Computational Traffic Experiments Based on Artificial Transportation Systems: An Application of ACP Approach

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***Abstract*—The Artificial societies, Computational experiments, and Parallel execution (ACP) approach provides us an opportunity to look into new methods that address transportation problems from new perspectives. In this paper, we present our work and results of applying the ACP approach on modeling and analyzing transportation systems, particularly carrying out computational experiments based on artificial transportation systems (ATSs). Two aspects in the modeling process are analyzed. The first is growing an ATS from the bottom up using agent-based technologies. The second is modeling environmental impacts under the principle of "simple is consistent." Finally, three computational experiments are carried out on one specific ATS, i.e., Jinan-ATS, and numerical results are presented to illustrate the applications of our method.**

***Index Terms*—Agent, Artificial societies, Computational experiments, and Parallel execution (ACP) approach, artificial transportation systems (ATSs), computational experiment, "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 15 major cities in China are losing about 1 billion RMB Yuan (about $150 000 000) every day due to traffic congestion. Motor vehicle ownership in Beijing, the capital of China, exceeded 4 510 000 on September 12, 2010. Thus, many vehicles have caused particularly serious congestions in this city. For example, the average commuting time for a Beijing resident has reached 52 min, which is the longest among all the 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 faced by the developers 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 a wide area but also very difficult—if not impossible—to transfer dynamic OD data into individual travel demand. 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 involvement. As environments exert a profound influence over traffic, it is impossible to build an accurate 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 that could be done to deal with them. However, the status has changed 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]–[9]. In the United States, more than 40% of large metropolis plan organizations (MPOs) and 20% of medium and small MPOs have adopted, or plan to adopt, TDGA models in their work [10]. 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 [11], the Los Alamos laboratory developed the epidemic simulation software based on individual behavior [12], and the Research Triangle Institute used and extended an iterative proportional fitting method to generate a synthesized geospatially explicit human agent database that represents the U.S. population in the 50 states and the District of Columbia [13]. All these achievements demonstrated that the integrative artificial society can be constructed from the bottom up. Third, high-performance computing is becoming increasingly popular. We have witnessed the rapid development of personal computers, both in software and hardware over the past decades. Recently, many novel

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networked computing technologies, such as cloud computing, have been proposed and are expected to provide far more computing and storage capability than traditional technologies. It is expected that the computing and storage demand of massive data will be easily satisfied in the near future [14].

The Artificial societies, Computational experiments, and Parallel execution (ACP) approach was originally proposed by Wang [3] as a coordinate research and systematic effort with emerging methods and techniques for the purpose of modeling, analysis, and control of complex systems. Basically, this approach consists of three steps: 1) modeling and representation with *A*rtificial societies; 2) analysis and evaluation by *C*omputational experiments; and 3) 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:

1) *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.
2) *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 aforementioned characteristics. For the two problems faced by transportation simulation, the ACP approach provides not only basic ideas for generating travel demand but the feasible approach for modeling the environmental impacts as well.

Based on the accomplishments of some pioneering research and application works, Wang further established a new mechanism for transportation control and management under the principles of continuous investigation and improvement in the milestone paper [15]. This paper gives a systematic introduction of the concepts, architectures, and applications of the ACP approach in transportation management and control. Wang's work has opened a new field in a new direction, many innovative ideas in the ACP approach have been applied in city transportation management and control, and remarkable effect has also been obtained. The application areas include traffic signal control, public transport scheduling, city traffic planning, etc. [16].

However, up to now, there is still lack of an integrated operational method for ACP-based modeling and analysis of transportation systems. This paper aims to address this problem, particularly for the first two steps of the ACP approach, i.e., growing artificial transportation systems (ATS) from the bottom up and carrying out computational traffic experiments. This paper has three contributions.

1) The specific models in growing ATSs from the perspective of behavior generation are proposed.
2) The environmental impacts are modeled under the principle of "simple is consistent," and the modeling process is demonstrated by generating transportation scenarios in adverse weather.
3) Traffic computational experiments based on ATS are carried out, and numerical results are analyzed to verify the rationality of the models.

