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Simulation Experiments on Theme Parks Using Complex Network Models

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Abstract

This study models a theme park environment using complex network theories such as regular graphs, small-world networks, and scale-free networks. The simulation reproduces visitor (agent) behaviors to propose an optimal structural model for efficient attraction utilization. Conventional network-based simulations often assume that all agents follow the same decision-making algorithm. However, in real theme parks, visitors act based on different criteria, such as attraction popularity and local congestion. To reflect this diversity, a hybrid decision-making algorithm that combines popularity and congestion factors is introduced, enabling agents to autonomously determine their visiting sequences. The proposed model is integrated with conventional coordination scheduling algorithms, and simulations are conducted across three network structures—regular, small-world, and scale-free—to compare the effects on congestion mitigation and average stay time. Through this comparative analysis, the study aims to identify a network structure that effectively disperses queue loads and enhances the overall efficiency of facility utilization in theme parks.

Keywords: Complex Network, Theme Park Simulation, Agent-Based Modeling, Congestion Avoidance, Hybrid Decision-Making Algorithm

1. Introduction

In recent years, advances in ubiquitous computing have promoted research that aims not only to support individual convenience but also to optimize the overall efficiency of society as a collective [1]. The theme park problem proposed by Kawamura et al. (2003) [2] represents a large-scale dynamic scheduling model that integrates individual behavior and group dynamics. A theme park can be regarded as a complex spatial system where visitor flows constantly occur among multiple attractions. Modeling this system using complex network theory enables the analysis of issues such as congestion and path optimization. However, in real theme parks, visitor behavior varies according to individual preferences and crowding conditions rather than uniform decision rules. To reflect such diversity, this study introduces a hybrid behavioral model that considers both popularity and congestion, and conducts simulations on three types of network structures to evaluate their effects on congestion mitigation and travel efficiency.

2. Modeling the Theme Park

In this study, simulation experiments were conducted on three types of theme park models that incorporate the structural characteristics of the regular graph, small-world network, and scale-free network. Each theme park is represented as an undirected graph, in which nodes correspond to spatial segments— namely, A (Attractions) and En/Ex (Entrance/Exit) —and edges represent pathways connecting these segments. Each agent moves between connected segments through undirected edges, circulating through the entire theme park.

The theme park model used in this study consists of:

- N attraction segments ($N = 40$),
- one En/Ex segment,
- n agents entering the park ($n = 300$).

The graph representations of the theme park generated using complex network models are shown in Figure 1.

