

MULTI-AGENT SIMULATION IN INTEGRATED PASSENGER TRANSPORTATION SYSTEM UNDER UNCERTAIN ENVIRONMENT

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ABSTRACT

With the rapid development of transportation technology, public passenger traffic system construction investment is getting more and more expensive. Determining the development trend and make the optimal allocation of transportation investment becomes more and more important to the government. To describe the relationship and development trends of the integrated passenger transportation system under uncertain environment, an uncertain multi-agent model is proposed. Then, uncertain variable simulation technique is introduced to estimate the uncertainties in the model. A simulation program based on swarm platform is developed to implement the proposed model. Finally, a numerical experiment is conducted to illustrate that this technique is effective and can be used in decision support.

Keywords: *Multi-agent Simulation, Uncertain Variable, Transportation System*

1. INTRODUCTION

In the traditional research on integrated transportation system, the factors which influence a passenger's decision are usually defined as certain variables. However, there are many uncertain factors in travelling between each pair of nodes as the travel is always affected by weather conditions, traffic conditions, accidents, etc. Usually, the uncertainty is characterized as random variables. But the environment in which real transportation problems occur is often imprecise and the parameters which influence the decisions can not be assessed exactly. In addition, when the data is sparse, the use of statistical methods to model an integrated transportation system may lead to inefficiency. As a result of this, fuzzy variables are employed to describe such uncertain factors. Many researches in this area have been carried out. Zadeh [1] introduced the concepts of fuzzy sets and possibility measures and outlined the generalized theory of uncertainty in a much broader perspective. Zhang [2] studied the fuzzy age-dependent replacement policy and proposed the fuzzy simultaneous perturbation stochastic approximation algorithm to determine the optimal solution. In an integrated transportation system the fuzziness and randomness are often mixed up with each other. Thus, both of the two uncertainties should be considered simultaneously. Xu [3]

discussed the age-dependent replacement policy, in which the inter-arrival lifetimes of components are characterized as random fuzzy variables.

As the integrated transportation system is a complex adaptive system, which composed by many independent companies and customers. Each individual are independent decision making, and seek their interests maximization. It is very difficult to analyze a complex adaptive system through the traditional mathematical method. In order to solve such problems, many new methods are proposed and agent based simulation has become one of the most attractive computational methodology in recent years. Its popularity results from the fact that it allows for a complex adaptive system to be simulated in a relatively straightforward way. Unlike traditional mathematical simulation tools, agent-based simulation based on components called agents and defines rules to determine the interactions of agents. To model and simulate complex system, Macal [4] proposed the basic concept for Agent-based modeling and simulation. Itami [5] simulated the complex interactions between human movement and the outdoor recreation environment. Jin [6] proposed a new methodology which tries to bridge the gap by integrating design and implementation to multi-agent systems. Cai [7] constructed a hierarchical architecture for virtual mine to simulate coalmine risk accidents based on virtual reality and Multi-

agent technology. Cointet [8] made the functional analysis tracking a railway system case through complex system model. Wu [9] found that existing models can be broadly categorized according to four usage scenarios and reviewed existing airport terminal passenger models by using a Concept of Operations (CONOPS) methodology to help structure the review of existing modeling capabilities and usage scenarios.

This paper focused on the model and simulation of integrated passenger transportation systems, which has different passenger transportation modes (railway, highway, civil aviation etc) under uncertain environment. Section 2 reviews some of the properties of uncertain variables and in Section 3, the uncertain simulation technique is considered, and a multi-agent simulation model is proposed. Finally, a numerical example is given to illustrate the proposed method.

2. UNCERTAIN VARIABLES

In an integrated transportation system, when a passenger travels from a city to another, there are many uncertain factors influence the user's decision, such as trip time, travel cost, etc. Such uncertain factors can be classified into three types: possible factors, probable factors and mixture of both.

