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AN AGENT-BASED SIMULATION APPROACH TO EXPERIENCE MANAGEMENT IN THEME PARKS

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ABSTRACT

In this paper, we illustrate how massive agent-based simulation can be used to investigate an exciting new application domain of experience management in theme parks, which covers topics like congestion control, incentive design, and revenue management. Since all visitors are heterogeneous and self-interested, we argue that a high-quality agent-based simulation is necessary for studying various problems related to experience management. As in most agent-base simulations, a sound understanding of micro-level behaviors is essential to construct high-quality models. To achieve this, we designed and conducted a first-of-its-kind real-world experiment that helps us understand how typical visitors behave in a theme-park environment. From the data collected, visitor behaviors are quantified, modeled, and eventually incorporated into a massive agent-based simulation where up to 15,000 visitor agents are modeled. Finally, we demonstrate how our agent-based simulator can be used to understand the crowd build-up and the impacts of various control policies on visitor experience.

1 INTRODUCTION

The tourism and entertainment industry plays an increasingly important role in global economy. In recent years, theme parks have been an important driver in the growth of the tourism and entertainment industry. Unfortunately, vibrant growth in the theme park industry comes hand-in-hand with worsening congestion and increased wait times. From field observations and our computational experiments, we can conclude that there are at least three major causes for severe congestions to happen predictably in a theme park: 1) the fact that a small set of highly popular attractions are preferred universally, 2) the design of connecting paths that would cause visitors to converge at a few bottlenecks, and 3) the lack of global information on both real-time and historical queue lengths at attractions.

Different theme park operators have their respective strategies in dealing with high wait times. Notable examples include the FASTPASS system implemented in Disney parks, and the (for-fee) Express Pass system implemented in Universal Studios parks. The FASTPASS system is essentially a crowd diversion system that incentivizes visitors to visit popular attractions at designated later times by providing express accesses if they follow the instructions. The Express Pass system, on the other hand, monetizes wait time reductions by allowing visitors to pay for the rights to use the priority queues. There are other more subtle congestion aversion tactics, e.g., try to slow down visitor traveling along certain paths by providing street shows or character greetings, so that visitors coming from different approaches don't converge at bottlenecks at the same time.

Crowd control strategies that are based on advanced mobile and communication technologies are technically viable; however, to accurately evaluate the impact of a particular control strategy, we need to have a good model for visitor behaviors. Due to the heterogeneity of visitor preferences and the spatial temporal complexity of modeling visitor movements exactly, we rule out the use of mathematical model and resort to the use of simulation technology. In particular, to deal with massive number of self-interested and heterogeneous individuals, we choose the paradigm of agent-based simulation.

To capture how individual visitors are making decisions in a theme park, we designed a unique field experiment to collect GPS traces and queueing decisions of survey participants. From these outcomes, we are able to create statistical models on how visitors move around and make queueing decisions. These models for agent behaviors are then incorporated into an agent-base simulator and is calibrated against observed wait times. Finally, we demonstrate how the simulator can be used to evaluate a crowd control mechanism adopted by theme park operators. More specifically, we evaluate the congestion at the park when people are advised using a route recommender application (on smartphones).

2 MOTIVATION

The rationale behind building an agent-based simulation for theme park operations is that there are indeed recognizable and measurable patterns of how visitors behave. In this section, we provide an example of such pattern from a real world dataset of wait times for a large theme park. The aggregate wait times we use in this initial analysis are from our industry partner who operates a theme park in a major Asian city; this operator belongs to one of the top-three theme park groups that has been expanding very quickly and aggressively in recent years. The dataset contains the wait time updates at all the attractions every 30 to 90 minutes throughout each day from September 2011 to August 2012. (To protect the identity of our industry partner, all mentions to the park and attractions within are anonymized.)

Although we cannot directly observe individual visitor's preference from the dataset, the average wait times, which can be viewed as the aggregation of all visitors' choices, can be used as a proxy. If an attraction is indeed universally preferred among visitors over time, we should expect its wait time to be consistently higher than other attractions in the park. Wait times at major attractions during peak days from September 2011 to August 2012 (Saturdays in June and December are considered as peak days) are summarized in Table 1. From Table 1, we clearly see that attractions can be categorized according to their average wait times. Attr-T is the clear star attraction in this park (averaging 67% more than the distant second), while Attr-C, H, J, and BH can also be viewed as popular attractions. All other attractions are relatively less popular.

