Dwell Time Analysis in Urban Railway Lines using Multi Agent Simulation

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ABSTRACT

In railway lines where trains are running densely, to prevent dwell times of trains from increasing is very important to keep punctuality. Thus, railway companies are making great efforts to shorten dwell times as much as possible; such as to introduce trains with wider doors or trains with more doors etc. However, it is difficult to know in advance how effective these efforts are. We have developed a simulator to estimate dwell times of trains when various kinds of improvements to shorten dwell times are taken. The simulator is based on a multi-agent model and simulates each passenger's behavior both in a train and on a platform. One of the characteristics of this simulator is that it simulates passengers' behaviour of boarding and alighting seamlessly. Thus, it is possible to estimate dwell times of trains considering the congestion of the platform and inside trains, which are sometimes very influential factor in congested railways.

Keywords: timetable, multi agent, passenger flow, simulation, dwell time

1 INTRODUCTION

In urban areas of Japan, there is a big demand for railways. In Tokyo, the capitol of Japan, about 38 million people use railways a day in average. In order to transport such a massive amount of passengers, trains are very densely operated: it is usual that 25 to 30 trains are running per hour per direction on one double track line. This means trains are running every two minutes or so.

One of the serious problems in urban railway lines in Japan is that small delays very often happen during rush hours. Because trains are running so densely, once a delay happens, the delay propagates to many other trains (so called knock-on-delays happen).

Major reason of small delays during rush hours is an increase of dwell times of trains. If more passengers than expected try to get on a train, or passengers do not behave smoothly, dwell times become longer than the planned dwell time and the train is delayed [1]. As mentioned above, the delay easily propagates to many other trains.

You may think one idea is to increase planned dwell times in a timetable, but it is impossible. Because trains are running so densely, if we increase dwell times, we cannot set up required number of trains and this means a lack of transportation capacity and congestion rate will increase significantly (please note that in many stations, there is only one track per direction).

So, railway companies are very anxious to prevent dwell times of trains from increasing and they are very interested in evaluating counter measures as introduced in 2.1 to shorten dwell times of trains.

One useful method to evaluate effectiveness of such counter measures is simulation. Dwell times are mainly determined by passengers' flow and environment, namely how smoothly passengers can get on and get off a train in a given environment. Analysis of passengers' flow in case of congestion is very complicated and to estimate necessary dwell times by simulation is the most practical and useful approach.

In this paper, we introduce a simulator to estimate a necessary dwell time of a train in a given environment. The simulator is developed based on a multi-agent model. In this model, a passenger is expressed as an agent which behaves autonomously in the environment interacting with other agents and the environment. We adopted this model in order to fulfill the complicated requirements as described in detail in section 2.2.

Characteristics of our simulator are:

- it can express differences of preference among passengers, which are likely to give influence to passengers' flow.
- it can simulate passengers' flow between inside a train and a platform seamlessly, which makes it possible to analyze complicated behaviours of passengers such as passengers get off a train to give a way to another passenger who alights at the station.
- it can deal with various kinds of counter measures to reduce dwell times into account.

We have conducted numerical experiments using real world data and confirmed that the results are very promising.

2 DWELL TIME ANALYSIS

2.1 Counter measures to reduce dwell times

Some of the counter measures which are considered to be useful to reduce a dwell time of a train is:

- Introduction of trains with wider doors. Usually, the width of one pair of doors of a train is 1300 mm, but railway companies are interested in introducing wider doors, such as width of 1800 mm , because it might make it possible for passengers to get on and off more smoothly.
- Introduction of trains with more number of doors. Usually, one car has four doors on each side, but railway companies are interested in introducing trains which have more doors such as six doors on each side of a car.
- Introduction of trains with no seats. Trains during rush hours are very congested and the congestion prevents passengers from moving smoothly. Thus, railway companies are interested in introducing trains with no seats because it is believed that more room is available inside a train and passengers can move a bit more smoothly.

- To change the location where trains stop. It is well known that when they get on a train, passengers tend to prefer a door of a train which is close to stairs (or an elevator) at their destination station. Thus, it might be effective to normalize congestion inside trains if the stopping locations of trains are different from one (big) station to another (big) station. From the same reason, it might be effective to reduce dwell times if we can change the location of stairs and elevators on a platform if possible.

2.2 Requirements for simulator

From the discussions above, we can conclude that in order to estimate dwell times by simulation, the simulator has to have the following functions.

- It has to deal with various kinds of parameters which might affect passengers' flow, such as the number of boarding / alighting passengers, congestion of inside/outside trains, width of the doors of the train, number of doors of the train and so on.
- It has to simulate realistic behaviour of passengers. One example is that in case of congestion, it is usually observed that some passengers get off a train to give a room for another passengers who alight at the station. The passengers wait on the platform for seconds and get on the train again. Such behavior give significant influence to the dwell time and should be exactly simulated. This means the simulator has to seamlessly simulate both inside and outside the train (namely, platform).
- It has to deal with differences among individual passengers such as walking speed, size of bodies and so on.
- It has to deal with sentiment of passengers. For example, if a passenger finds there are a lot of passengers already waiting (in Japan, passengers wait for a train making a queue. See Fig.1), he/she will go to another place where not so many passengers are waiting.