In contributions 1 and 2, special attention is paid to rule-based computational modeling of social and behavioral aspects of people, vehicles, roads, and environments involved in transportation activities. Although some ideas in this paper, such as behavior generation and activity-based travel demand generation, have been employed by some new developments of traffic simulations, particularly those agent-based simulations, ACP-based ATS differ markedly from traffic simulation programs, at least in the following three aspects: First, the objective of traditional traffic simulation is to represent or approach the true state of actual traffic systems [32]–[35], whereas the primary goal of ATSs is to "grow" live traffic processes in bottom-up fashion and provide alternative versions of the actual traffic activities. Second, ATS must deal with a wide range of information and activities. Most of the current traffic simulation focuses on direct traffic-related activities alone, whereas ATS generates their traffic processes from various indirect facilities and activities, such as the weather, and ecological and social involvements. Third, in the implementation of ATS, agents exchange messages and interact with each other by request mechanism rather than direct method calling. This can better satisfy the requirement of real-time and concurrent processing during traffic modeling and analysis.

The rest of this paper is organized as follows: Section II introduces the process of growing ATSs from bottom up and lists some basic rules in the implementation. Section III proposes the method to model environmental impacts 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 the Bottom Up

The urban transportation system is an inherent open giant complex system nearly involving all aspects of our society, which is a great challenge to traditional methodology. Not only are more and more facilities and activities involved in transportation but the connections between transportation system and urban environment are also getting increasingly closer [17]–[20]. As it is very ineffective to model transportation systems using top-down reductionism in traditional traffic simulation, theories and methods of complex systems and complexity science are adopted in the ACP approach to growing ATSs from the perspective of behavior generation.

The main idea of ACP-based ATS is to obtain deeper insight of traffic flow generation and evolution by modeling transportation systems using the basic rules of individual vehicles and local traffic behavior and observing complex phenomena that emerge from interactions between individuals. Based on this idea, our laboratory developed an ATS simulation engine, namely TransWorld, using the agent-oriented programming method. Working like a 3-D render engine, TransWorld can automatically compute and present a dynamic traffic scene

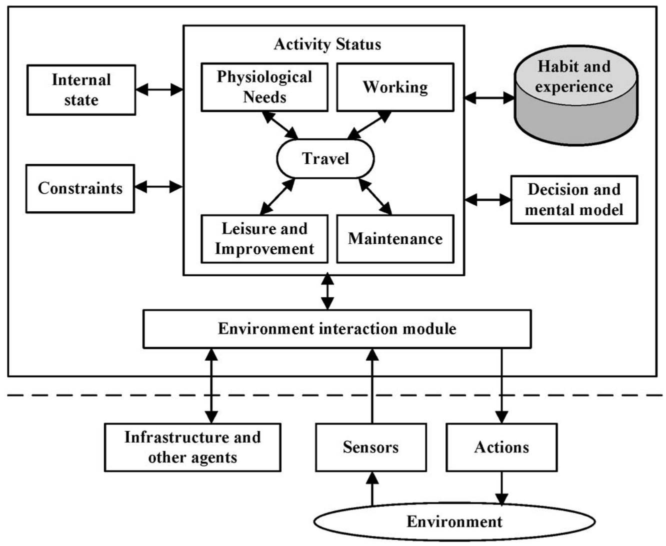

Fig. 1. Structure of one agent in ATS.

according to input model data and running parameters and output traffic measures and process data specified by users into a database for later analysis and evaluation.

A. Modeling Each Person as One Agent

In a traditional transportation simulation, the initial input data are usually OD matrices. However, in ATSs, the initial input is the data of population. One separate module, i.e., the artificial population module (APM), is designed to reach this requirement. Fig. 1 shows the structure of the agent that represents one person in the APM. Similar to one actual person, each agent has his own internal state and constraints. Common activities of an agent are classified into four types, i.e., physiological needs, working, leisure and improvement, and maintenance states. Each type contains several specific actions, in which only important ones are considered for simplicity. For example, in the physiological need, there are actions such as eating and sleeping; in maintenance, there are actions such as shopping and financing; and in leisure and improvement, there are actions such as going to a theater or playing basketball. All types are connected by a special activity, travel, i.e., 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 [36]–[38]. While one person is carrying out his 24-h activity plan, his autonomy is mainly reflected in two aspects: One is his habit and experience, and the other is his decision and mental model.

In addition to agent-based technologies, plenty of theories and models in sociology and economics are adopted in the APM. For example, the population structures in the APM are divided into three types, i.e., increasing type, decreasing type, and static type, which are also widely used by sociologists in classifying population. To implement the three types of population, APM provides mechanisms to assign attributes to an agent, as well as how these attributes change over time. The main attributes and assignment rules for an agent are shown in Table I. All these features, which form the foundation of the activity-based travel demand generation method, fit well into the paradigm of multiagent simulation and provide us feasible approaches to generate individual's travel demand.

