Modeling Passenger Behaviors in Non-Payment Areas at Rail Transit Station

by

Mingjun Liao
Associate Professor
Department of Civil Engineering
University of Beihua, 233 Yifu Building
Jilin, Jilin Prov., China 132013
Post-doctoral Research Center at College of Traffic, Jilin University, Changchun, China, 130012
Tel: 86-432-63361299
Email: mjliao@163.com

Gang Liu*
Research Assistant
Department of Civil and Environmental Engineering
University of Alberta, 4-110 NREF
Edmonton, Alberta, Canada T6G 2W2
Email: gliu2@ualberta.ca

TRB Paper No: 15-3427

Word count: 4125 words + 16 (13 figures + 3 table) * 250 words = 8125 words

*Corresponding author
ABSTRACT
The non-payment area at urban transit station in China usually becomes extremely crowded during peak hours, because a large number of passengers queue up for buying ticket and passing fare gates. How to evaluate the performance of these activities is a critical issue for the non-payment area design. This study utilizes a microscopic simulation tool to investigate passenger behaviors in the non-payment area; particularly, the queue choice model, passenger movement model, and path navigation model are investigated. Some new ideas are involved in this study. Firstly, this study introduces the concepts of dynamic queue length and dynamic distance between the current passenger and alternative queues into the queue choice model. Secondly, a new factor, named direction of goal, is proposed to navigate a passenger through the dynamic end of a queue or other mid-goals. This factor is used to construct the transition probability function of a Cellular Automata (CA) model. In addition, sensitivity analysis of this factor is investigated. Finally, the proposed model is calibrated and verified based on a field survey and sensitivity analysis. The results show that the proposed model can capture the behaviors of passengers in the non-payment area and performs well for queue estimation.
INTRODUCTION

In China, the air quality in urban area is deteriorating due to the gas emissions from millions of automobiles \( (I) \). Therefore, the Chinese government is strongly advocating the development of urban rail transit. There will be up to 289 urban rail transit lines with a total length of 11,700 km by 2050 in China \( (2) \). The rail transit is playing a much more important role in the urban transportation system. For example, the Line No. 1 of Beijing rail transit system carries over one million passengers each day. However, the rail transit system usually becomes extremely crowded during the peak hours. Especially at the transfer station, it is common to see long queues up for buying tickets and passing through automatic fare gates in the non-payment area \( (3) \). The transit station is a key component of the urban rail transit network. The service facilities in the non-payment area have become the capacity bottlenecks of the station. Current analysis tools for the non-payment area can be broadly classified into two categories: macroscopic analytical models and microscopic simulation models. Macroscopic analytical models are empirically based on the queue theory. They are limited to calculating the performance index of queue systems. In addition, macroscopic analytical models are deterministic tools. Once the input and model parameters are determined, the output is unique. Microscopic simulation models are based on the passenger flow theory and the queue theory. It is very useful to model physical queue components, time and space-evolving processes, and queue rules. Microscopic simulation models can be used as a tool to evaluate different design and management plans. The objective of this study is to use the microscopic simulation tool to model and investigate the passenger behaviors in the non-payment area at the rail transit station. The remaining parts of this paper are organized as follows. Section two reviews studies on passenger behaviors and related modeling methods. Section three discusses the methodology and model calibration. Finally, concluding remarks are given.

LITERATURE REVIEW

Extensive researchers have conducted studies on passenger behaviors in the transit station. Li et al. \( (4) \) described a general passenger flow chart which listed key activities: passenger arriving, queuing at ticket vending machines, ticket acceptance gates, and exit turnstiles in non-payment areas. Hoogendoorn et al. \( (5) \) discussed the modeling methods of pedestrian behaviors in the normal situation and divided the pedestrian behavior into three levels: operational (basic motion), tactical (such as queue selection and route choice), and strategic (general planning) behaviors. At tactical level, most routes or activities choice models is based on the discrete choice theory and considered pedestrian's preferences and running costs (distance, time) to maximize their utilities. Studies \( (6-8) \) discussed passenger activities in public transit stations, and built the route choice model and the queue model, which were implemented in a macroscopic model, SimPed. Those studies laid a very good foundation for modeling passenger behaviors in non-payment areas.