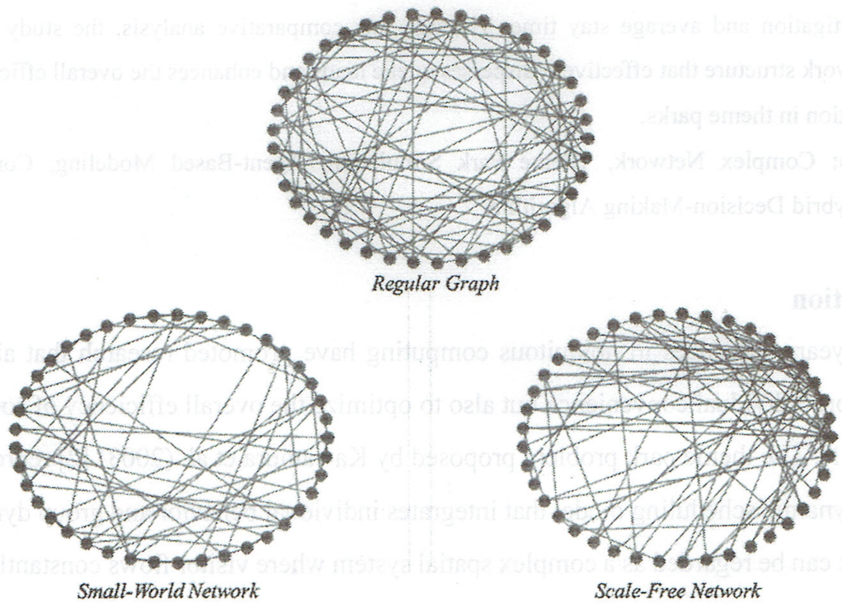

Figure 1. Theme Park models used in this study

The regular graph has a uniform degree for all nodes, forming an evenly connected structure. The small-world network combines a high clustering coefficient with a short average path length, balancing local clustering and global efficiency. The scale-free network follows a power-law degree distribution, where a few hub nodes have many connections while most nodes have few, enabling efficient flow and interaction within the network.

3. Simulation Design

3.1 Spatial Segments

Each spatial segment holds both static and dynamic elements. The following explains static elements first, followed by dynamic elements.

(1) Static Elements

Each spatial segment $S_i (0 \leq i \leq N)$ is associated with a set of static parameters. Specifically, each segment has a service capacity c_i, a service time st_i, and a popularity weight p_i. The parameter c_i represents the maximum number of agents that can be served simultaneously within segment S_i, while st_i denotes the time an agent spends in the segment during a single service. The popularity weight p_i captures the intrinsic attractiveness of segment S_i and is used in determining agents' visiting preferences and satisfaction. For the entrance/exit segment S_0, service and popularity do not apply.

Similarly, each edge connecting two segments is also assigned c_i and st_i. The parameters used for each spatial component in this study are summarized in Table 1.

Table 1. Parameters of spatial component

	c_i	st_i	p_i
En/Ex	∞	0	0
A1–A40	Random(1-3)	4	Dirichlet-generated
edge	∞	1	N/A

(2) Dynamic Elements

At simulation time t, each spatial segment S_i holds two dynamic variables: $a_i(t)$, representing the set of agents currently being served in the segment, and $r_i(t)$, representing the reservation list of agents waiting to enter when the capacity is exceeded.

Each agent $A_j (1 \leq j \leq n)$ maintains several internal dynamic variables during the simulation. $s_j(t)$ denotes the current position of the agent, $mt_j(t)$ and $wt_j(t)$ represent the cumulative travel time and cumulative waiting time of agent A_j up to time t, respectively. The total staying time $T_j(t)$ is incrementally updated as the cumulative sum of all time spent traveling, waiting, and receiving service. In addition, a binary variable $vs_{ij}(t)$ takes the value 1 if agent A_j has visited segment S_i at least once by time t, and 0 otherwise, and is used for computing satisfaction.

3.2 Simulation Rules

The simulation proceeds according to the following rules:

1. All agents start from the En/Ex segment.
2. After visiting all attraction segments, each agent returns to the En/Ex segment.
3. The simulation ends when all agents have returned to the En/Ex segment.
4. Each agent stays for its service time st_i before moving to the next destination.
5. If the following conditions are satisfied, the agent is added directly to the destination.
   - $|r_i(t)| = 0 \cap |a_i(t)| + 1 \leq c_i$
   - $|r_i(t)| > 0 \cap |a_i(t)| + 1 \leq c_i \cap$ agent is the head of $r_i(t)$
6. Otherwise, the agent is added to the reservation list $r_i(t)$, which follows a FIFO policy.
7. The total waiting time of each agent is updated at each time step according to Eq. (1):

$$wt_j(t+1) = wt_j(t) + 1_{waiting} \tag{1}$$

   where $1_{waiting}$ takes the value 1 if agent A_j is waiting in a reservation list at time t.

8. The total travel time of each agent is updated at each time step according to Eq. (2):

$$mt_j(t+1) = mt_j(t) + st_{s_j(t)} \tag{2}$$

   where $st_{s_j(t)}$ denotes the service time of the edge or segment at time t.

4. Adjustment Algorithms

The visiting order of each agent in this study is determined by two adjustment algorithms. Both algorithms share a common rule that agents move along the shortest path between their current location and destination.

