CHAPTER 10

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

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10.1 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 one billion RMB (about $150,000,000) every day due to traffic congestions. The number of motor vehicles in Beijing, the capital of China, had exceeded 4,510,000 by September 12, 2010. So many vehicles have caused particularly serious congestion in this city. For example, the average time of Beijing residents' commuter trips has reached 52 min, which is the longest among all the cities in China (Niu, 2010).

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 (Wang et al., 2004). 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 to 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 demands 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 paths. Second, almost all simulation softwares focus on direct traffic-related activities alone and neglect other indirect facilities and activities, such as weather, legal, and social involvement. As environment exerts a profound influence over traffic, it is impossible to build an accurate model for transportation R&D using traditional methods (Wang, 2007).

Although the limitations of traffic simulation software were noticed soon after it was introduced into transportation study, there has been little done to deal with this for a long time.

Advances in Artificial Transportation Systems and Simulation.

However, the status has changed evidently since the early 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 (Bhat et al., 1999; Davidson et al., 2007; Arentze et al., 2011a; Roorda et al., 2009). In the United States, 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 (Arentze et al., 2011b). Second, the theory of artificial life and artificial society has proved to be a feasible approach in the research of the complexity of society and many achievements have been recorded. For example, Epstein and Axtel established "the world of sugar" to simulate the human society (Epstein et al., 1996), Los Alamos laboratory developed the epidemic simulation software based on individual behavior (Barrett et al., 2005), 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 (Wheaton et al., 2009). 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 the 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 the heavy demand of computing and storage can be satisfied (Wang et al., 2007).

The ACP (Artificial Societies, Computational Experiments, and Parallel Execution) approach was originally proposed in (Wang et al., 2010a), as a coordinate research and systematic effort with those emerging methods and techniques, for the purpose of modeling, 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 (Wang et al., 2010a; Xiong et al., 2010):

- *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 on 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 chapter is to present our works and results of applying the ACP approach in modeling and analyzing a transportation system, especially establishing artificial transportation systems. The rest of this chapter is organized as follows: Section 10.2 introduces the process of growing artificial transportation systems from bottom up and lists some basic rules in the implementation; Section 10.3 proposes the method to model environment impact and demonstrates the process by modeling transportation scenarios in adverse weather; Section 10.4 shows the implementation architecture based on cloud computing; Section 10.5 verifies our method by illustrating one case study we carried out in Jinan, China; Section 10.6 draws conclusions with some remarks on future works and directions.

10.2 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 the transportation system and the urban environment are also getting closer and closer (Ahas et al., 2010; Hato, 2010). All these make the top–down reductionism method of traditional simulation very ineffective and there is 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 on the basis of 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, the ACP approach is proposed to grow holistic artificial traffic systems (ATS) from bottom up (Wang, 2004; Miao et al., 2011; Zhu et al., 2011).

Here the main idea of ATS 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 (Wang, 2008). Figure 10.1 is the structure of one agent that represents one person in ATS. Though there still is not a universally accepted definition about an agent, it is widely accepted that an agent can be regarded as a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives (Wang, 2005; Wang, 2002).

On the basis of the concepts and methods of artificial society and complex systems, ATS differs 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 (Charypar et al., 2005), whereas 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

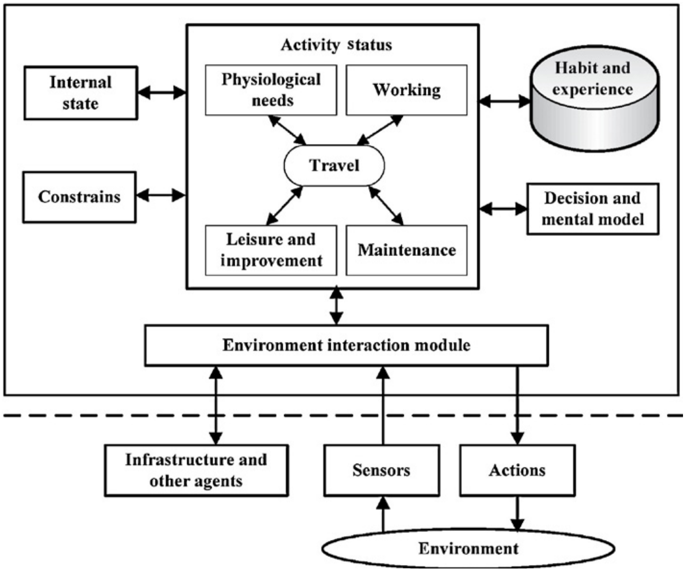


Figure 10.1: The structure of one agent in AT

direct traffic-related activities alone, whereas ATS generates their traffic processes from various 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, whereas 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 Wang (2004); Miao et al. (2011); and Wang (2008).

