Special edition paper

Development of a Simulation System Allowing Prediction of Changes in Flow of Passengers on Platforms



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Congestion is assumed to change in renovation of equipment on station platforms such as addition and relocation of stairways and escalators and setup of platform doors. Predicting and taking actions on that congestion change in advance would thus lead to improvement in safety and amenity.

The goal of this research is to develop a simulation system that can verify with high accuracy in planning of station renovation the change in passenger flow. In the research, we established technology to optimize reproducibility of simulations using data on actual phenomena at stations, achieving an approx. 7% increase in reproducibility. This system was also used to relieve congestion in an actual project to study how to set up temporary enclosures by predicting time to relieve queue of passengers when such enclosures are set up on platforms. In light of the research results, we are currently proceeding with development for practical application so as to be able to construct an environment that will allow optimal usage when applying the simulation system in actual work.

●Keywords: Station, Multi-agent model, Automatic search system for optimum parameters, Origin/destination (OD) estimation

1 Introduction

Renovation plans when constructing new equipment on station platforms such as stairways, escalators ("ESC" in the figures) and platform doors involved repeated considerations on how to prevent new places of congestion.

A method is available to predict level of congestion after renovation using passenger flow simulation (Fig. 1). However, there have been almost no methods to quantitatively identify actual phenomena of passenger flow itself (especially in the morning rush) that can evaluate the accuracy of simulation. So, we have only been able to confirm by comparing video measurement results and simulation results. Previous research[1] by JR East was the first successful quantitative identification of the actual phenomena of morning rush passenger flow. With that research, we were for the first time able to compare the results of simulation and the actual phenomena for morning rush passenger flow before and after equipment renovation.

The goal of this research is to develop a simulation system that can verify with high accuracy in planning of station renovation the change in passenger flow. We were able to for the first time anywhere to establish technology to optimize reproducibility of simulations using data on actual phenomena at stations, using that to relieve congestion in an actual project to study how to set up temporary enclosures by predicting time to relieve queue of passengers when such enclosures are set up on platforms. And now we are working on development to apply the system to practical situations through efforts such as development of a graphic user interface that can be operated by JR East personnel. Specifically, our research is proceeding according to the flow shown in Fig. 2.

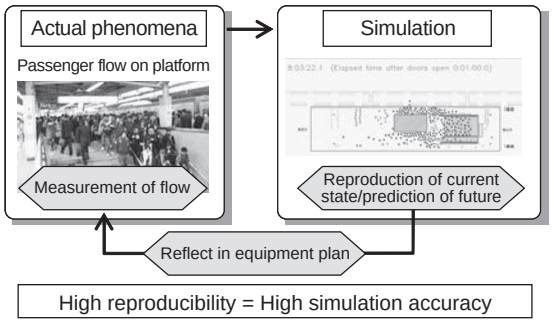

Fig. 1 Illustration of Use of Passenger Flow Simulation

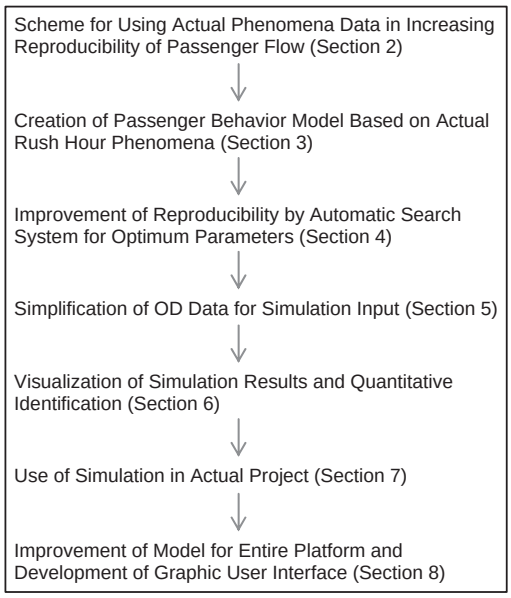

Fig. 2 Flow of Simulation Development

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2 Scheme for Using Actual Phenomena Data in Increasing Reproducibility of Passenger Flow

As expressed in the previous section, there have up to now been no tools or means to quantitatively identify passenger behavior and actual flow for passenger flow on platforms. Thus, no methods had been established for expressing the accuracy of reproducibility of simulation output results.

Through previous research[1)], however, we developed a technique to quantitatively identify passenger flow on platforms. Specifically, we were able to detect the positional coordinates of passengers on platforms in the morning rush approximately every one second. We took on the task of establishing technology to compare those coordinates with simulation output data and minimize error assessment values (see section 4 for details) so as to automatically approximate simulation results to actual phenomena and optimize simulation results. As a result, we succeeded in developing an automatic search system for optimum parameters (patent pending).