Table 1: Average wait times at major attractions.

Attr.	Avg.	Attr.	Avg.	Attr.	Avg.
T	82.0	BC	26.2	R	20.7
C	49.1	S	26.1	A	12.2
H	40.0	M	25.8	E	11.7
J	37.0	D	24.9	P	10.2
BH	31.4	L	22.7	K	7.8

Another interesting recurrent pattern we observe from the historical data is how average wait times fluctuate throughout the day. The wait time patterns of the top-4 attractions are plotted in Figure 1 (although the exact patterns change day by day, the shapes of the top-4 wait time patterns are pretty consistent and recurrent). For Attr-C, Attr-H, and Attr-J, the patterns are as expected: wait times increase gradually from 10am (the opening hour of this park) until 1-2pm, after which their wait times stay around the peak and fall slightly towards the park closure time. However, for Attr-T, which is characterized as the most popular star attraction in Table 1, a mysterious pattern can be observed: the wait time peaks quickly after the park

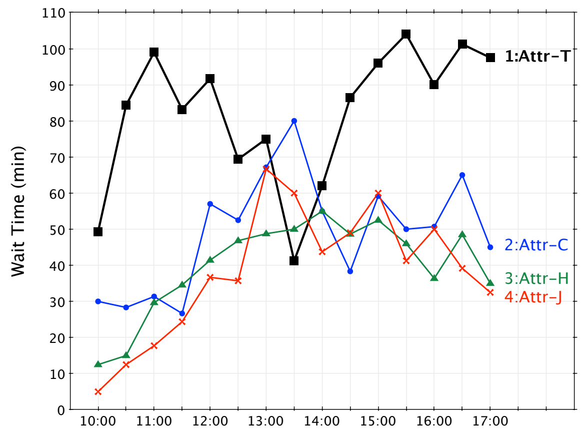


Figure 1: Two classes of wait time patterns: the “Star” (Attr-T) and the “Others”.

opens at 10am, and the wait time stays high except for the period of 1-2pm, during which its wait time plunges to level even lower than the rest of the other top-4 attractions. After 2pm, its wait time quickly return to the earlier peak and stay there. Since Attr-T is the unanimous star attraction of the park, there should be no reason why it would lose its appeal only during the period of 1-2pm.

Although these observations made at the macro level indeed demonstrate clear patterns, we still cannot infer the kind of individual behaviors that would produce such macro-level observations. In particular, we just cannot explain the mysterious wait time pattern of Attr-T shown in Figure 1. To go beyond macro data and have a clearer understanding of individual visitor’s behavioral patterns, we design a field experiment that can provide us with necessary data.

3 EMPIRICAL BEHAVIORAL MODEL FOR THEME PARK VISITORS

Behavioral models in the leisure industry are very different from ones in classical service and operations management. The main difference is the fact that people in leisure settings do not have concrete goals to achieve (though people do have a general objective of wanting to entertain themselves). Although past works on theme park operations do exist in literature, most of them are based on aggregate operational statistics or surveys (e.g., see Ahmadi (1997) and Kemperman et al. (2003)), and few shed light on how individuals make *real-time* decisions in theme park environments. This is not surprising, since theme park operators have limited means in tracking individual visitors. To bridge this gap, we designed a field survey that would allow us to track and collect individual visitor’s locations and activities (only for those who volunteered to be subjects). Based on this collected dataset, we can then create an empirical behavioral model for theme park visitors. (Although Disney Research seems to be actively doing research in the area of *Mobile App for Mitigating Theme-Park Crowding* (see http://www.disneyresearch.com/research-areas/behavioral-sciences/), there aren’t any publicly available research report or dataset.)