In terms of microscopic passenger movements, there are two primary models applied. One is social force model \( (9) \) and the other is Cellular Automata (CA) model. The former model assumes that the social force drives the passenger movement. The basic idea is to model the elementary impetus for motion with forces, which is similar to Newtonian mechanics. The forces, which influence the passenger motion, are caused by people’s intention to reach their destinations as well as by other pedestrians and obstacles. Thereby, other passengers can have both an attractive and a repulsive influence. The latter model is suitable for discrete dynamic systems, consisting of an array of nodes (cells) of n dimensions. Each cell is in the one of k different states at a given tick of the clock. At each discrete tick of the clock, each cell may
change its state in a way determined by the transition rules of the particular CA. The transition rules describe precisely how a given cell should change states, depending on its current state and the states of its neighbors (10). Burstedde et al. (11), Nishinari et al. (12), and Kirchner and Schadschneider (13) et al. built the transition function of CA by considering the index of psychological characteristics of pedestrians, such as the static floor field and the dynamic field.

The social force model and CA model are initially applied in the field of evacuation. There are few references discussing the microscopic behavior models of pedestrians in the normal situation. After being modified, these two models can be used to model the passenger movements in the normal situation in non-payment areas. However, the rules of CA model are relatively simple. In order to model the orderly activities in non-payment areas, it is relatively easy to add a factor of direction into the transition function of CA model. Therefore, this paper will choose the CA model to model the passenger movements in non-payment areas. This study intends to study the queueing behavior, activity choice behavior and path searching behavior in non-payment area.

METHODOLOGY

Passenger Behaviors in Non-Payment Area

The transit station consists of a payment area and a non-payment area (shown in Figure 1). In the non-payment area, there are usually many ticket service facilities (e.g. ticket windows and ticket vending machines) and automatic fare gates. The passenger activities in non-payment area mainly include:

- Arriving at the non-payment areas
- Choosing a queue to buy tickets;
- Walking to the ticket machine or window;
- Waiting in the chosen queue to buy tickets;
- Buying tickets and being serviced;
- Choosing a queue to pass automatic fare gates;
- Walking to automatic fare gates;
- Waiting in the chosen queue at automatic fare gates;
- Going through automatic fare gates.

![Figure 1: Passenger Activities in the Non-payment Area](image)

Passenger’s decision-making process is carried out at strategic, tactical and operational levels (14). At the strategic level, passengers decide on which activities they want to perform
 when they are in non-payment area. The tactical level pertains to short-term decisions of passengers based on the activity list made at the strategic level. The order in which pedestrians are going to perform these activities depends on prevailing conditions. Passenger movement behaviors belong to the operational level, in which microscopic motions (e.g. walking in non-payment area and moving in a queue) can be observed. The detailed categorization is shown in Figure 2. In addition, at the operational level, a passenger has different states in non-payment area, such as arriving, walking to a queue, queuing and leaving. Under given conditions, one state of passenger will transfer to another. The transition control of activities or behaviors in non-payment area is managed by the finite state machine (FSM), which is extensively applied in role games (15). It can be in a finite number of states at any given time and can operate on the input to make transitions from one state to another or to cause an output and action to take place. The state transition table of FSM is shown in Table 1.

![Strategic level](attachment: strategic_level.png) ![Tactical level](attachment: tactical_level.png) ![Operational level](attachment: operational_level.png)

**FIGURE 2 Levels of Passenger Behaviors**

<table>
<thead>
<tr>
<th>Current State</th>
<th>Condition</th>
<th>State Transition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arrive</td>
<td>No ticket</td>
<td>Walk to queue(for ticket)</td>
</tr>
<tr>
<td>Walk to queue</td>
<td>Has reached the end of queue(for ticket)</td>
<td>Queue</td>
</tr>
<tr>
<td>Queue</td>
<td>Has gotten no ticket</td>
<td>Queue</td>
</tr>
<tr>
<td>Queue</td>
<td>Has gotten ticket, next goal</td>
<td>Walk to fare gate queue</td>
</tr>
<tr>
<td>Walk to queue</td>
<td>Has reached the end of fare gate queue</td>
<td>Queue</td>
</tr>
<tr>
<td>Queue</td>
<td>Has not be checked</td>
<td>Queue</td>
</tr>
<tr>
<td>Queue</td>
<td>Has been checked</td>
<td>Leave</td>
</tr>
</tbody>
</table>

