Theme Park Simulation based on Questionnaires for Maximizing Visitor Surplus

Extended Abstract

Hitoshi Shimizu
NTT Communication Science Laboratories
Kyoto, Japan
hitoshi.shimizu.kg@hco.ntt.co.jp

Tatsushi Matsubayashi
NTT Service Evolution Laboratories
Kanagawa, Japan
tatsushi.matsubayashi.tb@hco.ntt.co.jp

Akinori Fujino
NTT Communication Science Laboratories
Kyoto, Japan
akinori.fujino.yh@hco.ntt.co.jp

Hiroshi Sawada
NTT Communication Science Laboratories
Kyoto, Japan
hiroshi.sawada.wn@hco.ntt.co.jp

ABSTRACT

The *theme park problem* is a research framework that evaluates measures for improving the satisfaction of visitors to crowded amusement parks on a multi-agent simulation (MAS). To make the MAS more realistic, we propose the followings: 1) *visitor surplus*, which evaluates visitors' satisfaction based on microeconomics, 2) *multinomial linear model*, a selection behavior model based on visitor surplus, and 3) *a tolerance limit model*, which estimates the distribution of the visitors' tolerance limits of waiting times by analyzing questionnaire results.

ACM Reference Format:
Hitoshi Shimizu, Tatsushi Matsubayashi, Akinori Fujino, and Hiroshi Sawada. 2020. Theme Park Simulation based on Questionnaires for Maximizing Visitor Surplus. In *Proc. of the 19th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2020), Auckland, New Zealand, May 9–13, 2020,* IFAAMAS, 3 pages.

1 INTRODUCTION

Kawamura et al. [15] defined the *theme park problem*, and proposed it as a testbed for guidance systems to mitigate congestion and increase visitors' satisfaction. Since then, various guidance methods have been proposed for the theme park problem [5, 6, 12–14, 18, 21, 24]. Although the problem's main purpose is developing guidance systems, it is also important to ensure the validity of MAS. Therefore we propose the followings about MAS of theme park problem in the rest of this paper: §2. *visitor surplus*, which evaluates visitors' satisfaction based on microeconomics, §3. *multinomial linear model*, a selection behavior model based on visitor surplus, and §4. *a tolerance limit model*, which estimates the distribution of the visitors' tolerance limits of waiting times by analyzing questionnaire results.

2 VISITOR SURPLUS

For the first issue, various indicators have been developed for evaluating congestion and visitors' satisfaction [1, 15, 16, 23, 31]. Fung [9]

Proc. of the 19th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2020), B. An, N. Yorke-Smith, A. El Fallah Seghrouchni, G. Sukthankar (eds.), May 9–13, 2020, Auckland, New Zealand.

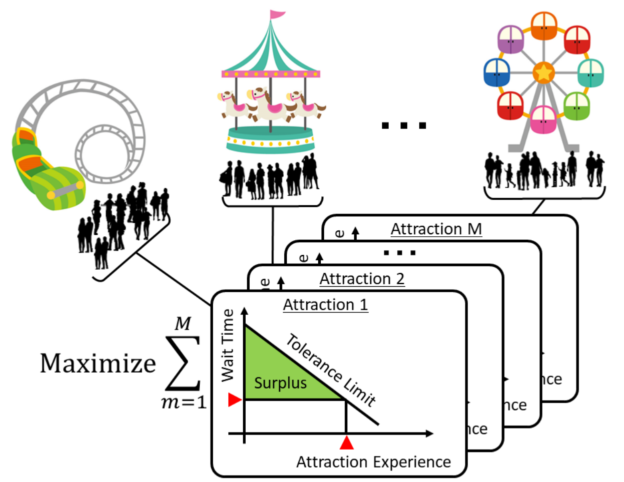

Figure 1: Each visitor gets surplus from attraction experiences. Visitor surplus is sum of surplus of all visitors (green area) for all attractions.