Figure 3 shows the scheme for increasing passenger flow simulation reproducibility using actual phenomena data. The simulation involves inputting data such as spatial data (platform shape, equipment), passenger origin/destination (OD) data, and train arrival/departure timing, operating a program, and outputting data. We made the scheme to be one where we develop a program to automatically search for optimal parameter values by comparing output results with measurement data of actual phenomena, secure greater reproducibility than before, and develop a platform passenger flow simulator where optimal parameters can be set even by those who are not experts.

3 Creation of Passenger Behavior Model Based on Actual Rush Hour Phenomena

3.1 Creation of Locomotion Model Suitable for Station Platforms

In this R&D, we employed a multi-agent type simulation model to accurately reproduce passenger movements such as following and collision avoidance at times such as the morning rush. This model is comprised of multiple passengers (agents) and their surrounding environment, and it is a model where passenger behavior is determined by the interaction with the environment and other passengers. Spatial form, start and end points of passenger flow, specifications of equipment such as platform doors, train schedules, and control data for passengers waiting at door loocations are set as individual passenger's surrounding environment in this R&D.

The developed system employs a locomotion model with an anticipatory search feature as shown in Fig. 4 to reproduce movements such as collision avoidance of individual passengers at stations. We added to the model differences in walking route according to formation of lines at train doors on platforms and at escalators and according to the presence or absence of platform doors, and we created a locomotion model specifically for stations that included avoidance of places of congestion (Fig. 5).

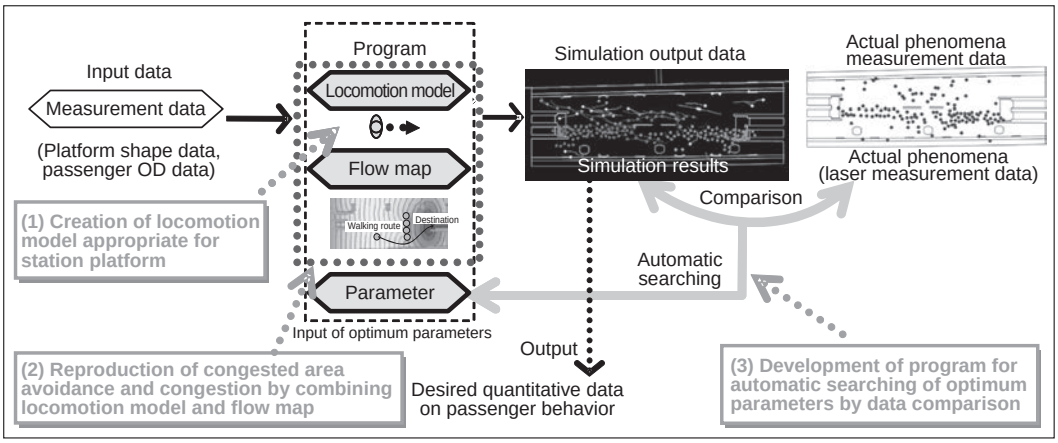

Fig. 3 Scheme for Using Actual Phenomena Data in Increasing Reproducibility of Passenger Flow

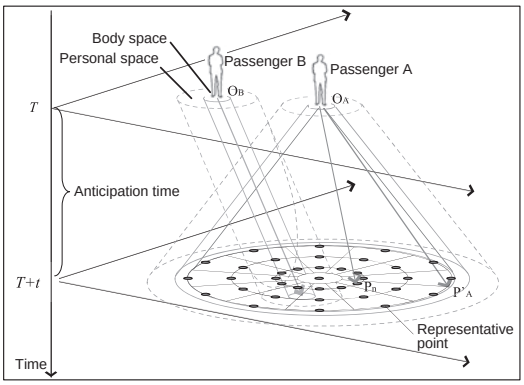

Fig. 4 Image of Locomotion Model with Anticipatory Search Feature

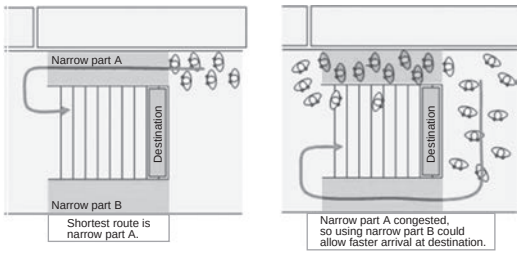

Fig. 5 Part of Improvement of Simulation Model Specific to Stations (Active Route Selection Function)

3.2 Creation of Program for Avoidance and Reproduction of Places of Congestion by Combining Locomotion Model and Flow Map

3.2.1 Reproduction of Avoidance Behavior for Places of Congestion by Automatic Generation of Flow Map

Preparation was made for accurately expressing passenger behavior on the platform with the aforementioned method. However, calculating judgment of collision and following of all passengers proved to be unrealistic for times such as the morning rush due to the sheer volume of calculations needed. We thus needed greater calculation speed for efficient calculation according to actual behavior.