Fig. 1: Passengers wait making a queue on a platform

3 RELATED WORKS

Several papers are already published which aim at estimating necessary dwell times of trains considering passengers' flow.

One approach is statistical one. Based on data collections, statistical models can be built using regression methods [2]. Statistical models could be used to analyze dwell times for current situation but it is difficult to apply them for the situation where parameters are drastically changed.

Another approach is simulation. Qi et al. [3] and Chi et al. [4] proposed a simulator based on the cellular automata model. The cellular automata model is based on a division of the space into square cells in which there is at most one passenger. This is a very strong assumption and this model is not effectively used for congested situation because in reality, the number of passengers which can exist in one cell varies a lot. Sourd et al. [5] proposed a multi agent simulation approach. Their approach and the aim are similar to ours, but we are interested in more congested situation and we have to simulate the complicated behaviour of passengers.

4 MULTI-AGENT SIMULATION

A multi-agent simulation model is a simulation model which consists of agents and an environment. Each agent perceives the environment and autonomously decides its bahaviour to fulfill its aim. An agent influences other agents and the environment. An agent is influenced by other agents and the environment as well.

4.1 Environment

We assume that the environment consists of a platform and a train. The details of the environment is as follows.

A platform has attributes such as: width and length, location of stairs, elevators, escalators, walls, pillars, a position where trains stop.

A train has attributes such as: number of cars, width and length of a car, positions of doors, number of doors, width of a door, positions of seats, number of seats and width, length of seats.

Thus, we can simulate the influence caused by the location of the stairs, the elevators, the escalators, the position where the train stops, number of doors of a train, width of doors of a train and so on.

4.2 Agent

We realize each passenger as an agent. Each agent calculates the speed and the direction to proceed every time unit (dt) considering the environment. From the result of the calculation, the agent decides the location where he/she must exist after dt, and moves to that location.

- Human Body

  A passenger's body is expressed by a circle. The diameter $2r$ corresponds to the width of a shoulder of a human body. From the literature[6], we assume r follows the Gaussian distribution and we set the mean and the standard deviation 43.28[cm] and 3.202[cm] respectively.

We also introduce a personal space. If another passengers enter in one's personal space, he/she feels uncomfortable. We set the diameter of the personal space R as 1.0m[7].

- Walking Speed

  Passengers' walking speeds are strongly influenced by obstacles and congestion. It is reported that if there are no obstacles and congestion, passengers' walking speed (free walking speed) is about 1.5 m/s [7]. But during rush hours, it is reported that the walking speed becomes faster. We assume that the free walking speed follows the Gaussian distribution with the mean 1.64m/s and the standard deviation 0.05. Also, we set the maximum walking speed v_{max} as 2.2m/s because there is a certain upper limit for the walking speed.

- Visible Area

  It is reported that visible distance of a human being is 5m for front and the range is from 110 to 160 degrees. In this paper, we set the visible range of an agent as a sector form with the center angle from 110 to 160 degrees.

- Visibility check of agents

  If equations (1) and (2) hold, we decide that Agent j can be seen by Agent i. In equations (1) and (2) , $\overrightarrow{f_{ij}}$ is a vector from the center of Agent i to the center of Agent j. $\theta_{d_i f_{ij}}$ is an angle between $\overrightarrow{d_i}$ and $\overrightarrow{f_{ij}}$, where $\overrightarrow{d_i}$ is a vector which denotes the line of sight of Agent i. θ is a visible range of Agent i, s is a radius of the scope and r_i and r_j is a radius of the body of Agent i and j, respectively.

$$\|\overrightarrow{f_{ij}}\| < s + r_i + r_j \tag{1}$$

$$\theta_{d_i f_{ij}} < \frac{\theta}{2} \tag{2}$$

- Visibility check of walls and an edge of a platform

  If $\theta_{f_{iw} m_w}$ satisfies Equation (3) and one of the following conditions is satisfied, we decide walls and edges of a platform which satisfies the condition can be seen by the agent.

$$\theta_{f_{iw} m_w} > 90^\circ \tag{3}$$

  Conditions:

  1. Either $\overrightarrow{left}$ which is a vector to the left periphery of the scope or $\overrightarrow{right}$ which is a vector to the right periphery of the scope intersects a wall or an edge of a platform w.
  2. Equations (4), (5) hold, where $\theta_{df_{iw}}$ is an angle between vectors $\overrightarrow{d}$ and $\overrightarrow{f_{iw}}$.