4.1 Preference-based Algorithm

When an agent reaches its current destination or has no assigned destination, its next destination is determined among unvisited attractions according to the popularity weight p_i. The agent prioritizes destinations with higher p_i.

4.2 Congestion-avoidance Algorithm

When an agent reaches its current destination or has no assigned destination, its next destination is determined among unvisited attractions according to the congestion scores C_i, calculated by Eq. (3). A higher C_i indicates a less crowded attraction, and the agent prioritizes such destinations.

$$C_i = \frac{1}{1 + |r_i(t)| \times (st_i/c_i)} \tag{3}$$

5. Determination of Agent Visit Order

In this study, the visiting order of each agent is determined by two behavioral types: P_{type}, which considers only popularity, and H_{type}, which considers both popularity and congestion. The ratio of these two agent types is controlled by parameter α, which represents the probability that an agent becomes P_{type}.

(1) P_{type} (popularity only)

Agents determine their visiting order according to the preference-based algorithm described in Section 4.1, selecting their next destination based solely on the predefined popularity weight p_i of each attraction.

(2) H_{type} (popularity and congestion)

Agents determine their visiting order by combining the preference-based and congestion-avoidance algorithms. The weighting between popularity and congestion is defined by HYBRID_BALANCE, as expressed in Eq. (4):

$$HYBRID\_BALANCE \times p_i + (1 - HYBRID\_BALANCE) \times C_i \tag{4}$$

where p_i and C_i denote the popularity and congestion of attraction i.

6. Experimental Results

Experiments were conducted using three network models: the Regular Graph, Small-World Network, and Scale-Free Network. The experimental parameters are listed in Table 2, and the experimental results are summarized in Table 3. The evaluation metric TS represents the average total staying time of all agents and is defined by Eq. (5):

$$TS = \frac{1}{n}\sum_j T_j \tag{5}$$

Each experiment was conducted 10 times, and the reported value corresponds to the average TS over all trials.

Table 2. Experimental parameters

Network Model	$HYBRID\_BALANCE$	α (P_{type})
Regular / SW / SF	0.3	0.8

Table 3. Experimental results

Network Model	TS $(avg.)$
Regular Graph	1056.37
Small-World Network	1053.64
Scale-Free Network	1043.73

6.1 Experiment with 30,000 Agents

Tokyo Disneyland accommodates approximately 30,000 visitors per day. To reproduce a more realistic level of congestion and evaluate the scalability of each network model, an extended experiment was conducted using 30,000 agents.

In this setting, the service capacities of all attraction segments were scaled to ten times their baseline values to maintain feasible throughput under high-density conditions. Additionally, to accommodate large-scale conditions, the service time for each attraction was reduced to 1 time step. All other simulation settings remained identical to those in the baseline experiment.

The purpose of this extended experiment is to examine whether the network characteristics observed in the baseline scenario are preserved when both the number of agents and the service capacities are increased. The simulation parameters for both the baseline and extended experiments are summarized in Table 4, and the experimental results are presented in Table 5.

Table 4. Experimental parameters for Baseline and Extended

Parameter	Baseline	Extended
n (Number of agents)	300	30,000
c_i (Service capacity)	baseline values	10 × baseline
st_i (Service time)	4	1
Network models	Regular / SW / SF	Same
$HYBRID\_BALANCE$	0.3	Same
α (P_{type})	0.8	Same

Table 5. Experimental results with 30,000 agents

Network Model	$TS\ (avg.)$
Regular Graph	1841.45
Small-World Network	1841.51
Scale-Free Network	1833.55

7. Additional Experiments

In the baseline experiment of this study, the simulation continued until all agents returned to the En/Ex segment. To compare network characteristics under different conditions, the additional experiments introduce a time-step upper limit $T_{\max}$ and incorporate new evaluation metrics. Unless otherwise noted, the number of agents and the number of attraction nodes are identical to those in the baseline setting.