3.1 The Field Survey

As described earlier, the emphasis of the field survey is to collect sufficient amount of information for constructing visitor’s behavioral model. In particular, we want to understand how people move around and why they choose to queue up at a particular attraction. Visitors’ locations and their queueing choices are therefore the most important pieces of information we need to collect. To ensure that we have comprehensive records on survey participants’ full journeys, we have to design our survey protocol in a way that it is pervasive and requires minimum inputs from participants (given all the distractions and the noise level, any survey technique that requires frequent interaction with survey participants will not be practical). After careful evaluation, we picked the iPhone family as our survey platform. The screenshot of the survey App

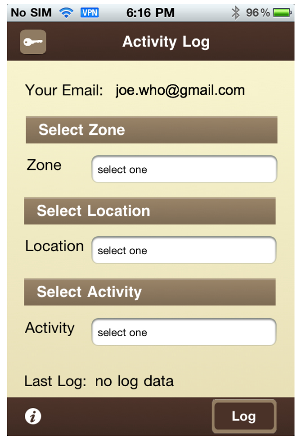


Figure 2: The smartphone app used in our field survey.

is shown in Figure 2. Users are asked to log when entering and leaving an attraction queue. The GPS coordinate is collected when an event is logged. The survey App also automatically gathers current GPS coordinate every 30 seconds.

50 groups were recruited for our field survey. All groups have at least two members and they are either students, staffs, or faculty members recruited from our institution. 9 out of 50 participating groups are families with young children. Participants were provided with free (for main participant) and discounted (for accompanying members) theme park tickets as incentives. To ensure that we have significant crowds in the park, the field survey was conducted on a Saturday in June 2012 (most crowded day of the week during the summer peak month).

Before entering the park on the day of the survey, all groups were asked to rank how they like thrilling, dark, and wet rides respectively from 1 (least preferred) to 5 (most preferred). From the park operator, we also received objective ratings on how thrilling, dark, wet, and child-friendly each attraction is. Besides collecting individual traces and logs, we also recorded the number of arriving / departing visitors to the theme park every 5 minutes and the official wait time estimations at all attractions every 15 minutes (all from 10am to 5pm).

3.2 Post Processing and Macro Analysis

A total of 86,376 data points were collected from all groups, but after initial processing, only 17,534 data points remained. The major post-processing steps are to remove data points that are: 1) duplicative, 2) recorded before park opening and after park closure, and 3) outside of park boundary (a data point can fall out of park boundary is the GPS reception is bad, e.g., if a visitor enters indoor attractions, or place the device in the locker, GPS signals recorded may be with very low accuracy). Equipment failure was experienced by one adult group, so all loggings from this device were removed. (After this adjustment, we have 40 adult groups and 9 family groups.)

The first interesting phenomenon we observe is the reconfirmation of the universal preference at individual level. At the macro level, the universal preference is confirmed via average wait times (see Table 1). At the individual level, the confirmation comes from the choice of attractions and the order of visit. Of particular interests are the queueing patterns at Attr-T (the “Star” attraction) and Attr-H (the third most popular attraction that is strongly favored only by children). As shown in Table 2, we can clearly see that the profile of our survey participants and wait times have strong influences on how queueing choices were made. For Attr-T, which is considered as a thrilling ride and is well-known to be the “Star” attraction of this park, adult groups indeed have almost universal attendance (34 out of 40 groups, or 85% of them, queued for Attr-T, 5 groups even attended it for the second time), and they are willing to queue for a long time for it (almost one hour on average). Family groups are more neutral towards Attr-T, as only half of

Table 2: Survey participants' queueing patterns at two popular attractions.

Attr-T (The Star Attraction)			
Profile	# Groups	# Trips	Avg. Wait Time (min)
Adult	34	39	58.4
Family	4	4	25
Attr-H (The Children's Attraction)			
Adult	4	4	23.8
Family	4	5	47.5

them (4 out of 9) attended the attraction, and their tolerances for wait times seem to be much lower (they queued on average 25 minutes). The pattern at Attr-H is very different: only 4 out 40 adult groups (10%)