$$\|\overrightarrow{f_{iw}}\| < s + r_i \tag{4}$$

$$\theta_{f_{ij} d} < \frac{\theta}{2} \tag{5}$$

- Visibility check for obstacles on a platform

  Obstacles o which satisfy equations (6) and (7) are decided to be visible, where $\overrightarrow{f_{io}}$ is a vecter from the center of Agent i to o, $\theta_{d_i f_{io}}$ is an angle between $\overrightarrow{f_{io}}$ and $\overrightarrow{d_i}$, r_o is a radius of o.

$$\|\overrightarrow{f_{io}}\| < s + r_i + r_o \tag{6}$$

$$\theta_{d_i f_{io}} < \frac{\theta}{2} \tag{7}$$

4.3 Destination of agent

Destinations of an agent vary depending on its situation. This is partly because an action of an agent consists of several steps, such as to go to a certain location on a platform to wait for a train, if there is a waiting queue, the agent goes to the tail of it, when a train arrives, the agent waits for passengers alight, then the agent gets on and so on. Another reason is that an agent decides its destination considering its state, its preference, information about train operation, obstacles and other agent inside its scope and so on. In this paper, we describe the behaviour of an agent by a state transition diagram shown in Fig.2and we decide the destination of an agent step by step based on the state transition diagram.

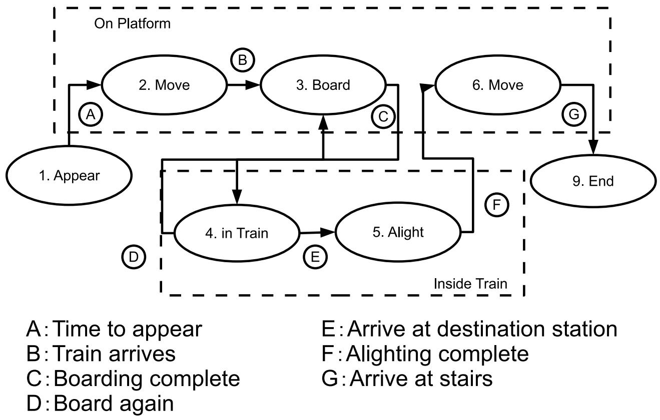


Fig. 2: Behaviour model of an agent

5 Simulation of agents' walking

5.1 Potential model

A potential model is a model which makes it possible to let an agent move by giving an electric charge to agents, obstacles and targets of agents. We give some charge to an agent and give the same homopolar charge to other agents and obstacles, which makes it possible for the agent to avoid other agents and obstacles because there occurs a repulsive force between them. Likewise, we give some charge to the destination of the agent, which makes it possible for the agent to move toward the destination, because there occurs an attraction force between them.

A potential model has the following merits compared with the cellular automata model.

1. Walking speeds of agents can be set freely (in our simulation model, we set the walking speed between $0[m/s]$ and max speed $[m/s]$).

   In contrast, in the cellular automata model, agents are only allowed to stay within a cell ($0[m/s]$) or to move (with free walking speed $[m/s]$).

2. We can set the time unit freely.

   On the contrary, in the cellular automata model, the unit of time depends on the size of a cell.

We concluded that the potential model is more flexible and suitable to simulate passengers' flow in case of congestion.

5.1.1 Attraction force from the destination

An attraction force of Agent i to its destination $\overrightarrow{E_{gi}}$ is expressed by Equation (8). Here, $\overrightarrow{e_{ig}}$ is the vector from the current position of Agent i to its destination g, and Q_g is the charge of electricity of g. This means that the strength of attraction force is irrelevant to the distance to the destination.

$$\overrightarrow{E_{gi}} = Q_g \cdot \frac{\overrightarrow{e_{ig}}}{\|\overrightarrow{e_{ig}}\|} \tag{8}$$

5.1.2 Attraction force from another agent who proceeds to the same direction

Let the speed vector of Agent i be $\overrightarrow{v_i}$, the speed vector of Agent j be $\overrightarrow{v_j}$ and the angle between them be $\theta_{v_iv_j}$. We set an agent which is the closest to Agent i among the agents which satisfy $\theta_{v_iv_j} < 15°$, as the agent which Agent i follows and denote Agent k. $\overrightarrow{E_{ki}}$ is an attraction force from Agent k and is calculated by Equation (9).

In Equation (9), $\overrightarrow{e_{ik}}$ is a vector from the current position of Agent i to the location of Agent k after dt has passed. Q_k is the charge of Agent k. S is the size of Agent i and m is the number of agents which are approaching to Agent i.