Usually, the probable factors can be characterized as random variables, the possible factors can be characterized as fuzzy variables and the mixture can be characterized as fuzzy random variables or random fuzzy variables.

2.1 Fuzzy Variables

In order to present the axiomatic definition of possibility, Nahmias [10] and Liu [11] proposed the definitions of possibility space, necessity measure and credibility measure.

Let $(\Theta, P(\Theta), Pos)$ be a possibility space, and A a set in $P(\Theta)$. Then the necessity measure of A can be defined as:

$$Nec\{A\} = 1 - Pos\{A^c\}. \quad (1)$$

Let $(\Theta, P(\Theta), Pos)$ be a possibility space, and A a set in $P(\Theta)$. Then the credibility measure of A can be defined as:

$$Cr\{A\} = \frac{Pos\{A\} + Nec\{A\}}{2}. \quad (2)$$

A fuzzy variable ξ can be defined as a function from the possibility space $(\Theta, P(\Theta), Pos)$ to the set of real numbers, and its membership function is derived by:

$$\mu_{\xi}(r) = Pos\{\theta \in \Theta \mid \xi(\theta) = r\}. \quad (3)$$

A random fuzzy variable ξ is nonnegative if and only if $Pos\{\xi \leq 0\} = 0$.

If ξ is a fuzzy variable on the possibility space $(\Theta, P(\Theta), Pos)$, based on the proposed credibility measure, the expected value $E[\xi]$ is defined by:

$$E[\xi] = \int_0^{\infty} Cr\{\xi \geq r\}dr - \int_{-\infty}^0 Cr\{\xi \leq r\}dr, \quad (4)$$

provided that at least one of the two integrals is finite. In particular, if the fuzzy variable ξ is positive, then

$$E[\xi] = \int_0^{\infty} Cr\{\xi \geq r\}dr.$$

Usually, the trip time between each pair of cities is assumed to be independent. The fuzzy variables $\xi_1, \xi_2, \dots, \xi_n$ defined on the possibility space $(\Theta, P(\Theta), Pos)$ are said to be independent, if and only if

$$Pos\{\xi_i \in A_i, i = 1, 2, \dots, n\} = \min_{1 \leq i \leq n} Pos\{\xi_i \in A_i\}. \quad (5)$$

If ξ_1 and ξ_2 are two independent fuzzy variables with finite expected values, then for any real numbers a and b , according to the definition of expected value of fuzzy variable, we have

$$E[a\xi_1 + b\xi_2] = aE[\xi_1] + bE[\xi_2]. \quad (6)$$

2.2 Random Fuzzy Variables And Fuzzy Random Variables

Based on the possibility measure, a random fuzzy variable is a function from the possibility space $(\Theta, P(\Theta), Pos)$ to the set of random variables.

Let ξ be a random fuzzy variable. Then the expected value $E[\xi]$ is defined by

$$E[\xi] = \int_0^{\infty} Cr(\theta \in \Theta \mid E[\xi(\theta) \geq r])dr - \int_{-\infty}^0 Cr(\theta \in \Theta \mid E[\xi(\theta) \leq r])dr \quad (7)$$

provided that at least one of the two integrals is finite.

A random fuzzy variable ξ is nonnegative if and only if for each $\theta \in \Theta$, $Pr(\xi(\theta) < 0) = 0$.

A fuzzy random variable is a measurable function from a probability space (Ω, A, Pr) to a collection of fuzzy variables.

Let ξ be a random fuzzy variable. Then the expected value $E[\xi]$ is defined by

$$E[\xi] = \int_0^\infty \Pr\{\omega \in \Omega \mid E[\xi(\omega)] \geq r\} dr - \int_{-\infty}^0 \Pr\{\omega \in \Omega \mid E[\xi(\omega)] \leq r\} dr \quad (8)$$

provided that at least one of the two integrals is finite.

A random fuzzy variable ξ is nonnegative if and only if for each $\omega \in \Omega$, $\text{Pos}(\xi(\omega) < 0) = 0$.