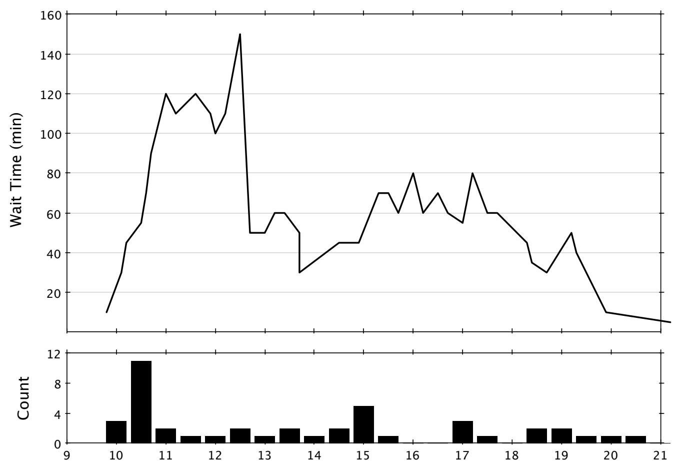


Figure 3: Wait time and count of visitors at Attr-T.

attended Attr-H, and the average wait time is 23.8 minutes; on the other hand, 4 out of 9 family groups attended Attr-H (same percentage as the star attraction), and they were willing to spend almost 50 minutes on average.

Another interesting observation is how survey participants timed their visits to Attr-T. From Figure 3 we can see that the visit pattern derived from our small sample is quite consistent with general park visitors: More than 50% of total trips at Attr-T are made before 1pm, and 60% of groups (23 out of 38) who visited Attr-T did so within the first hour after arrival.

3.3 Explaining the Bimodal Pattern at the Attr-T

With detailed location traces from our survey participants, we can finally begin our analysis on the mysterious bimodal wait time pattern at Attr-T. Based on our collected information, there were around 13,500 visitors on the day of survey; the number of field survey participants, on the other hand, is around 130. When examining the collected location traces, we can thus view them as sampled from the exact locations of all the visitors (with sampling rate at around 1%).

After testing a number of hypotheses, we finally found the reason that might contribute to the unique bimodal distribution at Attr-T. In summary, what we found is a close correlation between the wait time and the visitor flow at Attr-T (see Figure 4). To account for the inherent GPS errors, the visitor flow through Attr-T is estimated by monitoring any point that is within 100 meters from Attr-T. To count only unique visitors, for sequential traces that pass through the monitoring circle, we only count the first appearance. From Figure 4, we can see that the changes in visitor flows are more or less synchronized with wait times.

Although we cannot formally establish the causal relationship, the fact that such correlations also exist for other top attractions suggests that it's very likely that visitor flows indeed contribute to the wait times.

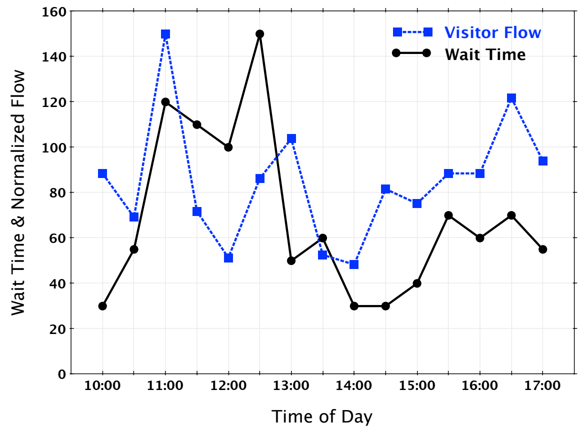


Figure 4: Patterns of wait times and visitor flows at Attr-T.

Now we know that the bimodal visitor flow pattern might contribute to the wait time pattern at Attr-T, a natural question to ask next is why visitor flow pattern is bimodal in the first place. It turns out that due to the park design, visitors can only reach Attr-T through two paths. One path can reach Attr-T almost immediately, while the other path would take visitors through rest of the park before reaching Attr-T. The expected difference in these two traversal times (considering expected attraction attendance along the way) are roughly three hours (based on the data we collected), and this explains why there's a gap of around three hours in between the first and the second peaks. The low wait times between 1-3pm can be explained by the lack of new visitors reaching Attr-T through both paths: for the first path, it runs out of new visitors since most visitors have already enter the park before noon and should have already walked past Attr-T by 1pm; for visitors following the second path, most of them are still on their ways.