By multiplying $\frac{m}{S}$, the attraction force becomes stronger as the congestion rate increases. Thus, we can simulate emergence of "lanes," which are usually observed in case of heavy congestion.

$$\overrightarrow{E_{ki}} = \frac{m}{S} \cdot Q_k \cdot \frac{\overrightarrow{e_{ik}}}{\|\overrightarrow{e_{ik}}\|} \tag{9}$$

5.1.3 Repulsion force to other agents

The repulsion force to Agent i from other agents is expressed by Equation (10). In Equation (10), $\overrightarrow{f_{ij}}$ is a vector from the current position of Agent i to the position of Agent j after a unit time dt has passed. Q_j is a charge of Agent j inside the scope of Agent i. $\theta_{E_{gi}f_{ij}}$ is an angle between $\overrightarrow{E_{gi}}$ and $\overrightarrow{f_{ij}}$. By multiplying cosine, we can reduce the influence from agents who are going away.

$$\overrightarrow{F_{pi}} = \sum_{j}^{n} \left(\frac{Q_j}{\|\overrightarrow{f_{ij}}\|^2} \cdot \frac{\overrightarrow{f_{ij}}}{\|\overrightarrow{f_{ij}}\|} \cdot \cos\theta_{E_{gi}f_{ij}} \right) \tag{10}$$

5.1.4 Repulsion force to walls and edges of platform

The repulsion force to obstacles such as the walls and edges of a platform is calculated by Equation (11), where f_{iw} is a vector from the current position of Agent i to the obstacle w, Q_w is a charge of the obstacle, $\theta_{E_i f_{ij}}$ is the angle between the attraction force E_i and f_{iw} and n is the number of obstacles. By multiplying cosine, we can reduce the influence when the agent is going apart from the obstacles.

$$\overrightarrow{F_{wi}} = \sum_{w}^{n} \left(\frac{Q_w}{\|\overrightarrow{f_{iw}}\|^2} \cdot \frac{\overrightarrow{f_{iw}}}{\|\overrightarrow{f_{wi}}\|} \cdot \left(\frac{1 + \cos\theta_{E_{gi} f_{iw}}}{4} \right) \right) \tag{11}$$

5.1.5 Repulsion force to obstacles on the platform

The repulsion force $\overrightarrow{F_{oi}}$ to obstacles on the platform is calculated by Equation (12), where $\overrightarrow{f_{io}}$ is a vector from the current position of Agent i to an obstacle o, $\theta_{E_{gi} f_{io}}$ is the angle between the attraction force of Agent i to the destination $\overrightarrow{E_{gi}}$ and $\overrightarrow{f_{io}}$. n is the number of obstacles. By multiplying cosine, we can reduce the influence when the agent is going away from the obstacles.

$$\overrightarrow{F_{oi}} = \sum_{o}^{n} \left(\frac{Q_o}{\|\overrightarrow{f_{io}}\|^2} \cdot \frac{\overrightarrow{f_{io}}}{\|\overrightarrow{f_{io}}\|} \cdot \cos\theta_{E_{gi} f_{io}} \right) \tag{12}$$

5.2 Calculation of the walking speed of agents

$\overrightarrow{E_i}$ is an attraction force to Agent i and is calculated by Equation (13). $\overrightarrow{F_i}$ is a repulsive force to Agent i and calculated by Equation (14). $\overrightarrow{V_{new}}$, the walking speed of Agent i after the unit time dt passed is calculated by Equation (16) using Equation (15).

$$\overrightarrow{E_i} = \overrightarrow{E_{gi}} + \overrightarrow{E_{ki}} \tag{13}$$

$$\overrightarrow{F_i} = \overrightarrow{F_{pi}} + \overrightarrow{F_{wi}} + \overrightarrow{F_{oi}} \tag{14}$$

$$\overrightarrow{V_{temp}} = v \cdot \frac{\overrightarrow{v_i} + (\overrightarrow{E_i} - \overrightarrow{F_i}) \cdot dt}{\|\overrightarrow{v_i} + \overrightarrow{E_{gi}} \cdot dt\|\|} \tag{15}$$

$$\overrightarrow{V_{new}} = \begin{cases} \overrightarrow{V_{temp}} & (\|\overrightarrow{V_{temp}}\| \leq v_{max}) \\ v_{max} \cdot \frac{\overrightarrow{V_{temp}}}{\|\overrightarrow{V_{temp}}\|} & (\|\overrightarrow{V_{temp}}\| > v_{max}) \end{cases} \tag{16}$$

5.3 Location of an agent after unit time dt passed

We can thus calculate P_{new}, the location of Agent i after a unit time dt passed by Equation (17).

$$P_{new} = P_i + \overrightarrow{V_{new}} \cdot dt \tag{17}$$

6 Behaviour of an agent

6.1 Walk to the boarding position

6.1.1 Boarding position

According to the survey in [8], it is known that passengers choose their boarding positions considering following conditions in this order.

1. close to stairs etc. at the station they alight.

2. close to stairs etc. at the station they start their travel.

3. concourse and trains are not so congested.

In our simulator, an agent decides their boarding position temporarily when it appears at the platform (as described later, the agent may change the boarding door if there is a change in the environment). An agent makes this decision based on P_w calculated by Equation (18). $getoff$ is a distance from the temporary boarding position to the door closest to stairs at the destination station. $geton$ is a distance from the current position to the temporary boarding position, $number$ is a number of passengers in a queue at the temporary boarding position, α,β,γ are weights to express difference of passengers' tastes.