3. UNCERTAIN INTEGRATED PASSENGER TRANSPORTATION SYSTEM MODEL

With the rapid development of transportation technology, public passenger traffic system construction investment is getting more and more expensive. Determining the development trend and make the optimal allocation of transportation investment becomes more and more important to the government. As the integrated passenger transportation system unavoidably is a complex adaptive system which is difficult to analyze using traditional mathematical modeling methodology. In order to model such a system, agent based modeling is employed. Often, when a passenger goes to another place, there are many uncertain factors affect his/her decision, some are fuzzy, some are random, and some are both the two mixed up with each other.

In this section, we will first introduce the uncertain simulation technique to estimate the uncertain variable. Then the multi-agent simulation model is established to mimic the integrated passenger transportation system.

3.1 Uncertain Variables Simulation

Let ξ be a discrete fuzzy variable with membership function $\mu(a_i) = \mu_i$ for $i = 1, 2, \dots, n$, assumed that $a_1 \leq a_2 \leq \dots \leq a_n$, it is easy to get that

$$E[\xi] = \sum_{i=1}^n \omega_i a_i, \quad (9)$$

where the weights ω_i , $i = 1, 2, \dots, n$ are given by:

$$\omega_1 = \frac{1}{2}(\mu_1 + \max_{1 \leq j \leq n} \mu_j - \max_{1 < j \leq n} \mu_j)$$

$$\omega_i = \frac{1}{2}(\max_{1 \leq j \leq i} \mu_j - \max_{1 \leq j < i} \mu_j + \max_{i \leq j \leq n} \mu_j - \max_{i < j \leq n} \mu_j), 2 \leq i \leq n-1$$

$$\omega_n = \frac{1}{2}(\max_{1 \leq j \leq n} \mu_j - \max_{1 \leq j < n} \mu_j + \mu_n).$$

According to equation (9), an algorithm for estimating the expected value of fuzzy variable ξ is designed, and summarized as follows:

Algorithm 1: Simulation algorithm for estimating the expected value of fuzzy variable.

Step1: Set $e = 0$.

Step2: Randomly generate θ_k from Θ such that

$\text{Pos}\{\theta_k\} \geq \varepsilon, k = 1, 2, \dots, N$, where ε is a sufficiently small number.

Step3: Set $a = \xi(\theta_1) \wedge \dots \wedge \xi(\theta_N)$, and

$b = \xi(\theta_1) \vee \dots \vee \xi(\theta_N)$.

Step4: Randomly generate r from $[a, b]$.

Step5: If $r \geq 0$ set $e = e + \text{Cr}\{\xi \geq r\}$ else set

$e = e - \text{Cr}\{\xi \geq r\}$.

Step6: Repeat Step4-5 for N times.

Step7: Return $a \vee 0 + b \wedge 0 + e(b - a) / N$.

Especially, when the fuzzy variable is positive, the algorithm for estimating the expected value of fuzzy variables can be simplified as follows:

Algorithm 2: Simulation algorithm for estimating the expected value of positive fuzzy variable.

Step1: Randomly generate θ_k from Θ and store the values into vector V , such that

$\text{Pos}\{\theta_k\} \geq \varepsilon, k = 1, 2, \dots, N$, where ε is a sufficiently small number.

Step2: Calculate $\mu(\xi_{\theta_k})$ and store values into vector U .

Step3. Sort U in ascending and adapt V , respectively.

Step4: Calculate ω_i and store the values into vector W .

Step5: Return $V \times W$.

When ξ is a fuzzy random variable, the fuzzy random simulation for estimating $E[\xi]$ is given as follows:

Algorithm 3: Simulation algorithm for estimating the expected value of fuzzy random variable.

Step1: Set $e = 0$.

Step2: Sample ω from Ω according to the probability measure Pr .

Step3: Set $e = e + E[\xi(\omega)]$, where $E[\xi(\omega)]$ can be calculated by the fuzzy expected value simulation algorithm given above.