The additional experiments employ the following three evaluation metrics:

$$WT = \frac{1}{n}\sum_{j} wt_j(T_{\max}) \tag{6}$$

$$MT = \frac{1}{n}\sum_{j} mt_j(T_{\max}) \tag{7}$$

$$S = \frac{1}{n}\sum_{j}\sum_{i} p_i \cdot vs_{ij}(T_{\max}) \tag{8}$$

The evaluation metrics WT and MT represent the average total waiting time and average total moving time of the agents, respectively. The metric S denotes the satisfaction level of the agents and reflects how many high-popularity attractions they can visit within the given time limit. The binary variable v_{ij} indicates whether agent A_j has visited attraction S_i at least once by time t. Repeated visits to the same attraction do not increase the satisfaction value.

7.1. Additional Experiment: Varying α

In this experiment, the behavioral parameter α, which represents the proportion of P_{type} agents (agents that consider only popularity), is varied from 0.0 to 1.0 in increments of 0.1. The time-step upper limit is set to $T_{\max} = 720$, and all other settings follow the baseline experiment. For each value of α, the simulation is conducted 10 times, and the evaluation metrics $\overline{WT}, \overline{MT}, \bar{S}$ represent the averages over all trials. The results of the averaged evaluation metrics for each α are presented in Figure 2.

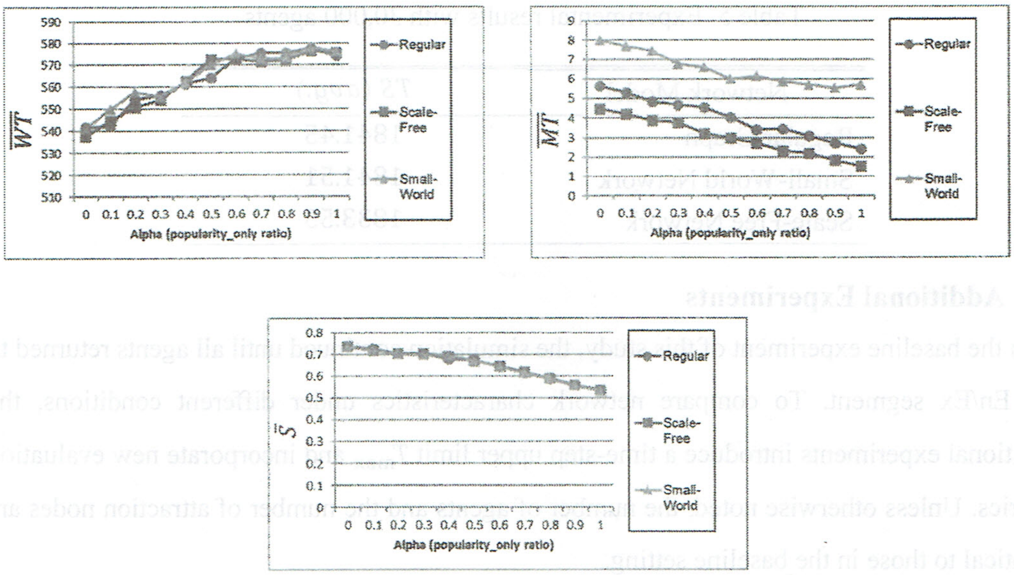

Figure 2. Averaged evaluation metrics (WT, MT, S) for different values of α

7.2. Additional Experiment: Varying the Number of Nodes

In this experiment, the number of attraction nodes is varied from 50 to 100 in increments of 10. The time-step upper limit is set to $T_{\max} = 720$, and all other settings follow the baseline experiment. For each number of nodes, the simulation is conducted 10 times, and the evaluation metrics $\overline{WT}, \overline{MT}, \bar{S}$ represent the averages over all trials. The results of the averaged evaluation metrics for each network size are presented in Figure 3.