To overcome that issue, we decided to combine a flow map with a locomotion model for individual passengers so as to express common walking routes and the like when individual passengers take actions. Passengers generally walk the shortest route to their destination. However, it becomes difficult for them to walk the shortest route when the platform is congested due to many passengers waiting in line for trains and when they accumulate in front of the escalators. Analysis showed that, in such situations, passengers avoid the lines at train doors by walking on the edge of the platform or take detours to avoid the queue in front of escalators.

In this research, we created a model that can reproduce avoidance behaviors at congested locations by reflecting ease of walking according to platform congestion and updating a flow map every few seconds (Fig. 6).

3.2.2 Reproducing Queue in Front of Escalators by Improving Flow Map Generation Technique

Passengers disembarking to the platform at train arrival all head for the escalator at once, so queue is formed at the escalator entrance. Analysis results showed that the shape of queue in front of escalators does not spread concentrically from the escalator entrance at the center; rather, it spreads to form a line parallel to the escalator.

In this research, we succeeded in reproducing queue in front of escalators by expanding the diffusion equation used in flow map generation (Fig. 7).

As a result, we could reproduce situations such as formation of lines waiting for trains, passengers disembarking from trains when they arrive, formation of queue around escalators, and gradual relief of queue. Those situations are shown in Fig. 8.

3.3 Further Improvement to the Locomotive Model of Passengers Walking on the Platform

In the fiscal 2011 development, we observed features such as the movement on the platform of individual passengers (agents) by video images and improved the locomotion model. As shown in Fig. 5, we included in the model differences in anticipatory actions between congested locations during rush hour and off-peak, and we improved on and added approx. 15 types of models to express passing behavior and collision avoidance actions for opposing passengers according to the level of congestion. For example, we improved models to allow the two settings of same destination or different destination with the bodily space radius used for judgment of passengers interfering with each other. We also improved models to allow handing and expression of items such as passengers rushing to stairs after avoiding train doors by expanding parameters related to walking speed.