Based on these initial analyses in this and last subsections, we find further supports for measurable universal preference, and more importantly, we can see that visitor's behavioral model can be decomposed into at least two components: 1) the movement model, which guides visitors through the park, and 2) the queueing model, which decides whether to join a nearby queue, given current state (e.g., waiting time, preference, attraction type, current time). We will elaborate on how to derive these two sub-models next.

3.4 Calibrating Visitor's Movement Model

Visitor's movement model can be derived from the collected dataset. In particular, we look at the sequence of GPS coordinates for each and every visitor. To reduce the state space to a reasonable size, we define 17 zones that are centered at major attractions. Let S_i^t be a collection of tuples that represents how visitor i moves between different zones in time period t:

$$S_i^t \equiv \{(s_{i,1}, s_{i,2}), (s_{i,2}, s_{i,3}), \dots, (s_{i,n_i-1}, s_{i,n_i^t})\},$$

in which $s_{i,j} \in \{1,2,\dots,17\}$ stands for the j^{th} zone visited by visitor i in time t, and n_i^t denotes number of zones visited by i in time t. The transition probability from a to b in time t is then:

$$p_{a,b}^t = \sum_i \left(\frac{c_{a,b}^{i,t}}{\sum_k c_{a,k}^{i,t}} \right),$$

where $c_{a,b}^{i,t}$ denotes number of times tuple (a,b) appears in S_i^t.

In the above derivation, it's implicitly assumed that the transition probability is Markovian and depends only on the current zone. This simplifying assumption is necessary since we have very limited amount of data (49 sets of traces). More state variables could be introduced if more data is available.

3.5 Calibrating Visitor's Queueing Model

The movement model determines how visitors should move around, and can be straightforwardly computed from movement traces. The decision on whether to join the queue, is more elaborated. Stated generally, the purpose of visitor's queueing model is to probabilistically decide whether to join a queue given observed state variables. Although there are many sophisticated techniques available from the machine learning literature that allow us to perform supervised learning on the set of labeled data from the field survey, we choose to implement a relatively straightforward *decision tree model*. Our choice of decision tree model is supported by researchers in the field of human judgment and decision making. As argued by Gigerenzer and Goldstein (1996) and Gigerenzer and Gaissmaier (2011), due to limited mental capabilities, human decision makers tend to monitor only one state variable at a time, ranked by the relative importance he or she perceives. Realizing the idea quantitatively, such *heuristic decision rules* can be represented exactly as decision trees.

3.5.1 Labeling Instances

The records of visitors joining attractions can be viewed as instances with a "positive" label, hinting the state (to be defined later) at that moment would lead visitors to join an attraction. The "negative" instances, unfortunately, are not available directly, and need to be inferred based on GPS traces. Intuitively speaking, we can define a negative instance when a visitor come close enough to an attraction, but chose not to join its queue. Formally speaking, if a visitor is ε meters from an attraction, this distance is considered as *close enough*. To avoid similar negative instances to be identified repeatively, a negative instance for an attraction will only be recorded if it's at least τ minutes from the last defined negative instance (for the same attraction). In our analysis, we let ε and τ be 50 and 15 respectively based on empirical tunings. In total, 273 positive instances and 47 negative instances are identified after our labeling process.

3.5.2 Decision Tree

The states of both positive and negative instances are defined as the tuple (E,T,L,P,W,H,M). E is the target attribute that is either positive (join the queue now) or negative (not now). T is the current time period, which can be one of the four ranges: 10-12, 12-2pm, 2-4pm, and after 4pm. L is the cumulative time a visitor has spent in the park (in minutes). P is the profile of the visitor, which can be 0 (*Adult*) or 1 (*Family*). W is the wait time at the attraction (in minutes). H is a boolean attribute indicating whether the attraction is among the most popular attractions (the top-4 thrilling rides). Finally, M indicates how well a visitor's preference matches the attraction's feature, which is computed using the following formula:

$$M = \sqrt{\sum_{k \in \{t,w,d\}} \left(\frac{r_v^k}{\sum_{k'} r_v^{k'}} - \frac{r_a^k}{\sum_{k'} r_a^{k'}} \right)^2}\,, \tag{1}$$

where r_v^k and r_a^k represent visitor's and attraction's ratings for feature $k \in \{t,w,d\}$. $\{t,w,d\}$ refer to *thrill*, *wetness*, and *darkness* respectively. Equation (1) is essentially the distance measure in the normalized feature space.