empirically pointed out that the difference between expected waiting time and actual one affects the satisfaction levels. Therefore, we propose *visitor surplus* as an evaluation index. In microeconomics, consumer surplus is defined as the price at which a consumer is willing to buy something (the willingness to pay) minus the transaction price, and it refers to the benefit obtained by the consumer from the transaction [17]. Figure 1 shows the same concept applied to the amusement park situation. If the *tolerance limits* for the attraction experience are the willingness to pay, we can draw a corresponding downward curve by arranging the tolerance limits in descending order from the left. If the actual *waiting time* is regarded as the transaction price, the total visitor surplus obtained from the attraction experience is the area of the green triangle. We simulate an amusement park for a single day. The park has M attractions, and N people visit and experience the attractions. Then, we define visitor surplus $S = \sum_n^N \sum_m^M \sum_\ell^{L_{m,n}} (\alpha_{n,m} - \hat{W}_{m,n,\ell})$, where $L_{m,n}$ is the number of experiences of attraction m by visitor n, $\alpha_{m,n}$ represents the tolerance limit of n for attraction m, and $\hat{W}_{m,n,\ell}$ is the actual ℓth waiting time of visitor n for attraction m. With reference to microeconomics, the larger the visitor surplus is, the greater is the benefit for visitors.

3 MULTINOMIAL LINEAR MODEL

The second issue concerns selection behavior models, which are rules that the visitors follow on MAS. In existing models [15, 20], there is the probability for any visitor to select an attraction with too long waiting time. Such behaviors are inconsistent with the idea of surplus that a visitor has a tolerance limit and doesn't select options beyond the limit. Therefore, we use a *multinomial linear model* where visitors select options within their tolerance limits.

We assume that a visitor acts according to the same rules as [25]. Visitors select attractions based on a *multinomial linear model*, which assumes the following attractions of facility m at time t and the probability of selecting facility m: $a_{m,n,t} = \max(0, \alpha_{m,n} - W_{m,t})$, and $\theta_{m,n,t} = \frac{a_{m,n,t}}{\sum_{m=1}^{M} a_{m,n,t}}$, where $W_{m,t}$ is the waiting time at time t of attraction m. When $\sum_{m=1}^{M} a_{m,n,t} = 0$, the visitor stays without selecting any attraction. The probability of selecting an attraction is in proportion to expected surplus $\alpha_{m,n} - W_{m,t}$.

4 TOLERANCE LIMIT MODEL

Regarding the third issue about reflecting the visitors' preferences into MAS, we analyze questionnaire results by a *tolerance limit model* to measure visitor preferences. Our model assumes that the preferences are proportional to the tolerance limits of waiting times, and that the distribution of the tolerance limits is continuous and smooth. This model enables us to evaluates the surplus on MAS. It was generally difficult to measure directly willingness to pay or surplus [7, 10, 11, 17, 30] though the travel cost method (TCM) estimates willingness to pay [4, 8, 27].

Each attraction m has popularity β_m and probability q_m to be in the candidate set. $x_{m,n} = 1$ denotes that m is in the candidate set of visitor n, and $x_{m,n} = 0$ denotes it is not, i.e. $x_{m,n} \sim \text{Bernoulli}(q_m)$. We assumed that attraction preference $\boldsymbol{\psi}_n = (\psi_{1,n}, \cdots, \psi_{M,n})$ follows Dirichlet distribution with parameter $\boldsymbol{\beta} \circ \boldsymbol{x}_n$, where $\circ$ represents the Hadamard product (element-wise product) operator, $\boldsymbol{x}_n = (x_{1,n} \cdots, x_{M,n})$, i.e. $\boldsymbol{\psi}_n \sim \text{Dir}(\boldsymbol{\beta} \circ \boldsymbol{x}_n)$. Then $\psi_{m,n} \geq 0$ and $\sum_m \psi_{m,n} = 1$. Perseverance ϕ_n, which is the maximum value of the tolerance limit of visitor n, is assumed to follow a lognormal distribution [29]: $\log(\phi_n) \sim \mathcal{N}(\mu, \sigma^2)$. Tolerance limit $\alpha_{m,n}$ can be estimated by product of perseverance ϕ_n and $\psi_{m,n}$, normalized to a maximum value of 1 to satisfy the assumption of a lognormal distribution: $\alpha_{m,n} = \phi_n \times \frac{\psi_{m,n}}{\max_m \psi_{m,n}}$.

5 SIMULATION RESULTS

We surveyed 32 office colleagues to identify their tolerance limits for five attractions. The parameters of the model in the previous section were estimated by PyTorch [22]. We performed the amusement park simulation using these parameters. The history of the waiting times and visitor surplus are shown in Fig. 2 and Fig. 3, respectively. Though the distribution of the visitor's parameters is homogeneous, when the number of visitors increases and the supply becomes short, the corresponding demand curve is pushed up nonlinearly. Since analyzing this situation is difficult with just mathematical formulas,

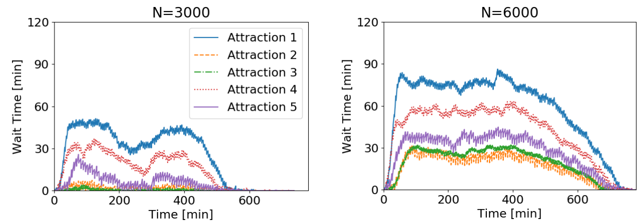

Figure 2: Waiting times of each attraction in the simulation with parameters obtained from questionnaire results. Waiting time peak for each attraction increases as N increases.