This procedure makes it possible for an agent to decide its boarding position reflecting its preference.

$$P_w = \alpha\cdot getoff + \beta\cdot geton + \gamma\cdot number \tag{18}$$

6.1.2 Avoidance of passengers in waiting queues

Because the width of platforms is usually small in size, passengers who are in a waiting queue become obstacles for walking agents. If a passenger encounters a waiting queue, he usually detour the queue.

6.2 Boarding

- Decision of the door to board

  The destination in the boarding state is the door to board. For an agent who is already in a waiting queue, its destination is the door which corresponds to the waiting place. If a train arrives during an agent is moving to its destination, we set the destination as the closest door from its current position.

- To wait while alighting passengers are geting off

  Passengers who want to board wait beside a door while alighting passengers are getting off. In our simulator, each agent decides the timing to board considering this. Details of the waiting process are as follows:

  1. Seek for alighting passengers in the scope.

2. Calculate θ, which is an angle between $\overrightarrow{A}$, a vector from the current position to the destination and $\overrightarrow{B}$, a vector from the current position to the nearest end of a door (the left end or the right end of a door).
3. If there exist alighting agents in the scope and if $\theta < 90°$, then set the nearest end of the door as the temporary destination.
4. If 3 does not hold, then move to the destination.

- Keeping the order in the waiting queue

  When passengers get on a train, they keep the order in the waiting queue. In our simulator, an agent gives priority to move to another agent in the prior position in the queue. Details of the boarding process is as follows:

  1. Seek for another agent in a scope who is in the prior position in the waiting queue.
  2. If there is another agent in the prior position and the agent is not boarding yet, go to 3. If the agent is already boarding, or there are no other boarding agent in front, go to 4.
  3. Set the agent in front as the temporary destination.
  4. Go to the destination.

6.3 Inside a train

6.3.1 Decision of destination inside a train

In general, passengers are thought to go to a vacant seat if they find ones in their scope. From our observation, passengers tend to choose a seat in the end or a seat whose neighbouring seats are still not occupied.

We make our agent behave like this by using P_s, which is calculated by Equation 19, where $distance$ is a distance from the current position to the target seat. α,β,γ are weights: α is used for a seat if both neibouring seats are vacant, and for an end seat whose neibouring seat is vacant, β is used for a seat if one of the neighbouring seats is vacant and for an end seat whose neibouring seat is occupied and γ is used for a seat if both of the neighbouring seats are occupied.

$$P_s = \begin{cases} \alpha * distance \\ \beta * distance \\ \gamma * distance \end{cases} \tag{19}$$

6.3.2 Decision of a position in a train to avoid congestion

When all the seats in the train are occupied, passengers like to keep a certain distance from other passengers so that they do not feel uncomfortable. In our simulator, we devide the space in front of the seats and the space near doors into smaller segments and estimate the congestion in each segment so that agents can avoid congestion.

c_i, congestion rate of segment i is calculated by Equation (20), where S_i is the size of segment i and n_i is the number of passengers in segment i.

$$c_i = \frac{n_i}{S_i} \tag{20}$$

We calculate c_i for all the segments in the scope and set the segment with the smallest c_i as the destination of the agent.

6.3.3 Decision of comfortable position

A passenger changes its position inside a train if he/she feels uncomfortable because of congestion. We think comfortability of an agent is influenced by the number of other agents and the distance from other agents in its personal space. Based on this observation, an agent seeks for a position where the number of other agents in its personal space becomes minimum or total sum of the distance to other agents becomes minimum.

6.3.4 Behaviour to step aside for alighting passengers

When trains are congested, passengers give way to alighting passengers so that they can smoothly get off the train.

In our simulator, if an agent finds another agent who is alighting and some possibility to collide, the agent steps aside to avoid collision. The agent sometimes get off a train to give a way and if the agent realizes that it is outside the train, the agent changes its state to "boarding" and then it gets on the train again.

6.4 Alighting

6.4.1 Decision of Alighting Door

The destination when the state is alighting is a door from which the agent will get off. We assumed that an agent chooses the nearest door from its current position.

6.4.2 Alighting from deep inside a train

Passengers make haste as much as possible if their positions are deep inside a train, because dwell times are short and passengers cannot get off the train if they behave too slowly. In our simulator, we realize this behaviour by giving a large amount of charge to the door (destination), so that those agents are strongly attracted by the doors and rush to the door in a haste.

6.5 Behaviour after getting off

The destination of a passenger after it gets off is either stairs, an escalator or an elevator on the platform. We set the destination of an agent after it gets off a train as the closest stairs, escalator or elevator.

7 Numerical Experiments

7.1 Simulation of passengers' behaviour

We have conducted numerical experiments in order to confirm that our simulator can appropriately simulate passengers' behaviour.

As the environment, we prepared an imaginary platform with stairs on both ends and a train, whose size is the same as the trains commonly used in urban railway lines. Parameters about the size of the train are as follows: total length $20000[mm]$, width $2800[mm]$, number of doors on one side / car 4, width of exit $1300[mm]$ seat width/passenger $450[mm]$, number of seats/car : 52, authorized capacity/car: 152. The numbers of boarding passengers and alighting passengers are both 30.