Step4: Repeat Steps 2-4 for N times.

Step5: Return $\frac{e}{N}$.

When ξ is a random fuzzy variable, the random fuzzy simulation for estimating $E[\xi]$ is given as follows:

Algorithm 4: Simulation algorithm for estimating the expected value of fuzzy random variable.

Step1: Set $e = 0$.

Step2: Uniformly sample θ_i from Θ such that

$Pos\{\theta_i\} \geq \varepsilon, i = 1, 2, \dots, N$, where ε is a sufficiently small number.

Step3: Let $a = \min_{1 \leq i \leq N} E[\xi(\theta_i)]$ and

$b = \max_{1 \leq i \leq N} E[\xi(\theta_i)]$.

Step4: Uniformly generate r from $[a, b]$.

Step5: If $r > 0$, then set $e = e + Cr\{\theta \in \Theta \mid E[\xi(\theta_i)] \geq r\}$, else set $e = e - Cr\{\theta \in \Theta \mid E[\xi(\theta_i)] \leq r\}$

Step4: Repeat Steps 2-5 for N times.

Step5: Return $a \vee 0 + b \wedge 0 + e(b - a) / N$.

3.2 Multi-Agent Simulation

To simulate the integrated transportation system, all agents' behavior mimics that of real entities. Agents in the model are the actual players in the system, which include transportation firms and passengers. There is a probability that a passenger may select the transportation firm. The probability depends on several factors including income levels, cost time and riding comfortableness, etc. The incoming level is assumed to be a random variable of normal distribution. Riding comfortableness is the passengers' subjective feeling, which can be characterized as a fuzzy variable. The cost time's uncertainty is usually mixed up with both fuzziness and randomness and can be indicated by a fuzzy random variable or random fuzzy variable.

When a passenger goes to another place, he/she will choose a transportation firm and pay for it according to his/her utility function which is defined as:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \quad (10)$$

where V_{ij} is the utility value of consumer i choosing company j as his service provider, ε_{ij} is the corresponding random error. Usually V_{ij} is a fuzzy random variable or a random fuzzy variable, ε_{ij} is a random variable. It is clearly that U_{ij} is a function of random variable, fuzzy variable, fuzzy random variable and random fuzzy variables

All agents act according to the predefined rules/schema and the decision goal is maximize its expected utility value. Every passenger has a certain amount of wealth, and will pay their transportation service. In this simulation, an integrated transportation system with three types of transportation modes (highway, high-speed railway and civil aviation) is considered and the following IF/THEN rules are used:

1. If the profit decreases for continually 10 periods, then the service provider will adapt its price to gain more market share.

2. If a service provider's market share decreases for more than continually 50 periods, then it will adapt its service and price strategy.

3. If a certain number of customers do not get service, then a new transportation company will be set up to meet the passenger's need.

4. If a civil aviation company's profit decreases, then it will compare the price with other service provider and decide to adapt its price or improve its service (it will increase the company's cost).

5. If a highway passenger transportation company's profit decreases, then it will improve its service.

6. If the high speed rail company's profit decreases, then it will improve the transportation network and expand its service scope.

As the utility value is a function of random variable, fuzzy variable, fuzzy random variable and random fuzzy variables, uncertain variables simulation technique is employed to estimate the value of such uncertain variables. The simulation system is developed using java programming language on a windows PC with an Intel processor base on swarm. Swarm is a multi-agent software platform for the simulation of complex adaptive systems, which was developed by the Santa Fe Institute based on java and C++. To validate the validity of the proposed method, a numerical example considered the transportation data of Beijing and Shanghai is conducted. In this example, the transportation data between Beijing and Shanghai is used to initialize the model.