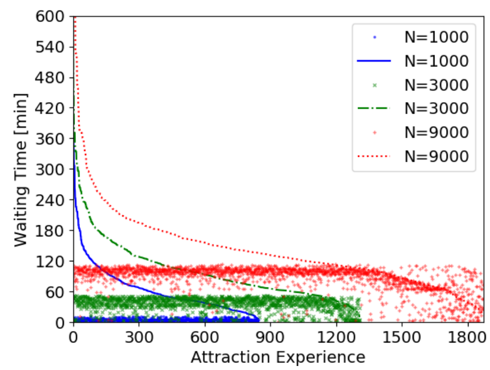

Figure 3: An example of surplus of attraction: Line shows tolerance limit of visitors who experienced attraction, and the point shows actual waiting times at that time. Sum of differences between lines and points corresponds to surplus.

MAS is a useful tool. Although we only described how the theme park problem can be treated as a surplus maximization problem by our proposed model, we want MAS to be used to estimate the surplus of general economic effects.

6 DISCUSSION

The theme park problem was originally proposed as an example for investigating a system to increase social welfare, based on the bounded rationality of individuals [15, 26]. Although traditional economists assume that humans make rational choices [2], behavioral economists are building a theory that considers bounded rationality [28]. However, many applied economists assume a multinomial logit model [19] as a behavior model whose selections are based on utility, and utility can be estimated from the observation of behavior. One problem is that a multinomial logit model assumes random utility maximization [3], which also cannot be implemented without rationality after fully understanding the options. The other problem is that estimating surplus from such estimated utility is not straightforward even though surplus is a critical indicator of social welfare in microeconomics. Therefore, we believe that economics needs to develop a choice behavior model based on surplus like our proposed model.

REFERENCES

[1] Reza H Ahmadi. 1997. Managing capacity and flow at theme parks. *Operations Research* 45, 1 (1997), 1–13.

[2] Kenneth J Arrow and Gerard Debreu. 1954. Existence of an equilibrium for a competitive economy. *Econometrica: Journal of the Econometric Society* (1954), 265–290.

[3] Moshe E Ben-Akiva, Steven R Lerman, and Steven R Lerman. 1985. *Discrete choice analysis: theory and application to travel demand*. Vol. 9. MIT press.

[4] Okmyung Bin, Craig E Landry, Christopher L Ellis, and Hans Vogelsong. 2005. Some consumer surplus estimates for North Carolina beaches. *Marine Resource Economics* 20, 2 (2005), 145–161.

[5] Liou Chu, Lin Hui, and Fu-Yi Hung. 2013. Simulation of theme park queuing system by using arena. In *2013 Ninth International Conference on Intelligent Information Hiding and Multimedia Signal Processing*. IEEE, 17–20.

[6] Liou Chu, Fu Yi Hung, and Yen Cheng Lu. 2014. Analysis and Simulation of Theme Park Queuing System. In *2014 Tenth International Conference on Intelligent Information Hiding and Multimedia Signal Processing*. IEEE, 9–12.

[7] Peter Cohen, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe. 2016. *Using big data to estimate consumer surplus: The case of uber*. Technical Report. National Bureau of Economic Research.

[8] Jeffrey Englin and J Scott Shonkwiler. 1995. Estimating social welfare using count data models: an application to long-run recreation demand under conditions of endogenous stratification and truncation. *The Review of Economics and statistics* (1995), 104–112.

[9] Kaiser Fung. 2010. *Numbers Rule Your World: The Hidden Influence of Probabilities and Statistics on Everything You Do*. McGraw-Hill Education.

[10] Glenn W Harrison and E Elisabet Rutström. 2008. Experimental evidence on the existence of hypothetical bias in value elicitation methods. *Handbook of experimental economics results* 1 (2008), 752–767.

[11] Kamel Jedidi and Sharan Jagpal. 2009. Willingness to pay: measurement and managerial implications. *Handbook of pricing research in marketing* (2009), 37–60.

