed the foundation of our activity-based travel demand generation method, which fit well into the paradigm of multi-agent simulation and provide us the feasible approach to generate individual travel demand.

Once the travel demand is generated, the agent needs to select the properties of travel activities. There are mainly two types of factors that influence the selection process. One is the internal properties of the options, such as the capacity of place, the length of travel path, etc. The other relates to individual's psychology and behavior, such as its familiarity of travel path, its feeling of the convenience of the travel mode, etc. Designing and establishing appropriate models for the latter is one of the focuses of our works. These factors are closely connected with the social and behavioral characteristics of individual and their effects are usually expressed using natural language. Modeling the autonomous ability of one agent using discrete choice models (DCM) is an simple but compelling method that has been verified in various areas, especially in social and economic researches, and is also adopted by our work. In the following, we will demonstrate some examples of them by showing their usages in the decision process of one agent.

- Probabilities of performing activity

The probability that an agent i performs the k_{th} activity in its complete all-day plan is calculated by a logistic model, as shown in below

$$P_{ik} = \frac{\exp(\alpha_k \cdot gender_i + \beta_k \cdot age_i + \gamma_k)}{1+\exp(\alpha_k \cdot gender_i + \beta_k \cdot age_i + \gamma_k)}$$

where $gender_i$ and age_i are gender and age of agent i, α_k and β_k are coefficients, γ_k is constant term. Typical values of α_k, β_k and γ_k will be listed in section IV of this paper.

- Selecting travel mode

The probability of agent k selecting travel mode m is calculated by the following random utility model (RUM):

$$P_m^k = \frac{\exp(e_k / M_{km} + f_k / T_{km} + g_k R_m)}{\sum_n \exp(e_n / M_{kn} + f_k / T_{kn} + g_k R_n)}$$

where M_{km} is the ratio of travel cost to individual k's income, T_{km} is the travel time using mode m, R_m is the degree of convenience (from 1 to 10) of mode m, e_k, f_k, and g_k are coefficients.

- Selecting activity place

Agent uses maximum entropy model (MEM) to select activity place:

$$P_{j|i} = \frac{\exp(\alpha D_{ij} + \beta \log(C_j) + \gamma)}{\sum_{r\in\Omega} \exp(\alpha D_{ir} + \beta \log(C_r) + \gamma)}$$

where $P_{j|i}$ is the possibility of selecting place j for the next activity when current place is i. D_{ij} is the distance from place i to place j, C_j is the capacity of place j, and Ω is the set of all the optional places for the next activity, α and β are coefficients, γ is constant term.

III. Modeling Environment Impacts

It is well known transportation is tightly connected with the social environment. From microcosmic individual's psychology and driving behavior to macro travel gross and travel distribution, all are heavily impacted by surrounding environment, such as economic, weather, etc [19]. The mechanisms by which the environment influences the traffic are very complex and there are still many disputes about how to represent them as a whole [20]. However, as to simple artificial objects, most of current conclusions about the influences they received from the environment are consentaneous. So if simple objects and local behavior are modeled using these widely approved conclusions, the complex integrative phenomena that emerged are also expected to be understandable and agreeable. We call this principle "simple-is-consistent". Using this principle, we have established the rule bases to model the influences that transportation subsystem received from other subsystems.

In the following, we will use adverse weather (rain) as an example to illustrate the models in ATS. For each individual in ATS, his experience of the influences of adverse weather can be expressed using a two-step model, which is composed of travel demand generation process and traveling process. In the first step, travel demand of individual i can be denoted as:

$$\begin{aligned}(\mathbf{A}_i, \mathbf{D}_i, \mathbf{P}_i, \mathbf{M}_i, \mathbf{ST}_i, \mathbf{ET}_i) = \\ (A_{i1}, A_{i2}, ..., A_{in}; D_{i1}, D_{i2}, ..., D_{in}; P_{i1}, P_{i2}, ..., P_{in}; \\ M_{i1}, M_{i2}, ..., M_{in}; ST_{i1}, ST_{i2}, ..., ST_{in}; ET_{i1}, ET_{i2}, ..., ET_{in})\end{aligned}$$

where $\mathbf{A}_i, \mathbf{D}_i, \mathbf{P}_i, \mathbf{M}_i, \mathbf{ST}_i, \mathbf{ET}_i$ are vectors of individual i's activities to be performed, travel destinations, travel paths, travel modes, travel start time and end time, respectively. Usually, when adverse weather happens, individual will adjust its activity plan to avoid unnecessary travel. According to the happen time of adverse weather, the adjustment measures include moving up or putting off the happening time, lengthen or shorten the duration, and so on. If there are not enough time in the schedule, some activities, especially those discretionary activities, such as shopping, sport, eating out, and entertainment, will be canceled eventually. Besides happen time and duration, destination and sequence can also be adjusted. All these adjustments can occur either before adverse weather, when we listen to the weather forecasting and rearrange our activities accordingly, or in adverse weather, when adverse weather happened unexpectedly. Obviously, no matter whenever the adjustment occurs, it can be well represented by adding new rules in our model.