Because individual's behaviors take the place of the OD matrix as input data in ATS, the first step in building ATS is to generate a reasonable population for a specified area. We implemented one separate module, namely an artificial population module (APM), for this task and, as mentioned before, modeled each person as one agent in this module. APM provides mechanisms to assign attributes to an agent as well as showing 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 (Figure 10.2), namely, increasing type, decreasing type, and static type, which are also widely used by sociologists in classifying population.

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 (Bhat, 1999). 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. Although one agent is carrying out its 24-h activity plan, its autonomy is mainly reflected in two aspects, one is his habit and experience, the other is the decision process that is based on his

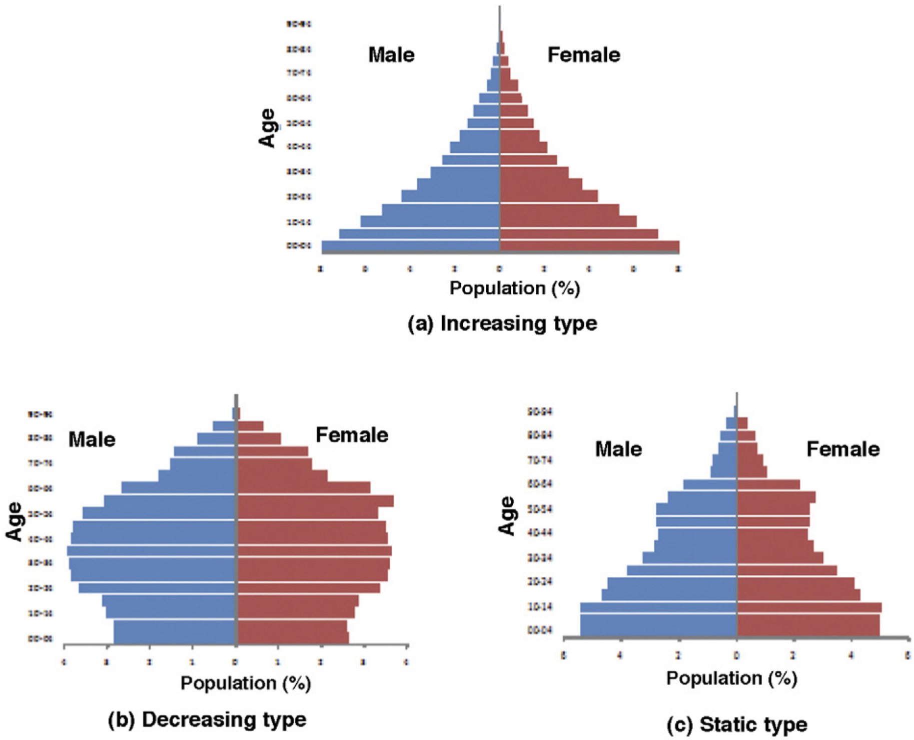


Figure 10.2: Three types of population structures

decision and mental model (Figure 10.1). All these features formed the foundation of our activity-based travel demand generation method, which fits well into the paradigm of multi-agent simulation and provides us with a feasible approach to generate an individual's travel demand.

Once the travel demand is generated, the agent needs to select the properties of the travel activity. 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 his familiarity with the travel path, his feeling for the convenience of the travel mode, and so forth. Designing and establishing appropriate models for the latter is one of the focuses of our work. These factors are closely connected with the social and behavioral characteristics of individuals and their effects are usually expressed using natural language. Modeling the autonomous ability of one agent using discrete choice models (DCM) is a simple but compelling method that has been verified in various areas, especially in social and economic research, and is also adopted in our work. In the following, we will demonstrate some examples of them by showing their usages in the decision process of one agent.

- 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 (a fuzzy indicator, ranging 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:

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

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, α, and β are coefficients, γ is a constant term.

- Selecting travel path

  There are three sources of travel path, namely, 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, minimum cost path is system-wide dynamic information, which will be updated using real-time data and broadcast in the whole system at fixed intervals. The probability of agent 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, Fk_l is the degree of the agent k's familiarity of path l. Fk_l is one fuzzy variable and the range of its value is 0~10. c_k, d_k are coefficients.

It is worth pointing out, besides providing feasible ways for modeling the decision process of one agent, there are many other advantages of modeling transportation systems from bottom up. For example, both Cyber-Physical Systems (CPS) and Cloud Computing are natural and embedded in this approach. As a matter of fact, CPS, as well as Cyber-Physical-Social Systems (CPSS) (Wang, 2010b), are special cases of intelligent spaces and an extension of our Intelligent Transportation Spaces (ITSp). Both were developed in our previous studies (Yang et al., 2007). As for cloud computing, it has already been used since the late 1990s in our work on agent-based control and management for networked traffic systems and other applications under the design principle of "Local Simple, Remote Complex" for high intelligence but low cost smart systems.