TABLE I
RULES ABOUT AGENT'S ATTRIBUTES

Attribute	Assignment Rule
Age	The range of agent's age is [0,100]. All the agents are divided into different groups by 5-year intervals. The proportion of the group i in total population is p_i, which satisfies $\sum p_i=1$. There 3 types of population structures in ATS, which are increasing type, static type and decreasing type.
Character	There are three types of agent's characters, *fast*, *medium* and *slow*. It influences the maximum speed, acceleration speed and deceleration speed of agent.
Learning	The exploring ability falls into *big*, *medium*, and *small*. It influences agent's route choice, travel probability, etc.
Marriage	Among all the unmarried agents, one male agent above 25 years old and one female agent above 23 years old are combined to be a new family with the probability of p.
Birth	Among the married agents, if one couple has no child and the wife in it is below 49 years old, it can bear a child. The gender of the child is randomly determined.
Death	The death probability of one agent meets "J" shaped distribution, as shown in below $q_x = \begin{cases} a_1\exp(b_1 x) & a_1>0,\ b_1<0 \\ a_2\exp\big(b_2(x-c)\big) & a_2>0,\ b_2>0,\ c>0 \\ a_3\exp(b_3 x) & a_3>0,\ b_3>0 \end{cases}$ Where x is the age of agent, a_1, a_2, a_3, b_1, b_2, b_3 and c are all coefficients.

B. Fusion of ATS With World Wide Web

The World Wide Web, commonly known as the Web, is also fused with ATSs. As the world's largest open-source information platform, the Web has been involved into people's daily life and had a profound effect on the development of human society. Information on the Web is all-inclusive, and there are always a great number of people online creating and sharing information and knowledge. By collecting desired actual information from the Web, a solid information foundation for construction and simulation of ATSs can be provided. ATSs can also be shown on the Web with rich media technologies so that the public can access ATSs and offer information just through web browsers. Furthermore, by web services, ATSs can interact with other modules of intelligent transportation systems, even in heterogeneous environments. In short, with the help of massive information and people's group intelligence, many information obstacles of ATSs can be overcome, and ATSs will become open. This is also one of the advantages of ATSs.

The process of web information extraction and retrieval for ATS is shown as Fig. 2. First, a web crawler is activated to crawl along hyperlinks, matching a certain regular expression and download webpage as offline documents into a local disk system. To reduce the data amount of downloading, only text information is requested. Second, if a webpage document is structured, mature document object model tree technologies [27] can be used to easily extract the desired data. Otherwise, some text-mining methods such as Natural Language Processing [28] must be used. The extracted data are stored into a relational database. Finally, information retrieval technology is utilized to build indexes for both webpage documents in the file

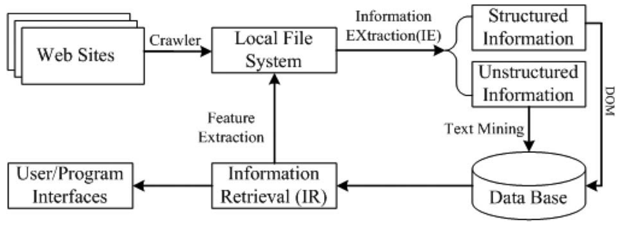

Fig. 2. Process of information extraction and retrieval.

system and structured data in database, so that friendly application programming interfaces for quick information lookup can be offered.

C. Generating Travel Demand

After constructing activity plans for each person in artificial population, travel demand is derived from the fact that consecutive activities at different locations need to be connected by travel. For each travel activity, its properties include start time, lasting time, destination place, travel path, travel mode, etc. 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 and the length of travel path. The other is closely related to the individual's psychology and behavior, which include his familiarity of travel path, his feeling of the convenience of the travel mode, etc. The effects of those factors are usually expressed using natural language, and how to design appropriate models for those effects is one of the main works in building ATSs. Discrete choice models (DCMs) are simple but compelling tools to modeling the autonomous ability of an individual, and their effectiveness has been verified in various areas, particularly in sociology and economics. This kind of models is also adopted by APM. In the following, some examples will be demonstrated by showing their usages in the decision process of an individual.

1) Selecting travel mode. The probability of individual k selecting travel mode m is calculated by the following random utility model:

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

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 (a fuzzy indicator, ranging from 1 to 10) of mode m; and e_k, f_k, and g_k are the coefficients.