In the traveling process, adverse weather can influence individual's driving behavior. Adverse weather can degrade the road performance due to the changes on the driving condition (e.g. reduced visibility and pavement friction). As one consequence, it may cause a serious disturbance of driver's emotion. All these can be represented by tuning individual's driving parameters (e.g. free speed and free time headway). It is possible, then, to define and calibrate the actual functional relationship between these effects and changes in different parameters of driving models [21]. Current driving models were mainly concerned with flow-based congestion effects and may not be applicable directly to the adverse weather conditions. To capture the rain effects, a new driving model is proposed on the basis of the conventional Intelligent Driver Model (IDM), denoted as the Generalized Intelligent Driver Model (GIDM). The main idea of this model can be expressed using the following equation:

$$v'_i(I) = a\left[1-\left(v_i / (g_{v_0^i}(I) v_0^i)\right)^{\delta} - \left(s_0 + g_{T^i}(I) T^i v_i + \frac{v_i \Delta v_i}{2\sqrt{ab}}\right)\frac{1}{s_i}\right]$$

Where $v'_i(I)$ is the acceleration of driver i in the next step when rainfall intensity is I. $v'_i(I)$ can be calculated using the following parameters:

- s_0, a, and b are jam distance, maximum acceleration and deceleration, respectively. The exponent δ is usually set to 4. These parameters are determined by transportation facilities and usually same for all drivers driving on the same road.
- v_i, s_i, and Δv_i are individual *i*'s current speed, gap and speed difference to the leading vehicle, respectively. These parameters represent current driving status of individual *i*.
- v_0^i and T^i are desired speed and safe time headway of individual *i*. The two parameters are determined by individual's features, such as psychology, age and sex, and are specific for each driver.
- $g_{v_0^i}(I)$ and $g_{T^i}(I)$, which are the scaled functions of v_0^i and T^i, represent the adjustment of individual driving behavior in adverse weather..

Intuitively, the higher the rainfall intensity, the lower the desired speed and the longer safe time headway. Therefore, the scaled functions should satisfy the following conditions:

(a) $g_{v_0^i}(I) \le 1$ is an decreasing function with respect to I implying that the driver's desired speed decreases while the rainfall intensity increases.

(b) $g_{T^i}(I) \ge 1$ is a increasing function with respect to I implying that the safe time headway increases while the rainfall intensity increases.

(c) $g_{v_0^i}(I) = 1$ and $g_{T^i}(I) = 1$ implying that when there is no rain this new driving model is equivalent to the normal IDM model.

According to the functional form of GIDM, it can be seen that the higher rainfall intensity the lower acceleration. The GIDM model can be regarded as an extension of the normal IDM model. Under no rain condition ($g_{v_0^i}(I) = 1$ and $g_{T^i}(I) = 1$), the two models are equivalent.

It should be pointed out that, besides rain intensity, there are several other characteristics to represent rain weather, such as wind force, humidity and visibility, as shown in our case study. For the sake of clarity, we use only rain intensity in designing GIDM. Clearly, other characteristics can be embedded in this model easily.

IV. EXPERIMENTS AND VALIDATION

A field study on the effectiveness of ATS has been carried out in a district of Jinan city, the capital of Shandong Province, a populous region and a major economic power in northeast China.

We have focused on the area within the second ring of the Jinan urban traffic arterial network. This selected area, covering 255 km^2, east to Lishan Road, west to 12th Wei Road, south to 10th Jing Road, and north to Beiyuan Avenue, is the central business district of the city (See Fig. 1). The area

Figure 1. The Area of Field Study in Jinan for Traffic Computational Experiments

includes 410 sites which are directly related to traffic flow generation: 163 residential communities, 88 office buildings, 59 schools, 37 restaurants and hotels, 21 hospitals, 19 shopping malls, 13 recreational parks, and 10 sport facilities. An artificial transportation system with 324 traffic nodes and 646 road links, called Jinan ATS, has been established for the selected area and various traffic computational experiments have been conducted based on it.