10.3 Modeling Environmental Impacts

It is well known that transportation is tightly connected with the social environment. From the microcosmic individual's psychology and driving behavior to macro-level travel and travel distribution, all are heavily impacted by the surrounding environment, such as economic, weather, and so forth (Hranac et al., 2006; Prevedouros et al., 2005; Ibrahim et al., 1994). 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 (Smith et al., 2004; Datla et al., 2008; Koetse et al., 2009). However, as to simple artificial objects, most of the 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 a transportation subsystem received from other subsystems, as shown in Figure 10.3.

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

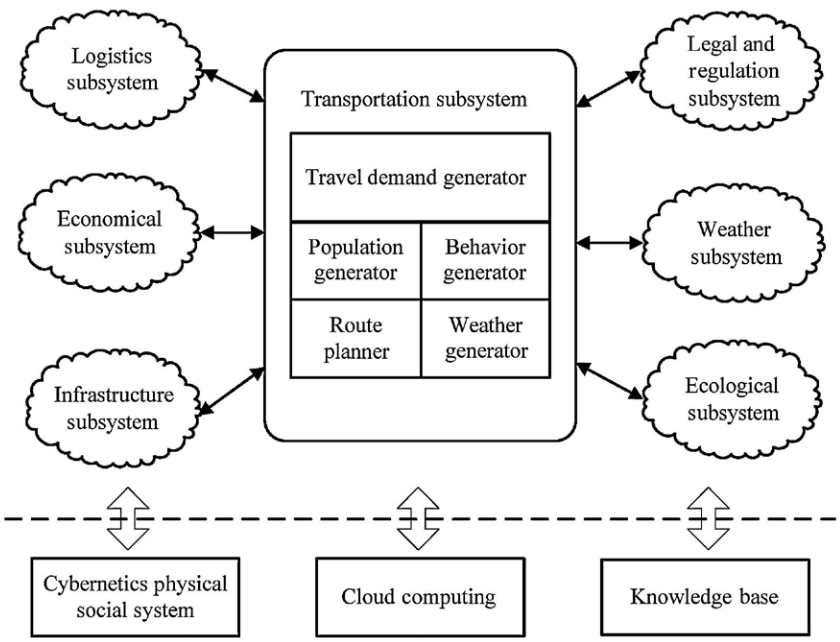


Figure 10.3: Environmental subsystems in ATS

expressed using a two-step model, which is composed of a travel demand generation process and traveling process. In the first step, the travel demand of individual i can be denoted as:

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

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, start time, and end time, respectively. Usually, when adverse weather happens, an individual will adjust his activity plan to avoid unnecessary travel. According to the happening time of adverse weather, the adjustment measures include moving up or putting off the happening time, lengthening or shortening the duration, and so on. If there has not been enough time in the schedule, some activities, especially those discretionary activities, such as shopping, sport, eating out, and entertainment, will be canceled eventually. Besides happening 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 forecast 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 to our model.

Here we will use the probabilities of performing activity as an example to illustrate the influence of adverse weather. Under normal conditions, the probability that an agent i performs the activity k in its complete all-day plan is calculated by a logistic model, as shown 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 a constant term. Typical values of α_k, β_k, and γ_k will be listed in Section 10.4 of this chapter.

When adverse weather happens, the probability will be adjusted as follows:

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

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, for example, the precipitation intensity of rain, d_j is the duration of W_j. The term between brackets represents a 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.

In the traveling process, adverse weather can influence an individual's driving behavior. Adverse weather can degrade the road performance due to the changes in the driving conditions (e.g., reduced visibility and pavement friction). As one consequence, it may cause a serious disturbance to the driver's reactions. All these can be represented by tuning an 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 (Lam et al., 2008). 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) (Treiber et al., 2000; Treiber et al., 2006), denoted as the Generalized Intelligent Driver Model (GIDM). The main idea of this model can be expressed using the following equation:

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

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 the following parameters:

- s_0, a and b are traffic jam distance, maximum acceleration and deceleration, respectively. The exponent δ is usually set to 4. These parameters are determined by transportation facilities and are usually the 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.
- $g(I, v_0^i)$ 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 safe-time headway would be. We defined the two-scaled functions as follows:

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

where $v_0^{\max}$ is the maximum individual's desired speed, and p is the coefficient that satisfies $p > 0$. We can see that, $g(I, v_0^i) \le v_0^i$ 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 individual safe time headway, and q is the coefficient that satisfies $q > 0$. We also can see that, $h(I, T^i) \ge T^i$ is an increasing function with respect to I implying that the safe time headway increases whereas 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 no rain condition ($g(I, v_0^i) = v_0^i$ and $h(I, T^i) = T^i$); the two models are equivalent.