**Queue Selection Model**

Queuing in non-payment area is a common phenomenon (shown in Figure 3 (a)). There are usually many queues in front of ticket windows, ticket vending machines and automatic fare gates. Before or during walking, a passenger will make decision to choose a queue to accept service based on his or her position and the queue lengths. Figure 3 (b) is an example for the scenario of queues before automatic fare gates. The scenario of queues before ticket windows and ticket vending machines is similar as that before automatic fare gates.
In the model, automatic fare gates are numbered as 1, 2, ⋯, i, ⋯, n, and the corresponding lengths of their queues are \( q_1, q_2, \cdots, q_i, \cdots, q_n \). The distances between a passenger and automatic fare gates are \( d_1, d_2, \cdots, d_i, \cdots, d_n \). The distance \( d_i \) is expressed as:

\[
d_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}
\]

where, \((x_i, y_i)\) is the coordinate of the cell representing the end of queue; \((x_0, y_0)\) is the coordinate of the cell representing the current passenger. In this model, \((x_i, y_i)\) and \((x_0, y_0)\) are the location attribute in the passenger class; \((x_i, y_i)\) is gotten by a method in queue class. Both are updated every time step.

The choice of an automatic fare gate primarily depends on the queue length as well as the distances between current passenger and the queues for maximum benefit. Combining the distance and queue length with passenger's average speed and average service time of facilities, we can convert the factors of distance and queue length into average travel time. The average travel time of each queue can be calculated and the chosen probability of each queue is finally obtained as follows.

Giving the average walking speed of passenger \( (v) \), the difference of walking time from current location to the end of queue is expressed as:

\[
t_i^d = \frac{\max_{i=1\cdots n} d_i - d_i}{v}
\]

Where, \( t_i^d \) is the difference between the maximum walking time and the walking time of walking to the queue \( i \).

Giving the average service time of service facility, \( \overline{t_i} \), the difference of expected queuing time is expressed as:

\[
t_i^q = \max_{i=1\cdots n} q_i - q_i \times \overline{t_i}
\]

Where, \( t_i^q \) is the difference between the maximum expected queuing time and the expected

---

**FIGURE 3 Queue Selection Illustrations**

(a)  
(b)
queuing time of queue $i$.

Based on Equation (2) and Equation (3), the total difference of travel time, $t_i$, is calculated as:

$$t_i = t_i^d + t_i^q$$  \hspace{1cm} (4)

According to Equation (4), the probability of choosing queue $i$ is given as:

$$p_i = \begin{cases} 
\frac{t_i}{\sum_{i=1}^{n} t_i} & \text{if } d_i \neq d_j \text{ and } q_i \neq q_j \\
\frac{1}{n} & \text{if } d_i = d_j \text{ and } q_i = q_j
\end{cases}$$  \hspace{1cm} (5)

### Transition Probability Function of CA Model

CA model has five components: cell, space, neighbor, state and transition probability function (16). Transition probability function is the core of CA model, which is an evolution rule that updates the states of the neighbor cells and realizes passenger movements. According to the computed result of transition probability, passengers can move from current location to a new position.

Passengers generally consider the shortest distance (static floor field), regardless of whether normal situation or evacuation (13). In normal situation, passengers have many activities (e.g., queuing for tickets and passing automatic fare gates). The goal of an activity is attractive to passengers. The goals in this paper refer to the end of queue, interim decision point, and the destination etc. Because the goal (the end of queue) is dynamic and the extension direction of the queue end is different from the static floor field, passengers cannot be navigated to the attractive point solely by static floor field and dynamic floor field. Therefore, a new factor, named direction of goal, is introduced without introducing the factors of static floor field and dynamic floor field.