This specific ATS provides us a platform for conducting computational experiments for systematic, continuous application of computer simulation programs to analyze and predict behaviors of actual systems in Jinan in different situations. In the following, we will demonstrate how to model and analyze transportation system based on Jinan ATS by showing the results of three computational experiments, which are constructing activity plan for each individual, generating travel demand based on activity and modeling the impacts of adverse weather.

A. Constructing activity plan for each individual

Travel demands are generated from individual's activity plan, which serves as the foundation of ATS. Before carrying out

TABLE I
Attributes of Activities (Workday)

	Time Range (HH:MM)	Duration (minute)	Probability		
			α_k	β_k	γ_k
School	[6:00-17:30]	*N*(450, 20)	0.1	0.01	12
Work	[6:30-20:00]	*N*(480, 40)	0.1	0.01	10
Hospital	[6:30-17:00]	*N*(60, 10)	-0.25	0.02	-1.65
Shopping	[10:00-20:30]	*N*(90, 20)	-0.91	0.01	0.56
Sport	[9:00-20:00]	*N* (90, 10)	0.13	0.02	-1.19
Eating	[16:00-19:00]	*N* (60,10)	0.25	0.01	-1.68
Entertain.	[15:00-20:00]	*N* (90,10)	0.57	0.03	-2.19

TABLE II
Attributes of Activities (Weekend)

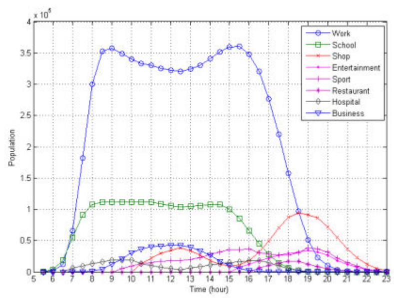
	Time Range (HH:MM)	Duration (minute)	Probability		
			α_k	β_k	γ_k
School	[6:00-17:30]	*N* (450, 20)	0.1	0.01	-2.4
Work	[6:30-20:00]	*N* (480, 40)	0.1	0.01	-2.2
Hospital	[6:30-17:00]	*N* (320, 80)	-0.18	0.02	-1.72
Shopping	[10:00-20:30]	*N* (240, 60)	-0.73	-0.01	0.64
Sport	[9:00-20:00]	*N* (120, 40)	0.13	0.02	-1.25
Eating	[9:00-19:00]	*N* (90, 30)	0.36	0.01	-1.81
Entertain.	[9:00-20:00]	*N* (320, 80)	0.63	0.03	-2.56

computational experiments, the rationality of individual's activity plan must be verified.

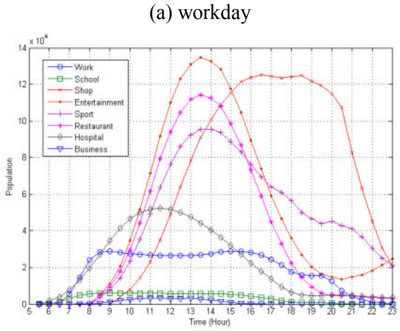
In ATS, we classified a person's activities into seven types, work, school, hospital, shopping, sport, eating (out), and entertainment. Start time, end time and duration are three basic attributes for one specific activity. We suppose they all obey normal distribution, though their means and stand deviations may be different. One shortcoming of normal distribution is its value range is infinite, which may generate meaningless values, for instance, negative for start time. So we use bounded normal distribution (BND) instead of common normal distribution, as shown in below:

$$\begin{cases} x \sim N(u,\sigma), \quad and \\ if \quad x < u-4\sigma \quad then \quad x = u-4\sigma, \; and \\ if \quad x > u+4\sigma \quad then \quad x = u+4\sigma \end{cases}$$

Calculated according to BND, the global attributes of these activities in workday and weekend for Jinan ATS are listed in table I and table II. Note that we use time range to represent start time and end time here. Table I and Table II also list the parameters for calculating the probabilities of activities, which have been explained in section II.



(a) workday



(b) weekend

Figure 2 Population Distributions performing different activities in one day

Based on the preconditions listed in table I and table II, each individual will generate his specific travel demand using the discrete choice models in section II. And then the macro results will be emerged naturally while numerous individuals are performing their activities. For example, figure 2 presents the distributions of persons performing different activities from 5:00 PM to 11:00 PM in Jinan ATS, where population size in this area is set to 700 thousands. Figure 2(a) is the distributions in one workday. We can see that the distributions of persons performing "work" and "school" are more regular than that of persons performing other activities. In addition, most people are performing "work" or "school" in daytime and the population that are participated in other activities are very small until 6:00 PM. Figure 2(b) is the distributions in weekend and, comparing to figure 2(a), it possesses markedly different features. In figure 2(b), because more people are participated in discretionary activities (including shop, sport, eating out and entertainment), not only these activities' frequencies increased sharply, but also their time spans are extended.