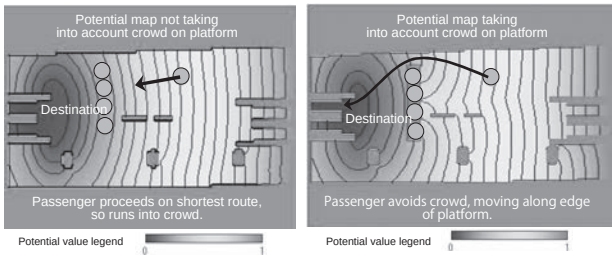

Fig. 6 Passenger Routes Before (Left) and After (Right) Update of Flow Map

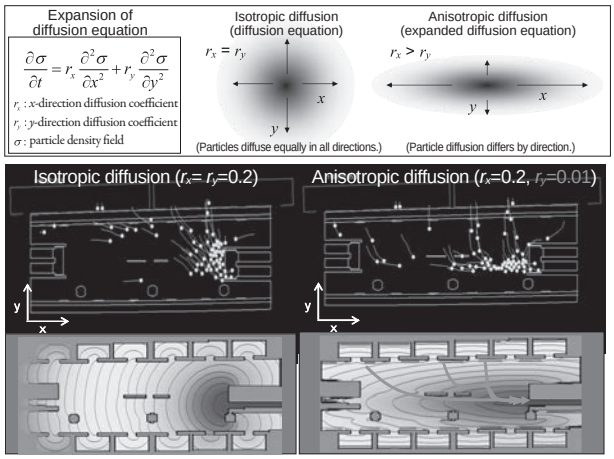

Fig. 7 Improvement of Flow Map Generation Method

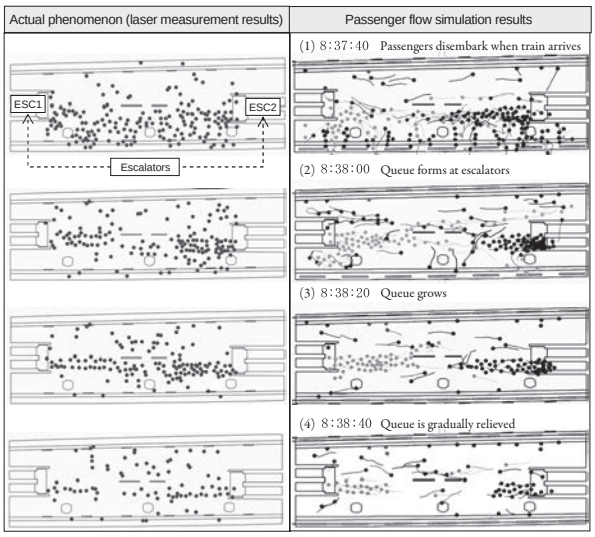

Fig. 8 Comparison of Actual Phenomena (Left) and Simulation (Right)

4 Improvement of Reproducibility by Automatic Search System for Optimum Parameters

4.1 Error Assessment Values and Method of Optimization

One possible method of evaluating deviation between simulation passenger data and measurement data is to compare location information of individuals for the full applicable time. However, when evaluating platform congestion level in situations such as the morning rush when many passengers are on the platform, fluctuation of individual passengers' locations becomes apparent in evaluation results with evaluation of miniscule amounts. Quantitative evaluation thus becomes difficult, so it is believed that an all-inclusive amount where locations of individual passengers are averaged would be effective. Therefore, we divided the platform space this time into 1 m^2 mesh cells and compared the congestion levels of each cell. We used a reciprocal of the person-to-person distance as defined below as the congestion level.

$$\text{Reciprocal of person-to-person distance} = \frac{\frac{1}{d_1}+\frac{1}{d_2}+\frac{1}{d_3}+\frac{1}{d_4}+\frac{1}{d_5}}{5}$$

The person-to-person distance is the average of the reciprocal of the distance from the closest five passengers for the passengers present in each cell. The reciprocal of person-to-person distance becomes larger as that distance becomes smaller and density increases.

We calculated the difference between measurement data and simulation results for the reciprocal of person-to-person distance as defined above, and the amount added for all cells for the entire applicable time expresses overall error for the simulation. With that as the error assessment value, we created a system to search for parameters to minimize this assessment value. That system is equipped with a program using a particle filter as the search algorithm (Fig. 9). In line with that, we optimized simulation parameters based on measurement data of actual phenomena (laser data) explained in section 2. Laser data gives location data of all regions and all times for all passengers on the platform, and it holds a vast amount of information. For that reason, we were able to decide on the optimum values that compensate for all parameters of the simulator.

4.2 Accuracy Evaluation Method

We evaluated accuracy by the method shown in Fig. 10. As a result of that evaluation, we were able to confirm that the system has 94.4% reproducibility (Table 1). Fig. 11 shows the change over time of the number of people in a place (station E). We found that the laser measurement results (actual phenomena) and the developed simulation show almost the same change.

4.3 Simplification of the Automatic Search System for Optimum Parameters

To simplify the system, we considered parameter compensation of the cross-sectional flow volume in the stairway area, using the following error estimation values as the optimization function. We found the difference between the measured and simulated cross-sectional flow volumes for each time, making the volume of all times added together as the error assessment value. As in 4.1, the system is equipped with a program using a particle filter as the optimization search algorithm. Fig. 12 shows time series variation of cross-sectional flow volume in the stairway area (for station C). Accuracy in relation to cross-sectional flow volume is 92.1%, demonstrating that actual and simulated passenger behaviors after optimization almost match.

$$\text{Error assessment value} = \sum_{\text{Individual time}} \left| \text{cross-sectional flow volume (video)} - \text{cross-sectional flow volume (simulation)} \right|$$

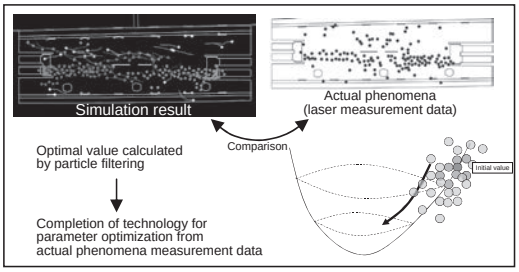

Fig. 9 Image of Particle Filtering

Accuracy evaluation method

(1) Separate target space into grids of 1 m to a side.
(2) Convert individual passenger locations to grid coordinates.
(3) Institute passenger fluctuation, and distribute probability of passenger presence in the nine cells surrounding each passenger grid coordinate.