In Fig.3, we show screen shots of the simulation for the congestion rate 132%. In Fig. 4, we show a detailed screen shot for the door in the left side: Green circles denote agents in a train, red circles denote agents who are alighting, yellow circles denote agents who are going to board. You can find green circles even outside the train. Although the current station is not their destination, they get off the train to give a way to alighting passengers. We observed that passengers' behaviour which are very often observed such as to step backward to give way to an alighting agents, to follow another agent, to get off so that alighting passengers can get out of the train smoothly and get on again etc.

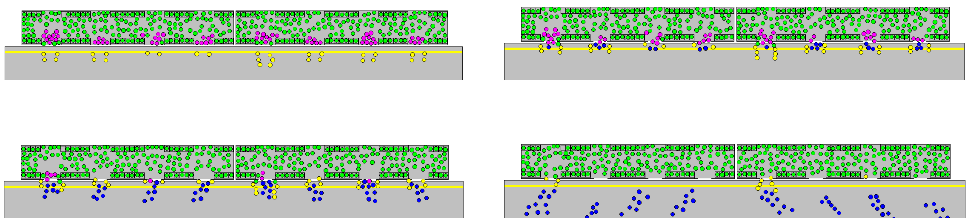


Fig. 3: Screen shots of passenger flow of boarding and alighting

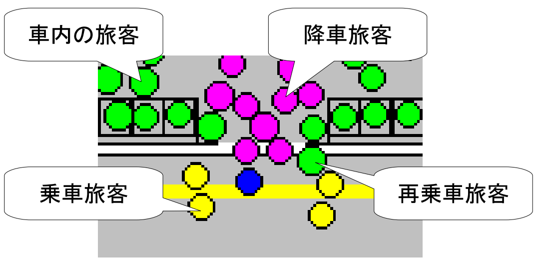


Fig. 4: Screen shot of passenger flow at the leftmost door

7.2 Comparison with actual dwell time data

In order to confirm how exactly our simulator can estimate dwell times, we have conducted simulation for a subway station in Tokyo area and we compared the results with actual dwell times we measured at the station.

We show the results of our numerical experiments in Fig.5 and Table1. Fig.5 shows the results of 10 trials using our simulator (drawn in blue) and the actual dwell times we got for three days (drawn in red). Table1 shows the average and the standard deviation of the simulation results and the actual dwell times. We may well insist that the averages are almost the same. The standard deviations are rather large. We analyzed the reason and came to a conclusion that dwell times are greatly influenced by a small change of passengers' behaviour and we should repeat simulation many times and obtain the average.

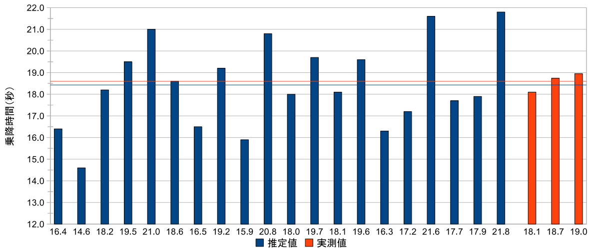


Fig. 5: Comparison of simulation results and actual dwell times

Table 1: Average of simulation results and actual dwell times

	actual	simulation
Average[$sec.$]	18.60	18.43
Std. deviation	0.362	1.930

7.3 Dwell time estimation as the congestion rate increases

We wanted to apply our simulator to estimate how the dwell time will be as the congestion rate in a train increases. We conducted simulation for an imaginary platform data 30 times. The number of the boarding passengers is 50 and the congestion rate inside the train is from 80% to 140%.

The results are shown in Table2. From the results, we confirmed how the dwell times increase as the congestion rate increases. The standard deviation for the simulation results is rather big especially when the congestion rate is high. We learned that the reason is the same as one we already mentioned in the previous section.

7.4 Dwell times and width of doors

We want to clarify how the dwell time is reduced when we introduce a train with wider doors especially when the congestion rate is high.

In Table3, we show our simulation results for an imaginary platform and a train with wider doors (1800mm wide) changing congestion rate from 80% to 140%. The number of boarding passengers is 50 and that of alighting passenger is also 50. We repeated simulation 30 times and we show the average. In Fig.6, we show a comparison with the results of normal doors (1300mm) which

Table 2: Simulation results for congestion from 80% to 140%

Congestion	Average[$Sec.$]	Std. Dev.
80 %	17.14	1.441
90 %	17.94	2.163
100 %	18.61	2.018
110 %	19.47	1.801
120 %	22.54	2.588
130 %	24.54	3.464
140 %	28.16	4.156

were already shown in 7.3. In Fig.6, the vertical axis is necessary dwell time, the horizontal axis is congestion rate and the blue line and the red line indicate the simulation results (necessary dwell times) of normal doors and wider doors respectively.