It should be pointed out that, besides rain intensity, there are several other characteristics to represent rain, 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. However, other characteristics can also be embedded in this model easily.

10.4 Implementation of Intelligent Traffic Clouds

Artificial transportation systems can use the autonomy, mobility, and adaptability of mobile agents to deal with dynamic traffic environment. However, the large-scale use of mobile agents will lead to the emergence of a complex, powerful organization layer that requires enormous computing and power resources. To deal with this problem, our implementation is based on intelligent traffic clouds (Youseff et al., 2008; Armbrust et al., 2009; Buyya et al., 2009).

Artificial transportation systems based on cloud computing have two roles: service provider and customer. All the service providers such as the test bed of typical traffic scenes, traffic strategy database, and traffic strategy agent database are all veiled in the systems' core: intelligent traffic clouds. The clouds' customers such as the urban-traffic management systems and traffic participants exist outside the cloud. Figure 10.4 gives an overview of artificial transportation systems based on cloud computing. The intelligent traffic clouds could provide traffic strategy agents and agent-distribution maps to the traffic management systems, traffic-strategy performance to the traffic-strategy developer, and the state of urban-traffic

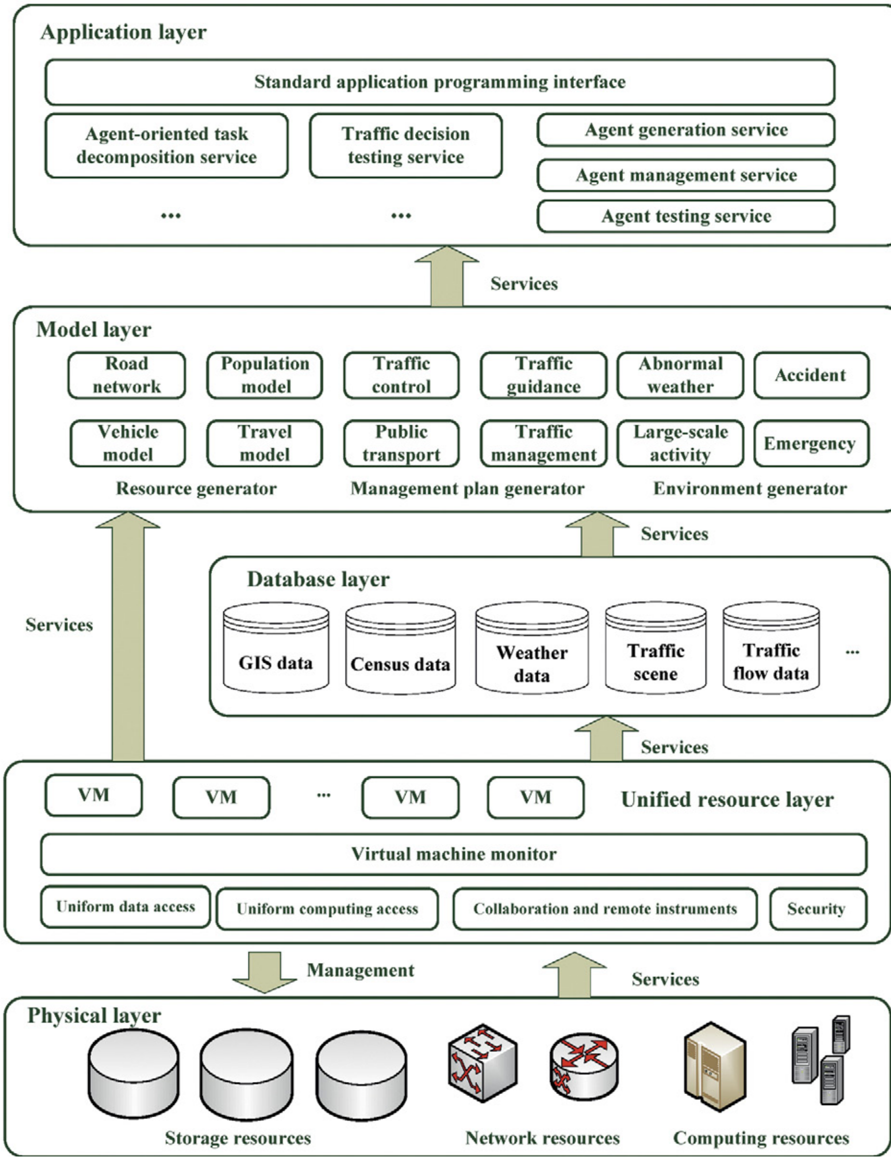


Figure 10.4: The architecture of artificial transportation systems based on cloud computing

transportation and the effect of traffic decisions to the traffic managers. It could also deal with different customers' requests for services such as storage service for traffic data and strategies, mobile traffic-strategy agents, and so on.