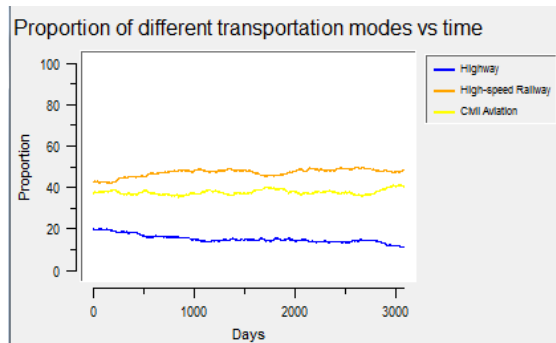


Figure 1: The proportion of different transportation modes

Figure 1 shows the proportions of different transportation modes vs. time. As the curve shows, the proportion of highway passenger transportation decreases while the other two modes increase. It implies that the government should lead social investment to the railway and civil aviation, especially high speed railway.

4. CONCLUSION

In this paper, the integrated passenger transportation system under uncertain environment was discussed. For the complexity of this system, we took advantage of agent based modeling to establish a multi-agent computer-aided analysis model to describe the system. Considered there are many uncertain factors affect passengers' travel utility function, random variables, fuzzy variables, fuzzy random variables and random fuzzy variables are employed to characterize such fuzzy uncertainties, random uncertainties and the mixture of both. In order to evaluate the passengers' utility value, the uncertain variables simulation technique is used to estimate the expected value of uncertain variables in the integrated passenger transportation system. To implement the proposed model, the swarm simulation platform is employed and a multi-agent simulation program is developed based on swarm using Java programming language. Finally, a simulation experiment is conducted to validate the proposed model and provide decision support.

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REFERENCES:

- [1] L. Zadeh, "Toward a generalized theory of uncertainty (GTU) – An outline", *Information Sciences*, Vol. 172, No.1, 2005, pp. 1–40.
- [2] J. Zhang, R. Zhao, W. Tang, "Fuzzy age-dependent replacement policy and SPSA algorithm based-on fuzzy simulation", *Information Sciences*, Vol.178, No. 4, 2008, pp. 573–583.
- [3] S. Xu, J. Zhang, R. Zhao, Random fuzzy age-dependent replacement policy, *Fuzzy Systems and Knowledge Discovery, PT 1, Proceedings*, Springer-Verlag Berlin, August 27-29, 2005 pp. 336-339.
- [4] C. Macal and M. North, "Tutorial on agent-based modelling and simulation," *Journal of Simulation* Vol. 4, No. 2, 2010, pp. 151–162.
- [5] R. Itami, R. Raulings, G. MacLaren, K. Hirst, R. Gimblett and D. Zanon "Simulating the complex interactions between human movement and the outdoor recreation environment," *Journal for Nature Conservation* Vol. 11, No. 2, 2003, pp. 278-286.
- [6] X. Jin, H. Zhe, "An Integrated Methodology for Multi-agent Systems Design", *Journal of Convergence Information Technology*, Vol. 7, No. 12, 2012, pp. 428-437.
- [7] L. Cai, X. Zheng, H. Qu, Z. Luo, "Risk Accident Simulation Using Virtual Reality and Multi-agent Technology", *International Journal of Digital Content Technology and its Applications*, Vol. 5, No. 2, 2011, pp. 181-190.
- [8] A. Cointet, C. Laval, "Complex system understanding back to basics! The functional analysis tracking a railway system case", *WIT Transactions on the Built Environment*, Vol. 128, No. 5, 2012, pp. 553-562.
- [9] P. Wu, M. Kerrie, "A review of models and model usage scenarios for an airport complex system", *Transportation Research Part A: Policy and Practice*, to be published, 2012
- [10] S. Nahmias, "Fuzzy variables", *Fuzzy Sets and Systems*, Vol. 1, No. 1, 1978, pp. 97–110.
- [11] B. Liu, Y. Liu, "Expected value of fuzzy variable and fuzzy expected value model", *IEEE Transactions on Fuzzy Systems*, Vol. 10, No. 4, 2002, pp. 445–450.