In each case of congestion, dwell times are decreased for a train with wider doors and we can conclude that trains with wider doors is effective to prevent dwell times from increasing.

Table 3: Average dwell time for a train with wider doors

Congestion	Ave.[$sec.$]	Std. Dev.	Difference from normal doors[sec.]
80 %	14.82	1.069	-2.32
90 %	15.99	1.732	-1.95
100 %	16.81	1.114	-1.80
110 %	18.19	2.051	-1.28
120 %	18.93	2.148	-3.61
130 %	21.70	3.305	-2.84
140 %	26.79	4.297	-1.37

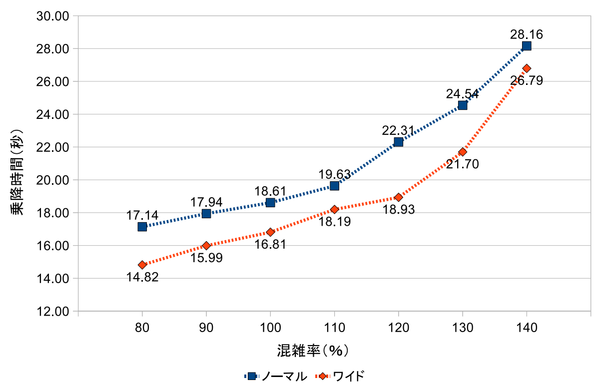


Fig. 6: Comparison of dwell times

7.4.1 Analysis of boarding times of a train with wider doors

We want to further analyze the effects of trains with wider doors. First, we focus on the boarding times. In Table 4 and Fig.7, a comparison of boarding times for normal doors and wider doors is shown. In Fig.7, the vertical axis is necessary boarding time, the horizontal axis is congestion rate and the blue line and the red line indicate the simulation results (necessary dwell times) of normal doors and wider doors respectively.

Table 4: Average boarding times of normal doors and wider doors

Congestion	Average boarding time [sec.]	
	Normal doors	Wider doors
80 %	10.73	10.02
90 %	11.07	10.74
100 %	11.92	11.15
110 %	12.70	12.21
120 %	14.86	13.38
130 %	16.73	15.22
140 %	20.05	19.46

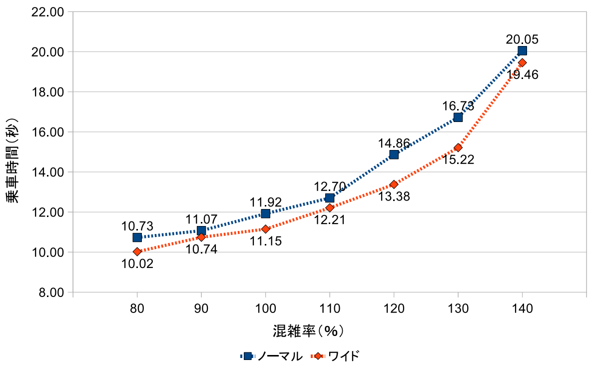


Fig. 7: Boarding times of a train of wider doors and normal doors

From these results, we learned that boarding times increase as the congestion rates increase both for trains with normal doors and wider doors. This means that congestion rate inside a train is influential for necessary boarding times.

We have also learned that the differences of boarding times between normal doors and wider doors are rather small. We analyzed the reason and realized that this is because agents who want to get on a train step aside a door in order to let the alighting agents get off smoothly and the width of wider doors is not fully utilized especially when agents begin to get on as shown in Fig.8(a) and Fig.8(b).

7.4.2 Analysis of alighting times for trains with wider doors

We then analyzed how effective wider doors are to shorten alighting times.

We show average alighting times for normal doors and wider doors, which we got by our simulation in Table 5 and Fig.9. Again in Fig.9, the vertical axis is necessary dwell time, , the horizontal axis is congestion rate and the blue line and the red line indicate the simulation results (necessary dwell times) of normal doors and wider doors respectively. We have learned that alighting times increase as the congestion rate increases. We have also learned that differences between normal doors and wider doors are larger compared with boarding times. We analyzed the reason and realized that this

(a) Wider door

(b) Normal door

Fig. 8: Passenger flows when boarding of wider doors and normal doors

is because the number of passengers who can get off simultaneously is two in case of normal doors but the number is four in case of wider doors as shown in Fig.10(a) and Fig. 10(b). From these results, we can conclude that trains with wider doors are very effective to prevent alighting times from increasing.