The decision tree learning algorithm we use is the standard C4.5 algorithm (Quinlan 1996). To validate the effectiveness of the learned decision tree, we divide the data set into 5 pieces and apply the cross-validation process. The performance of the decision tree model is shown in Table 3. From the result, we can see that the decision tree model can pretty accurately predict positive instances. As expected, negative instances are much harder to predict because of potential errors made during the labeling process.

Table 3: Performance of the learned decision tree model.

	True (–)	True (+)	Class Precision
Pred.(–)	20	19	51.3%
Pred.(+)	27	254	90.4%
Class Recall	42.6%	93.0%	

4 AN AGENT-BASED SIMULATOR

Our work is not the first attempt in applying simulation technique in modeling theme park operations. For example, Mielke et al. (1998) have created a discrete event simulation for theme parks, and Miyashita (2005) has created an agent-based simulation to model micro behaviors by the theme park visitors. However, a clear difference between our work and earlier works is the granularity of the model. While earlier simulation models utilize only macro-level data, with the aid of the field survey, we are able to create an agent-based simulation that is based on agent models built from empirical data. The design of the agents and the simulation engine are described next.

4.1 Agents

Agents in our simulation refer to theme park visitors. Every agent continuously makes two important decisions: 1) where to move to, and 2) whether to queue up for the closest attraction. These two decisions on movement and queueing are made according to the two models introduced in the previous section, and their implementations are straightforward. Inputs needed for both models (e.g., the current location and part of the state tuple) can be acquired from the simulation engine. However, the agent-dependent state information will need to be individually generated as simulator starts. Such information includes: agent's profile (adult or family), preference (the scale on thrill, darkness, and wetness).

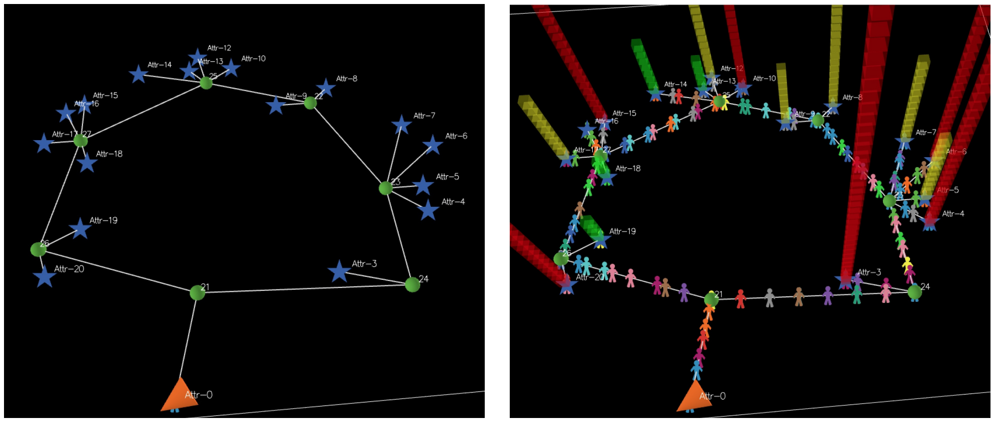
Visitor agents are assumed to move around on foot by default. However, it is also possible to define other types of transport like trams or shuttle buses. These transportation services could be incorporated by introducing addition agent classes with transport capability.