Figure 4 represents the model of direction of goal. The origin denotes the position of the current passenger cell. The direction of x-axis points to east, and the direction of y-axis points to south. The direction of neighboring cells is the direction of the line joining the center of current passenger cell and the center of neighboring cell denoted by E (East), NE (Northeast), N (North), NW (Northwest), W (West), SW (Southwest), S (South) and SE (Southeast). $\theta_d$ and $\theta_i$ denote the ranges of diagonal and off-diagonal cells respectively. Then, we define $\beta_{ij}$ ($0 \leq \beta_{ij} \leq 180$) as the minimum deviation angle (direction of goal) between the direction of line joining the current agent and neighboring cell ($ij$) and the direction of the line joining the current agent and the goal point. The smaller the $\beta_{ij}$, the larger the probability of the cell be chosen. So $\beta_{ij}$ should be modified, that is, $\theta_{ij} = 180 - \beta_{ij}$.

So the transition probability function model based on direction of goal is developed as follows:

$$p_{ij} = NM_{ij} \{\exp(k_{ij} \theta_{ij})\} (1-n_{ij}) \xi_{ij}$$  \hspace{1cm} (6)

$$n_{ij} = \begin{cases} 
0, & \text{vacant} \\
1, & \text{occupied}
\end{cases}$$

$$\xi_{ij} = \begin{cases} 
0, & \text{wall or other obstacles} \\
1, & \text{no obstacles}
\end{cases}$$
\[ N = \left[ \sum_{i,j} M_{ij} \{\exp(k_{ij}\theta_{ij})\}(1-n_{ij})\xi_{ij} \right]^{-1} \]

**FIGURE 4** Explanation of Direction of Goal

Where, \( p_{ij} \) is the probability of cell \((i; j)\), \( N \) is the normal factor to assure \( \sum_{i,j} p_{ij} = 1 \); \( M_{ij} \) is the matrix of preference \((17)\); \( n_{ij} \) is the occupied state of cell \((i; j)\); \( \xi_{ij} \) is the state to judge whether cell \((i; j)\) is the obstacle; \( \theta_{ij} \) is direction of goal (the modified included angle above), and \( k_{ij} \) are the sensitive factors of direction of goal.

**Avoiding Conflict**

There is possibility that two agents move to the same vacant cell at the same time step. So the conflict happens. In order to avoid conflict, transition possibility is used to determine the priority (see Figure 5). The priority is computed in the equation \((7)\) ~ \((8)\):

\[ p_1 = \frac{M_{1,0}^{(1)}}{M_{1,0}^{(1)} + M_{-1,1}^{(2)}} \quad (7) \]

\[ p_2 = \frac{M_{-1,1}^{(2)}}{M_{1,0}^{(1)} + M_{-1,1}^{(2)}} \quad (8) \]

**FIGURE 5** The Solved Method for Pedestrian’s Conflict \((17)\)
**Path Navigation**

Once the goal is specified, agents will search for their goals, avoid collision, and reach their goals. It is necessary to planning agents’ paths in tactical level. There are two types of path navigation: one is for avoiding fixed obstacles, and the other is for search for queues. There are static obstacles (pillars, or other facilities) and dynamical obstacles (queues) in non-payment area. So agents must recognize obstacles and find a shortest path to goal location. Assume that the shape of obstacles is convex (see Figure 6) and the shortest path is solved by the visibility graph algorithm. The details about visibility graph algorithm is included in reference (18).

There are more than two queues before ticket windows or ticket check gates in a transit station. The shape of these queues dynamically varies with time. In addition, agents will choose their queues according to their utility. A pedestrian usually detours some queues to reach another queue. The dynamic queues are treated as movable obstacles. When the queue is short or the space is enough, the shape of the queue is a straight line (see Figure 7(a)), or else is a curve. When the length of a queue is increasing, a queue will intersect the line between start point and mid-goal or goal point of agent. Agent will plan a path to detour the vertices of queue tail. If the shape of queue is curve, the queue head should be connected with the queue tail (see Figure 7(b)), and a movable and convex obstacle comes into being.

The path solved by above algorithm gives agents node sets in tactics level. The node sets provide the locomotion direction for agent in action level. And the transition probability of the current passenger is computed by Equation (6).