Using an intelligent traffic cloud, complex computing and massive data storage can be implemented on the cloud site, and the high performance can be achieved with low cost. All services are put into an intelligent traffic cloud. Besides transforming traffic control algorithms into control agents, the services also include agent performance test data and traffic detector data. Service consumers of an intelligent transport cloud include transport managers, control algorithm developers and transport control centers. According to the demands of service consumers, an intelligent transport cloud can provide the following services (Li et al., 2011):

- User identity authentication and permission management services.
- Transform services from public vehicle schedule algorithms to schedule agents. The services use a standard transform mechanism and universal API for traffic control algorithm developers. Once the schedule algorithm is implemented, the corresponding schedule agent can be generated in the cloud automatically.
- Performance test and evaluation services for vehicle schedule agent. On the basis of an artificial public transport system, the operation results, and performance of a vehicle schedule agent can be tested and evaluated in various traffic flows, using typical intersections and networks. The results, which are stored as a performance report of the agent, not only can provide decision support in selecting application conditions, but also can provide a reference for developers to improve algorithms.
- Storage management services for vehicle schedule agent. The services include vehicle schedule agent naming, redundancy, encryption, storage, and so on, and maintain load balancing of the whole storage system.
- Storage services for operation data and detector data. The services record the running process of vehicle schedule agents and traffic flow data collected by various detectors. By applying advanced data mining method in analyzing these data, traffic managers can acquire decision support to make and optimize vehicle schedule strategies.

With the support of cloud computing technologies, it will go far beyond other multi-agent traffic management systems, addressing issues such as infinite system scalability, an appropriate agent management scheme, reducing the upfront investment and risk for users, and minimizing the total cost of ownership.

10.5 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 Figure 10.5). The area includes 410 sites that 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 sports facilities. An artificial

Figure 10.5: The Area of Field Study in Jinan for Computational Traffic Experiments

transportation system with 324 traffic nodes and 646 road links, called Jinan ATS, has been established for the selected area and various computational traffic experiments have been conducted on its basis.

This specific ATS provides us with 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 a transportation system based on Jinan ATS by showing the results of three computational experiments, which are constructing an activity plan for each individual, generating travel demand on the basis of activity and modeling the impacts of adverse weather.

10.5.1 Constructing Activity Plan for Each Individual

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

In ATS, we classified a person's activities into seven types: (1) work, (2) school, (3) hospital, (4) shopping, (5) sport, (6) eating (out), and (7) entertainment. Start time, end time and duration are three basic attributes for one specific activity. We suppose they all obey normal distribution and set their mean and standard deviations to different values. One shortcoming

Table 10.1: Attributes of activities (workday).

	Time Range (HH:MM)	Duration (min)	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

of normal distribution is its value range which 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 below:

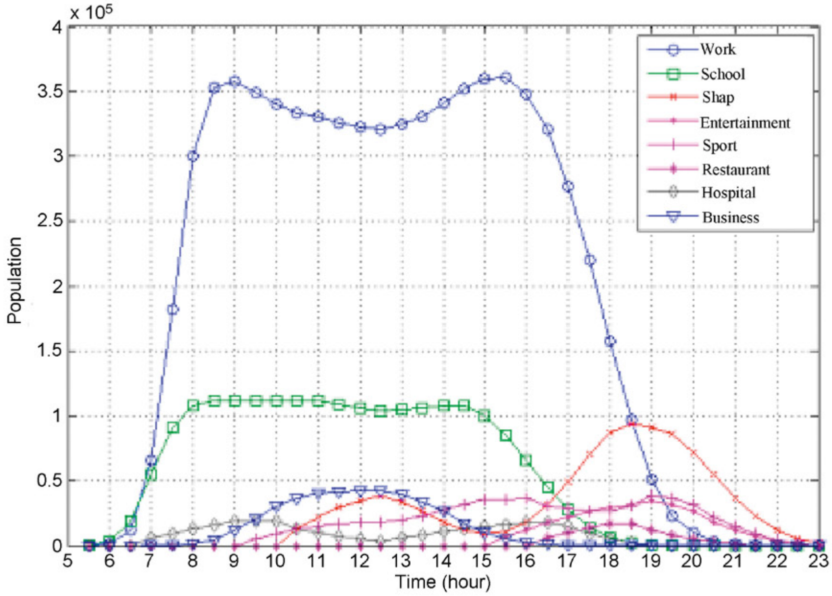
$$\begin{cases} x \sim N(u,\sigma), \quad and \\ if \quad x < u-4\sigma \quad then \quad x = u-4\sigma, \ and \\ if \quad x > u+4\sigma \quad then \quad x = u+4\sigma \end{cases}$$

Calculated according to BND, the global attributes of these activities on workdays and weekends for Jinan ATS are listed in Table 10.1 and Table 10.2. Note that we use a time range to represent start time and end time here. Table 10.1 and Table 10.2 also listed the parameters for calculating the probabilities of activities, which have been explained in Section 10.3.