[12] Takashi Kataoka, Hidenori Kawamura, Koichi Kurumatani, and Azuma Ohuchi. 2004. Distributed visitors coordination system in theme park problem. In *International Workshop on Massively Multiagent Systems*. Springer, 335–348.

[13] Takashi Kataoka, Hidenori Kawamura, Koichi Kurumatani, and Azuma Ohuchi. 2005. Effect of Congestion Reduction with Agents' Coordination in Theme Park Problem. In *Soft Computing as Transdisciplinary Science and Technology*. Springer, 245–254.

[14] Hidenori Kawamura, Takashi Kataoka, Koichi Kurumatani, and Azuma Ohuchi. 2004. Investigation of global performance affected by congestion avoiding behavior in theme park problem. *IEEJ Transactions on Electronics, Information and Systems* 124, 10 (2004), 1922–1929.

[15] Hidenori Kawamura, Koichi Kurumatani, and Azuma Ohuchi. 2003. Modeling of theme park problem with multiagent for mass user support. In *International Workshop on Multi-Agents for Mass User Support*. Springer, 48–69.

[16] Hidenori Kawamura, Ryota Ono, and Keiji Suzuki. 2014. Statement-based Cost Estimate for Co-utilization of Service Facilities. *Journal of Information Processing* 22, 2 (2014), 270–278.

[17] Paul Krugman and Robin Wells. 2012. *Microeconomics*. New York: Worth Publishers.

[18] Jin Li, Qinmin Wu, Daoli Zhu, and Yihong Hu. 2009. Multi-stage Dynamic Coordination Model for Large-Scale Crowd's Activities Based on Multi-agent. In *2009 WRI World Congress on Computer Science and Information Engineering*, Vol. 1. IEEE, 487–491.

[19] Daniel McFadden. 1978. Modeling the choice of residential location. *Transportation Research Record* 673 (1978).

[20] Kotaro Ohori, Mariko Iida, and Shingo Takahashi. 2013. Virtual grounding for facsimile model construction where real data is not available. *SICE Journal of Control, Measurement, and System Integration* 6, 2 (2013), 108–116.

[21] Yoshihiro Ohtani, Seiya Sawada, and Shinya Nogami. 2010. Study on congestion reducing in the theme park. In *8th Asia-Pacific Symposium on Information and Telecommunication Technologies*. IEEE, 1–6.

[22] Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. 2017. Automatic differentiation in PyTorch. *NIPS* 2017, Workshop (2017), Autodiff Workshop.

[23] Jorge E Prado and Peter R Wurman. 2002. Non-cooperative planning in multi-agent, resource-constrained environments with markets for reservations. In *AAAI 2002 Workshop on Planning with and for Multiagent Systems*. 60–66.

[24] Rudwiky Okta Putra, Sani Fathuddin Musoffa, Siti Nurhasanah, Erwin Anggadjaja, and Handri Santoso. 2017. QBLE-Theme park queueing system using wearable device. In *2017 IEEE 3rd International Conference on Engineering Technologies and Social Sciences (ICETSS)*. IEEE, 1–6.

[25] Hitoshi Shimizu, Tatsushi Matsubayashi, and Futoshi Naya. 2017. Simulation of Saturated Theme Park for Reduction of Waiting Time. *Journal of Japanese Society for Artificial Intelligence (in Japanese)* 32, 5 (2017).

[26] Herbert A Simon. 1955. A behavioral model of rational choice. *The quarterly journal of economics* 69, 1 (1955), 99–118.

[27] V Kerry Smith and Yoshiaki Kaoru. 1990. What have we learned since hotelling's letter?: A meta-analysis. *Economics Letters* 32, 3 (1990), 267–272.

[28] Richard H Thaler and Cass R Sunstein. 2009. *Nudge: Improving decisions about health, wealth, and happiness*. Penguin.

[29] Kenneth E Train. 2009. *Discrete choice methods with simulation*. Cambridge university press, Chapter 7.5 Contingent Valuation.

[30] Franziska Voelckner. 2006. An empirical comparison of methods for measuring consumers' willingness to pay. *Marketing Letters* 17, 2 (2006), 137–149.

[31] Yasushi Yanagita and Keiji Suzuki. 2009. Evaluation of Theme Park Problem on Complex Network Models—Comparison Methods of the Network Models. *Transactions of Information Processing Society of Japan (in Japanese)* 50, 1 (jan 2009), 437–446.