**FIGURE 6 Visibility Graph with Obstacles**

**FIGURE 7 Path Search**

**Simulation Framework for Non-Payment Area**

It is assumed that the physical size of non-payment area is 40 cell×50 cell and the size of a cell is 0.4m×0.4m. Considering that the average speed of passenger is about 1.2m/s, the simulation is set to 0.25s, and the $V_{\text{max}}$ is 1 cell. The simulation of passenger behaviors in non-payment area is built based on above-mentioned models. The simulation process of passenger unit, which is the
core of the simulation, is described as:

- The initialization of physical environment and passenger---mainly initialize the attributes of physical environment or initial states of physical environment or passengers.
- The selection of activity point---according to the drive of time or goal, and path selection model, select activity point.
- Updating the positions of passenger agents---considering the rules of motion and transition probability matrix, select the next cell and update the positions of passenger agents.
- The judge of goal---manage the simulation’s life cycle of passenger agent. If the passenger agent reaches the destination, the agent will be deleted from list.
- The end---if the simulation time is up, or all the passenger agents reach the goal, the simulation will end.

**Model Calibration**

**Data collection**

The data of queue performance for ticket selling facilities were collected from those stations in Shanghai, and Changchun in China during peak and off-peak hours by video camera and field survey. The service-time distribution and queue performance index are extracted from video. Based on the above surveys, it is founded that the delay of the automatic fare gates follows Uniform Distribution at the interval of [1.5, 2.5] s. The detail data from Guigu station, Furong station, and Yitong station respectively are listed as follows: (1) The arrival of passengers follows the Poisson Distribution with the arrival rate (λ) of 293 p/h and the service times have a negative exponential distribution with the service rate (μ) of 233 p/h; (2) The number of ticket windows(s) is equal to 2; (2) Arrival process: Poisson distribution with λ = 156 p/h; service process: Weibull distribution with μ = 130 p/h and s = 2; (3) Arrival process: Poisson distribution with λ = 400 p/h; Service process: Negative Exponential distribution with μ = 274 p/h and s = 2. The data of the arrival distribution are surveyed, and the data of queue performance index, for example, queue length and queue time, are surveyed at 20-second interval.

**The determination of the range of k_q**

Though the value range of k_q is [0, ∞), it is assumed the range of k_q is [0, 1] based on similar research (Kirchner and Schadschneider 2002). For a certain direction angle matrix, k_q varies from 0 to 1 with the increment of 0.05, then we can figure out the relationship of the probability of neighbor with k_q. The detail of the determination of the range of k_q is discussed as follows.

Obviously, the probability of neighbor is depended on not only its value but also the value of k_q. The direction angle matrix of a cell from a case is shown in Figure 8. Figure 9 shows the probability has a non-linear relation with k_q. When the value of k_q is equal to 0, the probabilities of all neighbor are 11.11%; when k_q is equal to 0.3, the probability of the neighbor cell with maximum value (165, that is, β =15) is approximate to 100%. Similarly, when 0≤β≤θ_d/2 or 0≤β≤θ_d/2, k_q always has the same rule as β = 15. So the range of k_q is between 0 and 0.3.
Model Calibration and Verification

According to survey data, we select a case for calibrating the model. The details of the case are:

1. The arrival of passengers follows the Poisson Distribution with the arrival rate ($\lambda$) of 293 p/h and the service times have a negative exponential distribution with the service rate ($\mu$) of 233 p/h; (2) The station has two ticket windows with the utilization factor ($\rho = \lambda/(2\mu)$) of 0.629; (3) The queue performance from the survey video is listed in Table 2. In simulation, $k_\theta$ starts from 0.05 to 0.3 with increment of 0.05 and each one-hour simulation runs ten times with input of the survey data. We can get the simulation results shown in Figure 10 and Figure 11. From Figure 10, Figure 11 and Table 2, it is easily found that the simulation results are close to that from field survey when $k_\theta$ is about equal to 0.1 (see in Table 2). Therefore, the optimum value of $k_\theta$ is 0.1. Figure 12 and Figure 13 are simulation results of system queue length, queueing time and sojourn time when $k_\theta$ is equal to 0.1 for a simulation run.
## Table 2 Queue Performance from Simulation and Field survey