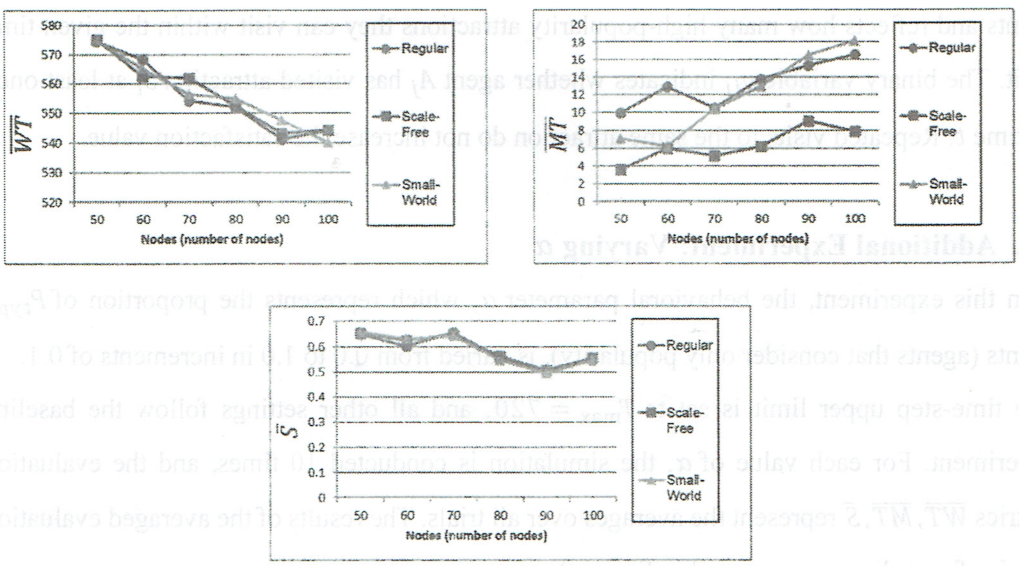

Figure 3. Averaged evaluation metrics (WT, MT, S) for different numbers of nodes

8. Conclusion

In this study, a theme park visitor-flow simulation model based on complex network theory was developed. Unlike previous approaches in which all agents follow uniform behavioral rules, the proposed model incorporates heterogeneous decision-making by allowing agents to behave either based solely on attraction popularity or by considering both popularity and local congestion. This enabled a more realistic comparison of different network structures under practical behavioral conditions. In the baseline experiment, the total staying time required for all agents to visit every node was used as the primary evaluation metric. Under realistic behavioral assumptions, the scale-free network yielded the shortest staying time. Furthermore, a large-scale simulation with 30,000 agents—designed to reproduce real-world congestion levels—revealed that this tendency remained consistent even under high-density conditions. These results indicate that the proposed model exhibits strong generality and that the scale-free structure is highly suitable for efficient circulation in theme park environments. Additional experiments introduced a time-step upper limit to reflect operational constraints such as park closing time, enabling more detailed comparisons using waiting time, moving time, and satisfaction as performance metrics. In the experiment varying the behavioral parameter α, values of α below 0.5 are unlikely under realistic conditions. Focusing on the region where $\alpha > 0.5$, the scale-free network exhibited the shortest moving time and demonstrated waiting time and satisfaction performance comparable to or better than those of the other network models. In the experiment expanding the number of nodes, no significant differences were observed in waiting time or satisfaction, but the scale-free network again exhibited a markedly lower moving time, confirming its strong routing efficiency.

Across all experiments, the scale-free network consistently demonstrated superior performance in reducing staying time and moving time under realistic behavioral conditions. This advantage is primarily attributed to the presence of hub nodes, which provide multiple routing alternatives, enhance global circulation efficiency, and mitigate localized congestion. These findings suggest that the scale-free structure is inherently well-suited for large-scale dynamic scheduling problems in which individual decision-making and collective dynamics interact, such as in theme park operations.

Future work will explore incorporating additional temporal and behavioral factors, including time-dependent fluctuations in visitor numbers and congestion patterns associated with event scheduling, to further improve the realism of the model.

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