2) Selecting activity place. One individual uses the maximum entropy model to select activity place, i.e.,

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

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

3) Selecting travel path. There are three sources of travel path in ATSs, i.e., habitual path, shortest path, and minimum cost path. Habitual path is a property of one agent. Shortest path is a property of the road network, and it is calculated in the initialization stage and kept constant until the road topology is modified. The minimum cost path is system-wide dynamic information, which will be updated using real-time data and broadcasted in the whole system in fixed intervals. The probability of individual k selecting path l is

$$P_l^k = \frac{\exp(c_k/L_l + d_k F_{kl})}{\sum_t \exp(c_k/L_t + d_k F_{kt})}$$

where L_l is the length of link l, F_{kl} is the degree of the individual k's familiarity of path l, F_{kl} is one fuzzy variable, and the range of its value is 0–10. c_k and d_k are the coefficients.

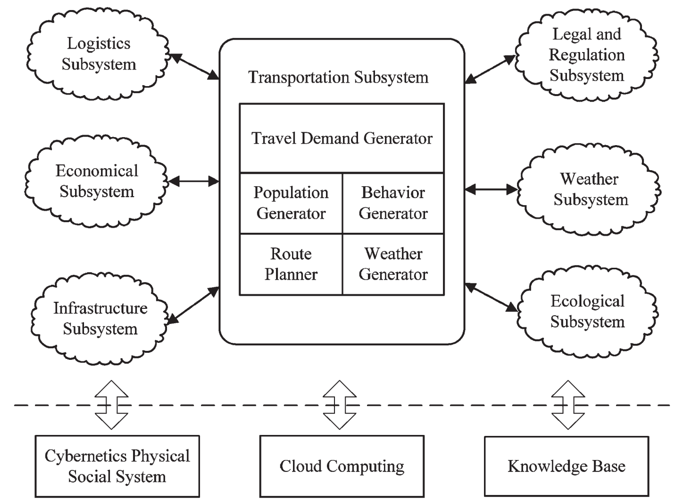

Fig. 3. Environmental subsystems in ATS.

III. Modeling Environmental Impacts

It is well known that the transportation system is tightly connected with the city environment. From microcosmic individual's psychology and driving behavior to macroscopical travel demand gross and distribution, all are heavily influenced by environmental factors, such as economic development and weather conditions [41]–[43]. The mechanisms by which the environment influences the traffic are very complex, and there are still many disputes about how to represent them from an overall perspective [44]–[47]. However, as to simple artificial objects, most conclusions about the influences that they received from the environment are consentaneous. Thus, if simple objects and local behavior are modeled using these widely approved conclusions, the "emerged" complex integrative phenomena are also expected to be understandable and agreeable. This is the basic idea of the "simple is consistent" principle. Under this principle, we have established the rule bases to model the influences that transportation systems received from environmental subsystems, as shown in Fig. 3. In the following, one kind of adverse weather, i.e., rain, is used as an example to illustrate the models of the environmental impacts in ATSs.

A. Modifying the Probabilities of Performing Activities

The first step is to modify the probabilities of performing activities. Under normal conditions, the probability that an agent i performs activity k in its complete all-day plan can be calculated by a logistic model, which is shown as follows:

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

where $gender_i$ and age_i are the gender and age of agent i, α_k and β_k are the coefficients, and γ_k is a constant term. Then, in adverse weather, the probability of activity k can be modified using the following formula:

$$W_{kj}^{\oplus}(P_{ik}, I_j, d_j) = \left(\frac{1}{1 + \exp\left[\delta_{kj}(I_j d_j - \phi_{kj})\right]}\right) P_{ik}$$

where δ_{kj} and ϕ_{kj} are constant properties of activity k and adverse weather W_j; I_j is the index to denote the intensity of W_j, e.g., the precipitation intensity of rain; and d_j is the duration of W_j. The term between brackets represents an S-shape function with an asymptotic maximum of one (either the intensity or the duration is zero) and an asymptotic minimum of zero (both the intensity and the duration are very high). δ_{kj} indicates the marginal effect of W_j at the inflexion point.

B. Adjusting the Attributes of Travel Demand

The second step is to adjust the attributes of travel demand. The travel demand of individual i can be denoted as

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

where $\mathbf{A}_i$, $\mathbf{D}_i$, $\mathbf{P}_i$, $\mathbf{M}_i$, $\mathbf{ST}_i$, and $\mathbf{ET}_i$ are vectors of individual i's activities to be performed, travel destinations, travel paths, travel modes, start time, and end time, respectively. Usually, when adverse weather happens, the individual will adjust his 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, lengthening or shortening the duration, etc. If there is insufficient time in the schedule, some activities, particularly those discretionary activities, will be eventually canceled. In addition to happen time and duration, destination and sequence can also be adjusted. All these adjustments can occur either before or in adverse weather happening. Obviously, no matter when the adjustment occurs, it can be described by simple rules in ATSs.