4.2 Simulation Engine

The simulation engine needs to keep the current time, manage the states of all attractions, and provide information services. The list of services to be provided by the simulation engine are listed below:

- It maintains network topology of the park, which is represented by an undirected graph made up of attractions (nodes) and connections between them (edges). We assume that the network topology is common knowledge among all agents (a mild assumption since all theme parks provide free maps at entry). The network topology is generically specified by a list of nodes (each with additional attraction-related parameters like service time, batch size, and attraction name) and a list of links (each edge is defined by the two end points and distance). This design allows us to model any theme park we have data for.
- It manages attraction queues. Each attraction has its respective service frequency and capacity per batch, and there will be at least one normal queue and in some cases a priority queue as well. (Visitor agents will need special privilege to use the priority queues.) Based on the queue length, the simulation engine also computes estimated wait times for all attractions. By default, an agent can only observe the wait times at visible attractions; if information service is available, park-wide wait time information can also be sent to selected agents.
- Agents can receive route guidance, in which case they will follow the suggested routes and not the empirical behavioral model. This service allows us to evaluate different crowd management mechanisms (which will be presented in the next section).

- Random events like attraction breakdowns or street shows can dynamically occur, resulting in changes to service rates and travel times on edges.



(a) (b)

Figure 5: Snapshots of the simulation: (a) Right after initialization. (b) During the peak hour.

When implementing the simulator, an important consideration is to make it easily configurable. All the above-mentioned physical settings and visitor's empirical behaviors can be easily changed by updating external configuration files. Our agent-based simulation is developed using NetLogo 5 plus customized Java extensions. Two snapshots of the simulation at initialization and during the peak hour can be seen in Figure 5. As illustrated, the 3D visualization allows us to denote queue lengths directly as colored vertical bars. All other statistics generated during the simulation are recorded and visualized separately.

4.3 Validation

One of the most important steps in completing an agent-based simulation is to provide proper validation. In our theme park simulator, the real-world phenomenon we would like to reproduce is the disproportional wait time distribution resulting from universal preference over a small set of attractions.

To objectively evaluate the fit, we compare relative wait times between the real-world and the simulated datasets. Although the raw wait times at the major attractions are not exactly the same, when we normalize the wait times in both scenarios respectively (against the maximum average wait time observed), the relative order and scales are reproduced exactly. This shows the applicability of our simulation in reproducing wait time patterns.

5 CASE STUDY: ROUTE RECOMMENDATION

In this section, we present a case study on using the simulator for evaluating the impact of a dynamic route guidance App for visitor experience management.

5.1 Dynamic Route Guidance

The route guidance App is designed to provide personalized route guidance to theme park visitor. Algorithmically speaking, it solves a single-agent dynamic and stochastic variant of the orienteering problem (DSOP) (Lau et al. 2012). The classical OP is a planning problem whose goal is to find a sequence of vertices in a graph that maximizes the sum of rewards from those vertices subject to the constraint that the sum of edge lengths along that sequence is no larger than a threshold (Tsiligrides 1984). In DSOP, the wait times at attractions and the travel times between attractions are stochastic and dynamic (i.e., time-varying).

The user rewards are tied to two factors: firstly, his preference and profile; and secondly, the wait times and travel times between attractions. Each attraction is available within stipulated time windows and its operational status may change dynamically (due to weather, technical failures, etc). The goal is to generate a route (i.e. sequence of attractions) which maximizes the user's rewards subject to his start time and end time constraints and attraction time-window constraints.

The dynamic route guidance App can be used to generate initial itinerary, and if needed, it can also generate revised itinerary in response to the change in environment. This App is capable of diversifying route recommendations for users of the same profile automatically; however, the wait time information is assumed to be exogenous and not affected by the route guidance. For small-scale deployment, this route diversification should be sufficient in avoiding the alterations of wait time patterns. However, for larger-scale deployment, visitors' collective actions might significantly alter the wait times, and the generated itineraries relying on these wait times might see their performance deteriorating. This may or may not be a major concern in deploying the App. As it's almost impossible to comprehensively test this in practice, we resort to the use of simulation in making the evaluation.

To prepare for the evaluation, we introduce a new mode of park navigation: the dynamic route guidance, which is linked to the simulator to compute itineraries for routed visitor agents. We vary the fraction of agents having this technology (with the assumption that all routed agents will follow the given itineraries exactly), and assume that all other agents would follow the default behavioral model described earlier.