Table 5: Alighting times for wider doors and normal doors

Congestion	Average Alighting time [sec.]	
	Normal	Wider
80 %	7.78	5.41
90 %	7.82	54.2
100 %	7.94	5.79
110 %	7.98	6.19
120 %	8.55	6.39
130 %	9.18	7.11
140 %	9.59	7.36

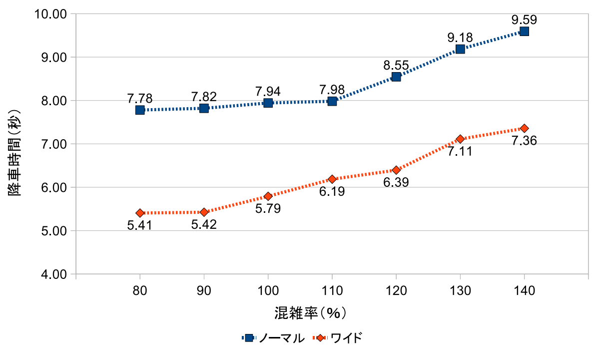
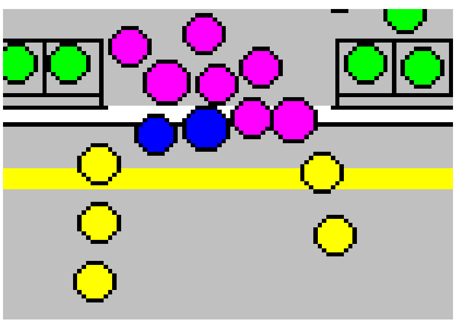


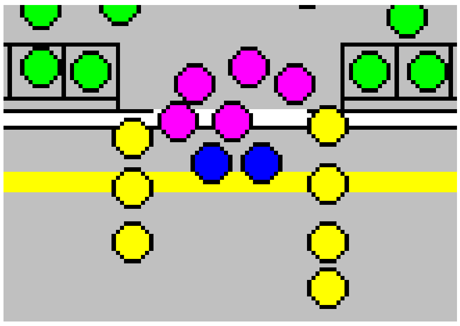
Fig. 9: Alighting times for a train with wider doors

7.5 Analysis of trains with wider doors and normal doors

"A train with wider doors" literally means a train whose doors are all wider doors. But in reality, because of some limitation of design, there exist a train which have both wider doors and normal



(a) Wider doors



(b) Normal doors

Fig. 10: Passenger flow when alighting

doors. Typically, two doors (headmost and aftermost doors) are normal because they are close to driver's cabin and other doors are wider doors. This type of train, however, is suspected to be not so effective to reduce dwell times for stations, where stairs exist in the both ends of the platform. We conducted simulation to learn if this is true or not for three types of trains, namely, a train with normal doors (normal), a train with wider doors (all wider) and a train with normal and wider doors (normal and wider).

We repeated simulation 20 times. We assumed the train consists of two cars, the number of boarding passengers is 100, the number of alighting passengers is 50 for each car, congestion rate is from 80 to 140.

We show the average dwell times in Table 6 and Fig. 11. Please note that n Fig.11, the vertical axis is necessary dwell time, , the horizontal axis is congestion rate and the blue line, the red line and the yellow line indicate the simulation results (necessary dwell times) of "normal" doors, "normal and wider" doors and "all wider" doors respectively. As you see, the results for a train with normal doors and the results for a train with normal and wider doors are almost the same, which means the latter is not so effective to reduce dwell times for a station with stairs in the both end of the platform.

Table 6: Average dwell times for normal doors, wider doors and mixed

Congestion	Ave. Dwell time [sec.]		
	Normal	All wider	Normal and Wider
80 %	19.63	16.44	19.70
90 %	19.76	17.14	19.80
100 %	20.81	17.82	20.42
110 %	22.11	18.15	21.04
120 %	22.43	18.75	22.15
130 %	24.00	20.47	23.28
140 %	27.35	22.63	26.89

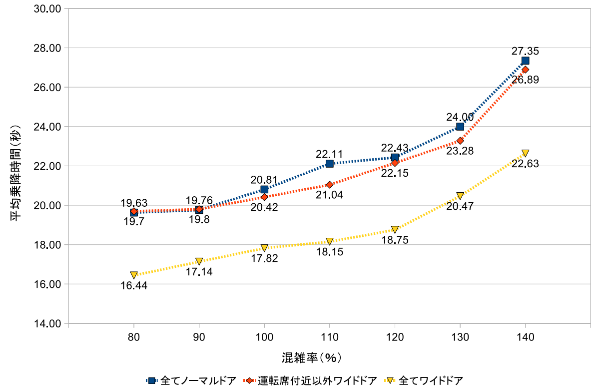


Fig. 11: Dwell times for three types of trains

8 CONCLUSIONS

We have developed a simulator to estimate necessary dwell times when various kinds of counter measures to reduce dwell time are introduced. The simulator is developed based on a multi-agent model and it can simulate complicated behaviour of passengers' flow by regarding each passenger as an agent who has own mind and preference. One of the characteristics of our simulator is that it can simulate passengers' flow between inside a train and a platform seamlessly and this makes it possible to simulate passengers' behaviour such as to wait for a train in a queue and to step away even to outside a train to give a room for alighting passengers, which are often observed in case of congestion.

We have applied our simulator and learned the results are very promising. We have also applied our simulator to know how much time could be spared when we introduce a train with wider doors.

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