C. Modeling Vehicle Movement

The last step is modeling vehicle movement in adverse weather. Adverse weather can degrade the road performance due to changes in the driving condition (e.g., reduced visibility and pavement friction). As one consequence, it may seriously disturb the driver's emotions. All these can be represented by tuning the individual's driving parameters (e.g., free speed and free time headway). It is then possible to define and calibrate the actual functional relationship between these effects and changes in different parameters of driving models [48]. 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) [49], [50], which is denoted as the Generalized IDM (GIDM). The main idea of this model can be expressed using the following equation:

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

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 four parameters.

1) s_0, a, and b are the jam distance, maximum acceleration, and deceleration, respectively. Exponent δ is usually set to 4. These parameters are determined by transportation facilities and usually the same for all drivers driving on the same road.
2) 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 the current driving status of individual i.
3) v_0^i and T^i are the desired speed and safe time headway of individual i. The two parameters are determined by the individual's features, such as psychology, age, and gender, and are specific for each driver.
4) $g(I, v_0^i)$ and $h(I, T^i)$, 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 is, the lower the desired speed and the longer the safe time headway would be. Thus, the scaled functions $g(I, v_0^i)$ and $h(I, T^i)$ are defined as follows:

$$g\left(I, v_0^i\right) = \frac{v_0^{\max}}{1 + \left(\frac{v_0^{\max}}{v_0^i} - 1\right)\exp(pI)}$$

where $v_0^{\max}$ is the maximum of the individual's desired speed, and p is the coefficient that satisfies $p > 0$. It can be seen that $g(I, v_0^i) \leq v_0^i$ is a decreasing function with respect to I, implying that the driver's desired speed decreases while the rainfall intensity increases

$$h(I, T^i) = \frac{T^{\max}}{1 + \left(\frac{T^{\max}}{T^i} - 1\right)\exp(-qI)}$$

where $T^{\max}$ is the maximum of individual safe time headway, and q is the coefficient that satisfies $q > 0$. It can be seen that $h(I, T^i) \geq T^i$ is an increasing function with respect to I, implying that the safe time headway increases while the rainfall intensity increases.

When I is 0, $g(I, v_0^i) = v_0^i$ and $h(I, T^i) = T^i$, 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 the rainfall intensity, the lower the acceleration. The GIDM model can be regarded as an extension of the normal IDM model. Under a no-rain condition ($g(I, v_0^i) = v_0^i$ and $h(I, T^i) = T^i$), the two models are equivalent.

Fig. 4. Area of field study in Jinan for traffic computational experiments.

It should be pointed out that intensity is only one of the characteristics of the rain weather. Other characteristics include wind force, humidity visibility, etc., as shown in the case study of this paper. For the sake of clarity, only the effect of intensity is shown in designing GIDM. Obviously, other characteristics can be embedded in this model in the same way.

In addition to GIDM, we implement the whole driving process in adverse weather, including the car-following model, lane-changing model, passing-intersection model, etc. All these models in adverse weather are similar to those in normal weather. The structures of these models are the same under both weather conditions, and only some parameters, such as desired speed and safe time headway in the IDM model, need to be modified. Therefore, for the sake of clarity, only the car-following model in adverse weather is demonstrated in this paper. Other models are extended in the same way.

IV. Experiments and Validation

A field study on the effectiveness of our models has been carried out in a district of Jinan city, which is the capital of Shandong Province and is 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. 4). The area 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 ATS 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, i.e., Jinan-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 systems based on Jinan-ATS by showing the results of three computational experiments, which are constructing an activity plan for each individual, generating travel demand based on activity, and modeling the impacts of adverse weather.

TABLE II
Attributes of Activities (Workday)

	Time Range (HH:MM)	Duration (minute)	Prob. Parameters 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 III
Attributes of Activities (Weekend)

	Time Range (HH:MM)	Duration (minute)	Prob. Parameters 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

A. Constructing Activity Plan for Each Individual

Travel demands are generated from the individual's activity plan, which serves as the foundation of ATSs. Before carrying out computational experiments, the rationality of individual's activity plan must be verified.