Clearly, the results in figure 2 are consistent with the reality very well. Intuitively, School and work are regular activities and their times are usually limited between 8:00 AM and 6:00 PM, while other activities are more flexible and individuals have more freedom to schedule them. It is worth mentioning that figure 2 is the emerged macro phenomena while individuals are doing their activity plans independently. As environment is modeled using basic rules and each individual can adjust their activities deliberately, reasonable travel demands under various situations can be easily generated by changing experimental conditions.

B. Modeling the impact of adverse weather

To investigate the impact on traffic by adverse weather in the selected area of study, a computational experiment has been designed and conducted using Jinan ATS.

According to the degree of their impacts on traffic, we have divided rain weather into four levels, light rain, middle rain, heavy rain and rainstorm, as shown in table III. Each kind of adverse weather is simulated for one whole day. Because Jinan ATS simulated the detailed traveling process of each individual in computational experiments, extensive evaluation indices can be generated. Because it is very difficult to show many of them due to space constraint, we will only show part of them as examples. In reality, average speed and vehicles in network are two important indicators to represent traffic congestion status and are widely used in urban traffic control and management. We will also use them here to illustrate the results.

Table III
The Levels of Rain Weathers

	Precipit. (mm/24h)	**Wind Force (km/h)**	**Humidity (%)**	**Visibility (m)**
Light rain	<10	<5	<40	>200
Middle rain	10~25	6-19	30~60	100~200
Heavy rain	25~100	20~38	50~80	20~100
Rainstorm	>100	>38	>80	<20

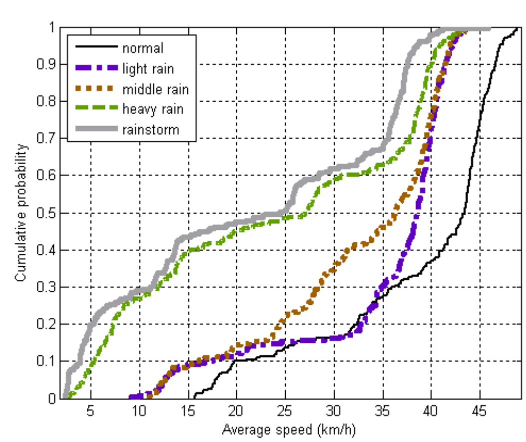


Figure 3 Cumulative Distribution Curves of Average Vehicle Speeds under Different Weather Conditions

Table IV
Statistical Characteristics of Average Vehicle Speeds under Different Weather Conditions

	Mean	Std	Min	Max	15%Q	85%Q
Normal	38.73	9.23	15.66	48.85	26.01	46.05
L. rain	34.87	8.89	9.14	43.82	24.53	40.89
M. rain	32.46	9.29	10.94	44.10	21.22	40.77
H. rain	23.77	14.08	2.61	43.82	6.38	39.43
RS	21.60	13.75	2.32	45.91	4.33	37.16

Figure 3 shows the cumulative distribution curve of average vehicle speeds in one day under five weather conditions: normal, light rain, middle rain, heavy rain, and rainstorm, respectively. This figure illustrates the impact of adverse weather on traffic status. As expected, the average speed of vehicles in the network decreases gradually when the weather changed from normal to rainstorm.

Table IV show some statistical characteristics of average vehicle speeds under different weather conditions. We can see that when weather conditions are getting worse, the mean, minimum and maximum are almost all decreased (some exceptions may be caused by random errors), while the standard deviation is increased. The 15% and 85% quantiles, which are common indices used in urban traffic evaluation, are also shown in table IV.

V. CONCLUSIONS

The ACP approach has provided us an opportunity to look into new methods in addressing transportation problems from new perspectives. In this paper, we present our works and results of applying ACP approach in modeling and analysis transportation system, especially carrying out computational experiments based on artificial transportation systems. Two aspects in the modeling process are analyzed. The first is growing artificial transportation system from bottom up using agent-based technologies. The second is modeling environment impacts in simple-is-consistent principle. Two computational experiments are carried out on one specific ATS, Jinan ATS, in the case study and numerical results are presented to illustrate the applications of our method.

Recently, an intensified effort has been launched to set up standards and procedures to construct artificial transportation systems based on ACP approach. Unlike conventional traffic simulation programs, those ATS are intended to be in running continuously in cyberspace through web computing and computer gaming technologies, just like real traffic systems in real cities. We believe it has opened a new field in a new direction that could significantly advance the level of effectiveness and intelligence of intelligent transportation systems and promote their future applications.

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