<table>
<thead>
<tr>
<th>Type</th>
<th>System Queue length(p)</th>
<th>Queueing time(s)</th>
<th>Sojourn time(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>Std. Deviation</td>
<td>mean</td>
</tr>
<tr>
<td>Field data</td>
<td>1.6</td>
<td>1.41</td>
<td>20.26</td>
</tr>
<tr>
<td>Simulation data</td>
<td>1.57</td>
<td>1.35</td>
<td>17.62</td>
</tr>
<tr>
<td>2 M/M/1 queues</td>
<td>1.70</td>
<td>-</td>
<td>26.15</td>
</tr>
<tr>
<td>M/M/2 queue</td>
<td>1.04</td>
<td>-</td>
<td>10.16</td>
</tr>
</tbody>
</table>

### Figure 10 Relationship between Queue Length and $k_0$ from Simulation Test

### Figure 11 Relationship between Queueing time or Sojourn time and $k_0$
The queue model in this paper is different with two M/M/1 queues, or a M/M/2 queue (19). The performances of two kinds of queue system (given in Table 2) are also calculated, respectively. The results in Table 2 show that M/M/s queue system is more advantageous than two independent M/M/1 queue system, and the queue system in this paper is a mixture of M/M/s queue system and two independent M/M/1 queue system.
The scenarios of with those detail data from Guigu station, Furong station, and Yitong station are respectively numbered as case 1, case 2, and case 3. Besides the case used for calibration, two cases are added to verify the model. The parameters of the three cases. Similarly, we can get the queue performance of simulation and field results of the other two cases, which is shown in Table 3. From Table 3, the mean error indicates that the above models perform well for queue performance estimation.

<table>
<thead>
<tr>
<th>Case No.</th>
<th>System Queue length(p)</th>
<th>Queuening time(s)</th>
<th>Sojourn time(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Simulation mean</td>
<td>Actual mean</td>
<td>Simulation mean</td>
</tr>
<tr>
<td>1</td>
<td>1.57</td>
<td>1.6</td>
<td>17.62</td>
</tr>
<tr>
<td>2</td>
<td>1.35</td>
<td>1.45</td>
<td>13.27</td>
</tr>
<tr>
<td>3</td>
<td>4.76</td>
<td>5.12</td>
<td>51.15</td>
</tr>
<tr>
<td>Mean error (%)</td>
<td>-5.27</td>
<td>-9.08</td>
<td></td>
</tr>
</tbody>
</table>

CONCLUSIONS AND REMARKS
This paper investigates the passenger behaviors in the non-payment area at rail transit stations using a microscopic simulation tool, CA. The queue selection model considers dynamic distance between a current passenger and the dynamic end of a queue and the dynamic queue length. This distance can be converted into total travel time based on the average travel time and average service time. The queue choice model reflects the dynamic decision-making process of passengers. Due to the dynamic extension of the queue, the direction of goal ($\theta$) is the key factor of the transition probability function to navigate a passengers to the dynamic end of queue. As $k_q$ plays a crucial role in the determination of a microscopic route, sensitivity analysis of $k_q$ is conducted, the result shows that when $k_q$ is about equal to 0.1, the difference between field and simulation results is little.

This microscopic simulation provides a greater clarity that how the system behaves with the visually dynamic process by considering the details of different passenger behaviors. Above all, the proposed model can adapt to different scenarios with different types of arrival and service time distribution, input parameters and behavior rules. In addition, the microscopic-simulation can provide a visual evaluation tool to determine the number of service facilities in different times of a day. Obviously, the proposed model still needs to be modified for more complicated geometry design and passenger behaviors, such as, intelligent interaction between passengers, facilities, and environment. Those will be done in the future studies.

ACKNOWLEDGEMENT
China Postdoctoral Science Foundation (2012M511343), the State Key Program of National Natural Science of China(Grant No. 51338008) and Science Foundation of Jilin education bureau (2010126) have funded this work. I would thank their support. I would also thank the anonymous reviewers and editors who give me valuable comments.
References


Glossary

**Finite state machine (FSM):** It is a mathematical model used to design both computer programs and sequential logic circuits.

**Non-payment area:** It is the area where passengers buy tickets or get proof of payment before entering into the paid area at a transit station.

**Static floor field:** It describes the shortest distance to an exit (or other destination point), which does not evolve with the time and is not changed by the presence of passengers.

**Visibility graph:** It is a graph of intervisible locations, typically for a set of points and obstacles in the Euclidean plane. Each node in the graph represents a point location, and each edge represents a visible connection between them.