As mentioned in Section II, there are at most seven types of activities that can be performed by one person in ATSs. These activities are work, school, hospital, shopping, sport, eating (out), and entertainment. Start time, end time, and duration, which are the three basic attributes for one specific activity, are supposed to obey normal distributions with different means and different stand deviations. One shortcoming of normal distribution is that its value range is infinite so that meaningless values can be generated, for instance, a negative value for the start time. To conquer this problem, bounded normal distribution (BND), instead of common normal distribution, is adopted, as shown in the following:

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

Calculated according to BND, the global attributes of these activities in workday and weekend for Jinan-ATS are listed in Tables II and III. (Note that both the start time and end time are represented by the time range column.) Tables II and III also list the parameters for calculating the probabilities of performing activities, which have been explained in Section III.

Based on the preconditions listed in Tables II and III, each individual will generate his specific travel demand using the DCMs in Section II. In addition, the macroscopic results will

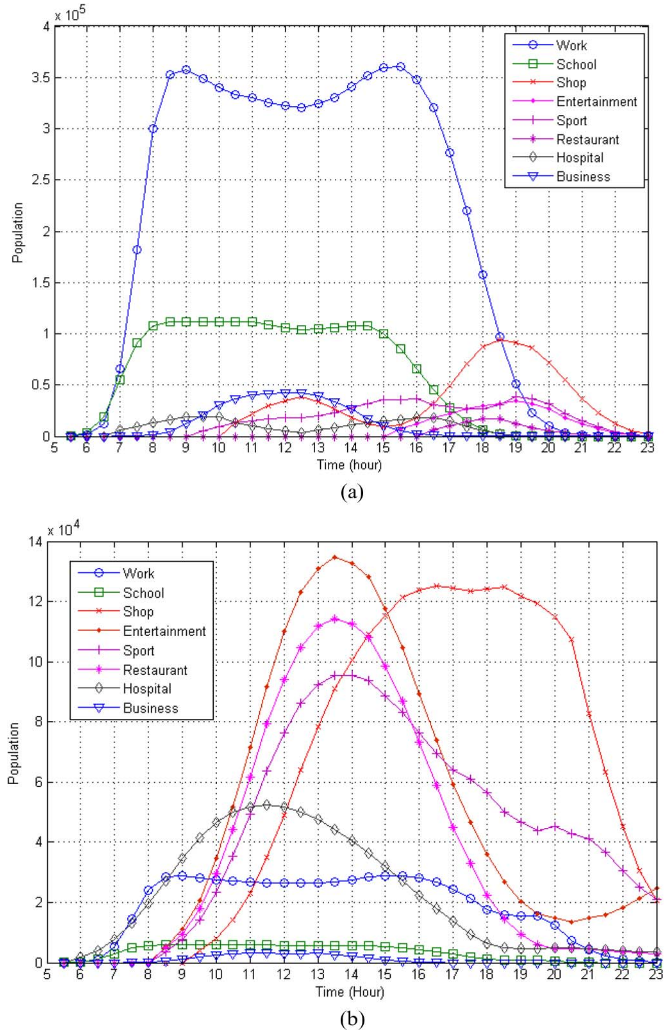

Fig. 5. Population distributions performing different activities in one day. (a) Workday. (b) Weekend.

then be naturally emerged while numerous individuals perform their own activities and interact with each other. As one example, Fig. 5 shows the distributions of persons performing different activities from 5:00 A.M. to 11:00 P.M. in Jinan-ATS, whose area has a population of 700 000. Fig. 5(a) shows the distributions in one workday. It can be seen that the distributions of persons doing "work" and "school" are more regular than those of persons doing other activities. In addition, most people do "work" or "school" in daytime, and the population that do other activities is very small until 6:00 P.M. Fig. 5(b) shows the distributions during the weekend, and compared with Fig. 5(a), there are significant differences. In Fig. 5(b), because more people do discretionary activities (including shopping, sport, eating out, and entertainment) during the weekend, not only do these activities' frequencies sharply increase but their time ranges are notably extended as well.

Clearly, the results in Fig. 5 are quite consistent with reality. Intuitively, "school" and "work" are regular activities, and their times are usually limited between 8:00 A.M. and 6:00 P.M.; on the other hand, other activities are more flexible, and individuals have more freedom to schedule them. It is worth mentioning that Fig. 5 is the emerged macro phenomena while individuals are independently doing their activity plans. As environment is