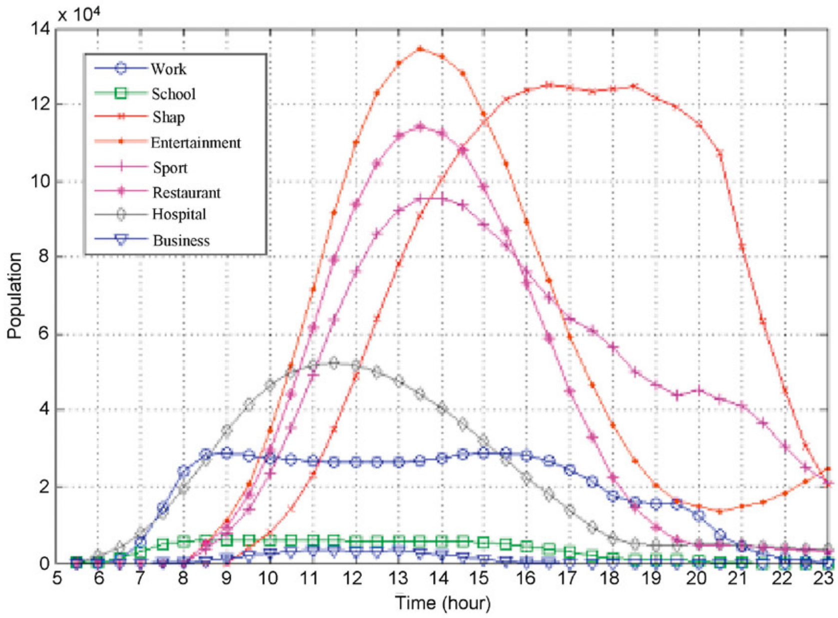
Based on the preconditions listed in Table 10.1 and Table 10.2, each individual will generate his specific travel demand using the discrete choice models in Section 10.2. And then the macro results will emerge naturally while numerous individuals are performing their activities. For example, Figure 10.6 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

Table 10.2: Attributes of activities (weekend).

	Time Range (HH:MM)	Duration (min)	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



(a) workday



(b) weekend

Figure 10.6: Population Distributions performing different activities in a day

at 700,000. Figure 10.6a shows the distributions on 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 the daytime and the population that participated in other activities is very small until 6:00 PM. Figure 10.6b shows the distributions at the weekend and, compared to Figure 10.6a, it possesses markedly different features. In Figure 10.6b, because more people are participating in discretionary activities (including shopping, sport, eating out, and entertainment), not only do these activities' frequencies increase sharply but also their time spans are extended.

Clearly, the results in Figure 10.6 are very consistent with reality. Intuitively, school and work are regular activities and their times are usually limited to 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 10.6 is the emerged macro phenomena while individuals are doing their activity plans independently. As the environment is modeled using basic rules and each individual can adjust their activities deliberately, reasonable travel demands in various situations can be easily generated by changing experimental conditions.

10.5.2 Generating Travel Demand on the Basis of Activity

Just as travel is an induced activity in reality, an agent travels to perform activities in different places. After constructing activity plans both on workdays and at weekends for each person, travel demands in 1 week in the Jinan ATS can be derived directly. In the following, we will illustrate the generated travel demand with traffic flow data collected on Lishan Road in the Jinan ATS.

Figure 10.7 shows the traffic flow data of each day (from 5:00 AM to 12:00 PM) in 1 week (from Sunday to Saturday) that is generated by one computational experiment in the Jinan ATS. Though traffic flow curves fluctuate from day to day in Figure 10.7, we can distinguish workdays and weekends easily. From Monday to Friday, the traffic flow data follows an M-shape curve. Morning peak and evening peak are both obvious on workdays and their times are around 7:00 AM and 6:00 PM. However, there is only one peak in the weekend traffic flow and the traffic flow stays at a high level for most of the daytime, though the maximum is a bit lower than the peak hour on workdays.