5.2 Experimental Results

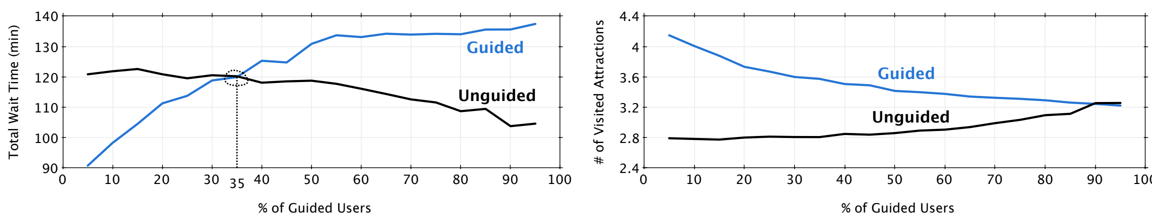


Figure 6: Average wait time and average number of visited attractions (per visitor).

The results of the above experiments are summarized in Figure 6. For the group of visitors receiving guidance, we can indeed see that their performances continue to drop in both the wait times experienced and the number of major attractions attended. More interestingly, we see that although unguided visitors are not adpative and act exactly the same way, their performances improve as more visitors begin to follow the route guidance (more specifically, when guided visitors are at 35%, guided visitors are beginning to have longer wait times than unguided visitors). This outcome is consistent with the past research on dynamic route guidance in the transportation domain. A widely accepted explanation on why unguided visitors can enjoy the benefit is that guided visitors are moving out of the way from unguided visitors' paths; and since wait times are not a function of actual routes, guided visitors will be having wait time estimates of worsening quality as percentage of guided visitors increases.

As it is non-trivial to construct an equilibrium seeking router that treats wait times as a function of visitors' routes (both conceptually and computationally), this simulation study can be used in quantifying the potential benefit of the new development.

Besides the above performance evaluations under different router percentages, another important usage of our simulation is to treat it as a blackbox for evaluating router performance in the presence of other routers. Such problem, which is similar to the identification of dynamic user equilibrium in routing, is known to be hard, and traffic simulations are commonly incorporated in the equilibrium searching procedure in the absence of analytical impedance function representation (e.g., see Wunderlich et al. (2000)).

6 FUTURE WORK

The test case presented in this paper is merely one example of what we can do with this agent-based simulator. A number of other research and operational problems can also be addressed with our simulators. Here are a list of selected topics we are currently pursuing:

- Employing game-theoretic approaches to solve dynamic routing considering the impact of routing on congestion. In this case, the simulator will be the blackbox which can be used in finding wait time estimates given certain combination of routing policies.
- Given a set of routes we would like to recommend to visitors, a practical issue is how to present the recommendation so that visitors would willingly follow them. One promising approach is to attach *incentives* to every fragment of the recommended route. The simulator can be used to evaluate different schemes of incentive designs.

7 CONCLUSIONS

In recent years, agent-based models and simulations have increasingly become an important tool for explaining and generating emergent behaviors. In areas such as finance or transportation, the agent-based approach has been quite successful in filling in the gap between real-world phenomenon and the theory (e.g., the formation of asset bubbles and the urban congestion). Our work follows the same trend as we attempt to explain and model crowd behaviors that are composed of leisure-seeking individuals.

Our first major contribution in this paper is the empirical methodology used in creating behavioral models for leisure-seeking individuals. With entertainment and tourism industry flourishing in recent years, we are really seeing urgent need in understanding how human behaves when “having fun” is the top priority. However, human behaviors in such setting have rarely been studied. We adopt the heuristic decision theory (in the form of a learned decision tree) and design and carry out a field experiment to collect necessary data for model building. Our second major contribution is the creation of an agent-based simulator that is based on the created behavioral models for leisure-seeking individuals. Finally, we design and implement a test case to quantitatively evaluate the benefit of having routing aids in a theme-park setting.

We show that our agent-based simulation is good for evaluating and experimenting park design and operational policy. Although crowd behaviors are hard to explain and control, with proper incentives and coordination, all visitors’ experience can be jointly improved. Realizing the full potential of our approach remains one of our major research direction in the future.

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