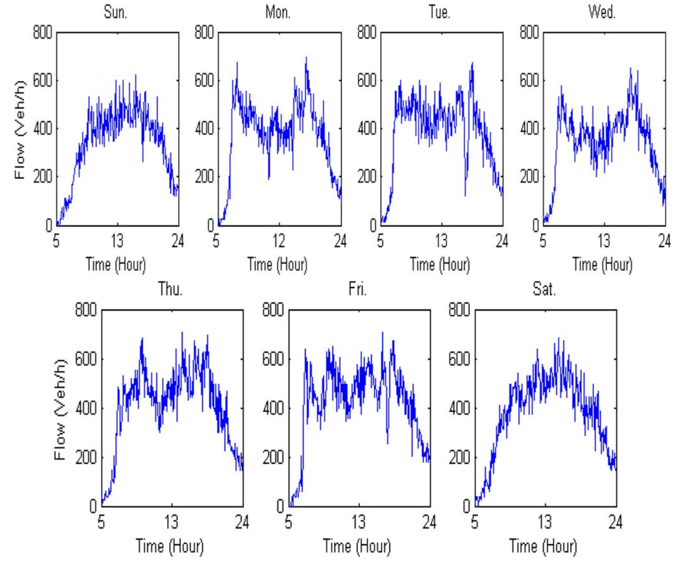

Fig. 6. Traffic flow from Sunday to Saturday.

modeled using basic rules and each individual can deliberately adjust their activities, reasonable travel demands under various situations can be easily generated by changing experimental conditions.

B. Generating Travel Demand Based on Activity

Just like travel is an induced activity in reality, an agent travels to perform activities in different places in ATSs. After constructing activity plans for both workday and weekend for each person, travel demands in one week in Jinan-ATS can be directly derived. In the following, the travel demand generated in ATSs will be illustrated using the collected traffic flow data in Lishan Road in Jinan-ATS.

Fig. 6 shows the traffic flow data of each day (from 5:00 A.M. to 12:00 P.M.) in one week (from Sunday to Saturday) that is collected from Lishan road in one computational experiment on Jinan-ATS. Although traffic flow curves fluctuate from day to day in Fig. 6, workdays and weekends can be easily distinguished. From Monday to Friday, the traffic flow data follow an M-shape curve. Both morning peak and evening peak are very obvious in workday, and their happening times are around 7:00 A.M. and 6:00 P.M., respectively. However, there is only one peak in weekend's traffic flow, and the traffic flow keeps at a high level for most of the daytime, although the maximum is a bit lower than that in a peak hour of workday.

Fig. 7 shows the curves of the average values of the traffic flows in Fig. 6. Putting the two curves together, the differences between workday and weekend are more obvious. In addition, this figure enables us to analyze the traffic flows in detail. During the workday, the morning rush hour times range from 6:00 A.M. to 8:00 A.M., and the maximum flow in this period is about 500 veh/h. Compared with the morning rush hour, the evening rush hour is shorter by about half an hour, and the maximum flow in it is bigger about 100 veh/h. In weekend, the start time of the morning rush hour is about 9:30, which is much later than that during the workday. The peak period in weekend lasts for a long time, and the traffic flow remains higher than 500 veh/h until 7:15 P.M.

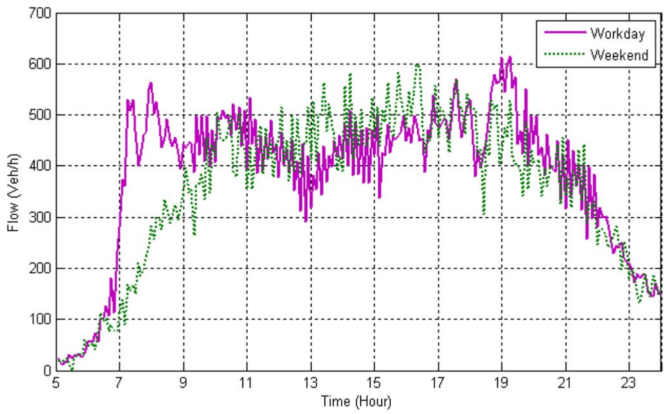

Fig. 7. Average speed of workday and weekend.

TABLE IV
LEVELS OF RAIN

	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

From Figs. 6 and 7, it can be seen that the generated traffic flows in ATSs can reproduce the peak phenomena in actual transportation systems, and the results are supported by actual data. Therefore, the feasibility of the activity-based travel demand generation is also verified. Using a traditional simulation software, travel demand is generated based on OD matrices; to generate the similar result, one day is divided into several intervals, and the OD matrices have to be calibrated interval by interval. In addition to the calibration of OD needing painstaking effort, the process is very inflexible; even a minor adjustment may cause the results to be completely invalid. Furthermore, because the impact on traffic conditions by local population's social and economic activities are completely omitted in OD matrices, it is very difficult to generate reasonable traffic environments under different management and control strategies.