Figure 10.8 shows the curves of average values of the traffic flows in Figure 10.7. Putting the two curves together, the differences between workdays and weekends are more obvious. In addition, this figure enables us to analyze the traffic flows in detail. On workdays, morning rush hours last from 6:00 AM to 8:00 AM, and the maximum flow in this period is about 500 vehicles per hour. Compared to the morning rush hour, the evening rush hour is shorter by about half an hour, and the maximum value is bigger by about 100 vehicles per hour.

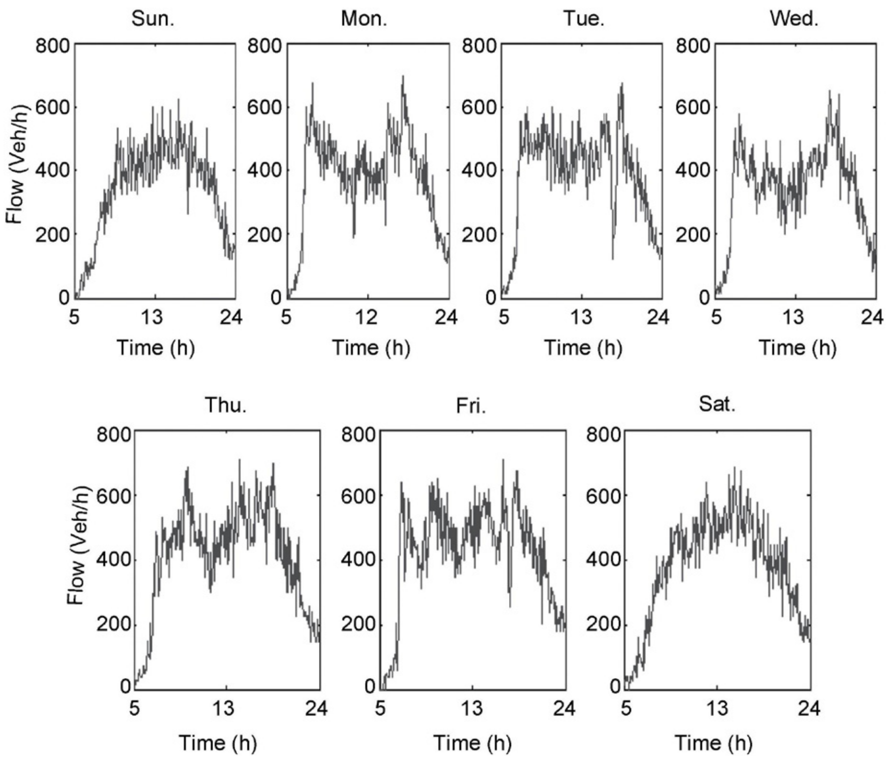


Figure 10.7: Traffic Flow from Sunday to Saturday

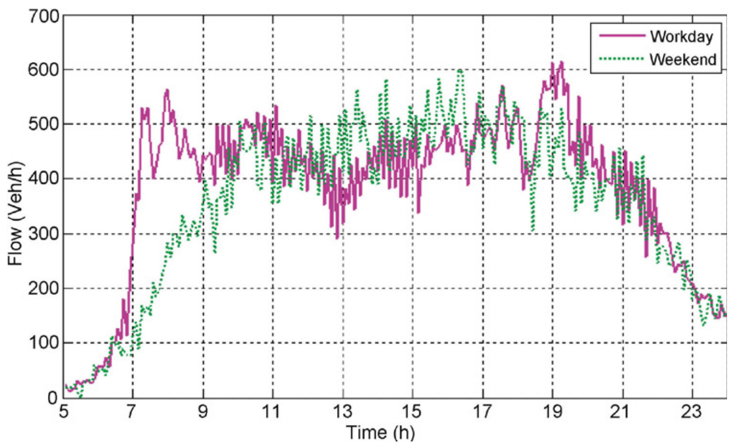


Figure 10.8: Average speed of workdays and weekends

At weekends, the start time of the morning rush hour is about 9:30, which is much later than on workdays. The peak period at weekends lasts for a long time and the traffic flow is higher than 500 vehicles per hour until 7:15 PM.

From Figure 10.7 and Figure 10.8, we can see that the generated traffic flows can represent the peak phenomena in a real transportation system and the results are supported by actual data.

Therefore, the feasibility of the activity-based travel demand generation is also verified. Using traditional simulation software, travel demand is generated based on an OD matrix and, to generate the similar result, one day is divided into several intervals and the OD matrixes have to be calibrated interval by interval. Also, the calibration of OD needs painstaking efforts. 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 the local population's social and economic activities are omitted in OD completely, it is very hard to evaluate the performances of different control strategies in various conditions.