C. Modeling the Impacts 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 based on Jinan-ATS.

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

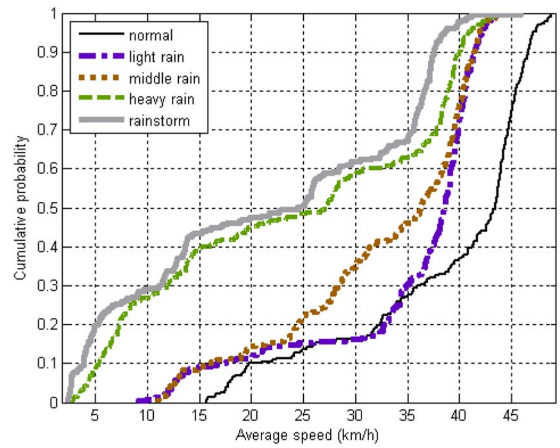

Fig. 8. Cumulative distribution curves of average vehicle speeds under different weather conditions.

TABLE V
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

Fig. 8 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 gradually decreases when the weather changes from normal to rainstorm.

Table V shows some statistical characteristics of average vehicle speeds under different weather conditions. It can be seen that, when weather conditions are getting worse, the mean, minimum, and maximum values almost all decrease (some exceptions may be caused by random errors), whereas the standard deviation increases. The 15% and 85% quantiles, which are common indices used in urban traffic evaluation, are also shown in Table V.

Fig. 9 shows the cumulative distribution curves of vehicles in the network in the same day under different weather conditions. As expected, the number of vehicles in the network gradually increases when the weather changes from normal to rainstorm. Table VI also shows some statistical characteristics of vehicles in the network under different weather conditions. It can be seen that, when weather conditions get worse, almost all these indices increase (some exceptions may be caused by random errors), which means the traffic status is getting increasingly worse. One interesting conclusion that can be drawn from Figs. 8 and 9 is that the impact of light rain and middle rain are very close, as are the impact of heavy rain and rainstorm. It seems that, in the perspective of the impact on transportation system, rain can be represented using even fewer categories.

V. CONCLUSION

The ACP approach provides us an opportunity to look into new methods in addressing transportation problems from

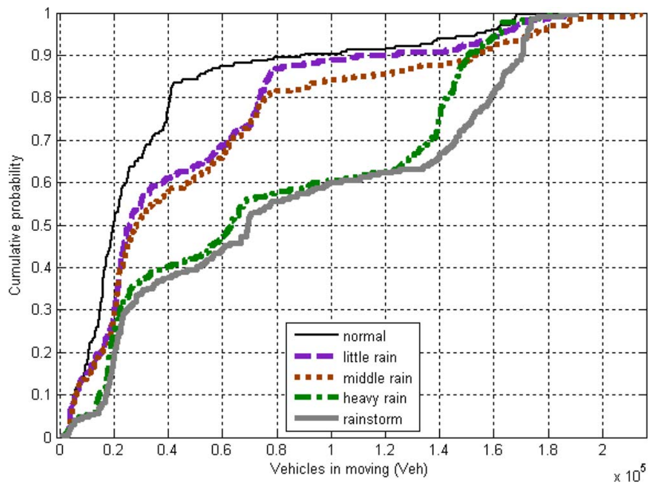

Fig. 9. Cumulative distribution curves of vehicles in network under different weather conditions.

TABLE VI
STATISTICAL CHARACTERISTICS OF VEHICLES IN NETWORK UNDER DIFFERENT WEATHER CONDITIONS

	Mean	Std	Min	Max	15%Q	85% Q
Normal	35079	40847	950	177150	9250	52000
L. rain	47226	45734	850	189950	10350	76900
M. rain	53293	52512	1150	214000	10400	108600
H. rain	77581	57661	1000	185850	17700	146600
RS	85058	62067	1150	190250	19300	163500

new perspectives. In this paper, we have presented our works and results of applying the ACP approach in modeling and analyzing transportation systems, particularly carrying out computational experiments based on ATSs. Two aspects in the modeling process have been analyzed. The first is growing ATSs from bottom up using agent-based technologies. The second is modeling environment impacts on the "simple is consistent" principle. Three computational experiments have been carried out on one specific ATS, i.e., the Jinan-ATS, in the case study, and numerical results have been presented to illustrate the applications of our method.

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

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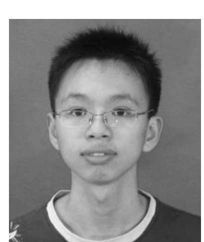

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