10.5.3 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 impact on traffic, we have divided rainy weather into four levels, light rain, middle rain, heavy rain, and rainstorm, as shown in Table 10.3. Each kind of adverse weather is simulated for one whole day. Jinan ATS simulated the detailed traveling process of each individual in computational experiments and extensive evaluation indices can be generated. Because it is very difficult to show many of them due to space constraints, we will only show part of them as examples. In reality, average speed and vehicles in the 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.

Figure 10.9 shows the cumulative distribution curve of average vehicle speeds on 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 changes from normal to rainstorm.

Table 10.3: The levels of rain.

	Precipit. (mm/24 h)	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

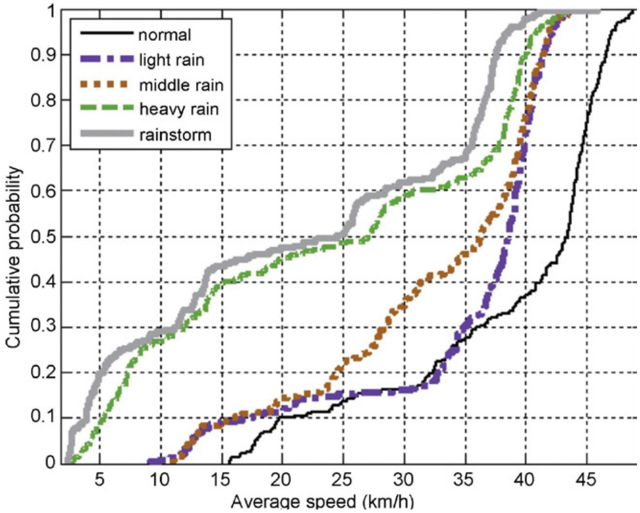


Figure 10.9 The Cumulative Distribution Curves of Average Vehicle Speeds under Different Weather Conditions

Table 10.4 shows 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% quartiles, which are common indices used in urban traffic evaluation, are also shown in Table 10.5.

Figure 10.10 shows the cumulative distribution curves of vehicles in the network on the same day as Figure 10.9 under different weather conditions. As expected, the number of vehicles in the network increases gradually when the weather changes from normal to rainstorm. Table 10.4 also shows some statistical characteristics of vehicles in the network under different weather conditions. We can see that when the weather condition is getting worse, almost all these indices are increased (some exceptions may be caused by random errors), which means the traffic status is getting worse and worse. One interesting conclusion that can be drawn from Figure 10.8 and Figure 10.9 is that the impact of light rain and middle rain is very close, while the impact of heavy rain and rainstorms is also very close. It seems

Table 10.4: 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

Table 10.5: Statistical characteristics of vehicles in the network under different weather conditions.

	Mean	Std.	Min.	Max.	15%Q	85% Q
Normal	35,079	40,847	950	1,77,150	9,250	52,000
L. rain	47,226	45,734	850	1,89,950	10,350	76,900
M. rain	53,293	52,512	1,150	2,14,000	10,400	1,08,600
H. rain	77,581	57,661	1,000	1,85,850	17,700	1,46,600
RS	85,058	62,067	1,150	1,90,250	19,300	1,63,500

that, in the perspective of the impact on transportation systems, rain can be represented using even fewer categories.

10.6 Conclusions

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

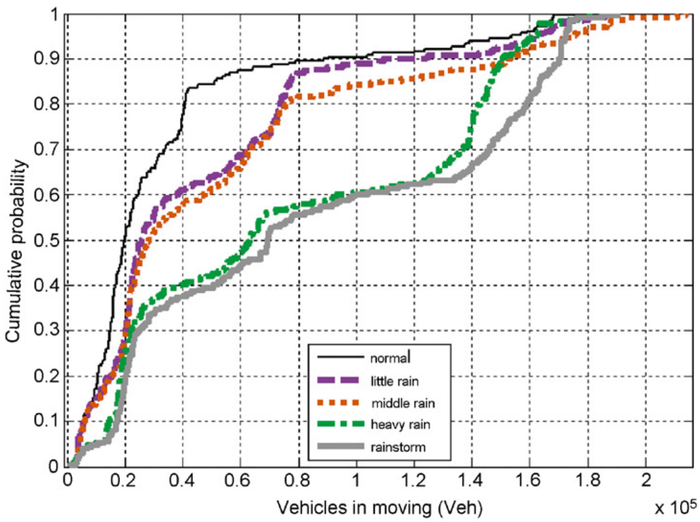


Figure 10.10: The cumulative distribution curves of vehicles in the network under different weather conditions

Recently, an intensified effort has been launched to set up standards and procedures to construct artificial transportation systems based on the ACP approach. Unlike conventional traffic simulation programs, those ATS are intended to be running continuously in cyberspace through web computing and computer gaming technologies, just like real traffic systems in real cities. We believe it has opened up 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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