0.016	0.094	0.016
0.094	0.563	0.094
0.016	0.094	0.016

(4) Calculate the number of passengers in each mesh cell at each time from log data of actual phenomena and simulation data.
(5) Compare number of passengers in each mesh cell at each time in laser measurement results and simulation results, and judge whether simulation is correct or incorrect.

$$\left| N^{sim}_{i,j,t} - N^{laser}_{i,j,t} \right| \le 0.9 \Rightarrow \text{Correct} \quad N^{sim}_{i,j,t} : \text{Number of passengers in cell } i, j \text{ at a time } t \text{ (simulation)}$$

$$N^{laser}_{i,j,t} : \text{Number of passengers in cell } i, j \text{ at a time } t \text{ (laser measurement results)}$$

(6) Calculate rate of correct responses for each cell, and calculate average of rate of correct responses for all times subject to accuracy evaluation.

Fig. 10 Accuracy Evaluation Method

Table 1 Accuracy Evaluation Results (Station E)

	Before model improvement	After model improvement
Accuracy (person-to-person distance)	93.6%	94.4%
Accuracy for total people in the place	90.5%	95.2%

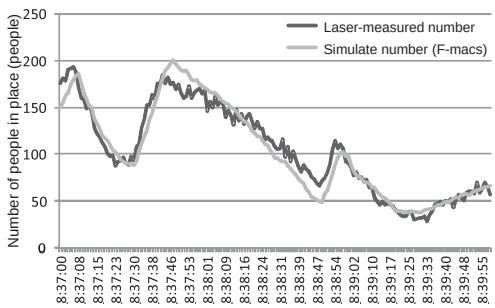

Fig. 11 Change in Number of People in Place Over Time (Station E)

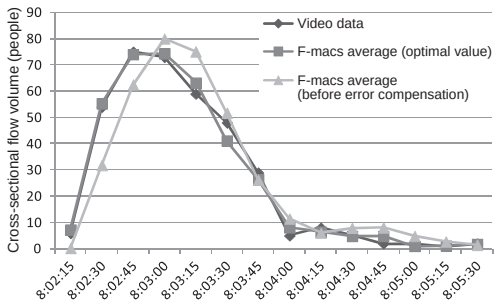

Fig. 12 Time Series Variation of Cross-sectional Flow Volume in Stairway Area (Station C)(comparison of video measurement data and simulation results)

5 Simplification of OD Data for Simulation Input

5.1 Issues in Acquiring OD Data

OD data in simulation of passenger flow on platforms has two roles. One is data for input, and the other is data for verifying accuracy to increase reproducibility.

In this research, we traced behavior of all passengers by video data and created OD data so as to increase the accuracy of OD data for input to the simulation (Fig. 13). With this technique, the accuracy evaluation covered in the previous section becomes possible, greatly contributing to increase of the simulation accuracy. However, this technique would involve much labor for measurement and data queue in actual use, so it would prove to be a burden in terms of cost and time. We thus worked to simplify acquisition of OD data as follows.

5.2 OD Data Estimation Model Developed and Outlook for the Future

In order to simplify acquisition of OD data, we studied how much we could reduce the measurement locations at actual stations. Specifically, we started by creating an OD estimation model taking into account the travel distance from train doors to stairways and escalators. Then we compared (1) data when measuring all cross-sectional flow volumes at doors and stairways and (2) estimation results when measuring only some cross-sectional flow volumes, and from that we evaluated accuracy. Fig. 14 shows an overview of OD estimation, and Fig. 15 the estimation model and OD estimation results. As a result, correlation was high with a correlation coefficient of 0.986 in the estimation model (1) where the cross-sectional flow volume was known. Results equivalent to when tracking all passengers were gained as shown in Fig. 16, so we found that estimation could be used favorable as input data for simulation.

6 Visualization of Simulation Results and Quantitative Identification

Fig. 16 shows fours methods of comparing measurement data and results of simulating OD estimation results.

As a method of quantitative evaluation, we made changes to allow display of time series variation of the number of people passing through stairways and the time until queue is relieved. This is in addition to the conventional method of using flow simulation videos. Additionally, we developed a way to display density distribution and incidence of different congestion levels.

To visualize those items, we made so that we can quantitatively compare time until queue is relieved for each case. We also made so that we can quantitatively identify how much the level of congestion in each place changed before and after renovation.

7 Use of Simulation in Actual Project

The following covers use of the developed system in actual work.

Fig. 17 shows an example of consideration of passenger congestion after setup of temporary enclosures when those were set up near a staircase at renovation work for station C in the

Fig. 13 Example of OD Measurement Work by Tracking Passengers in Video

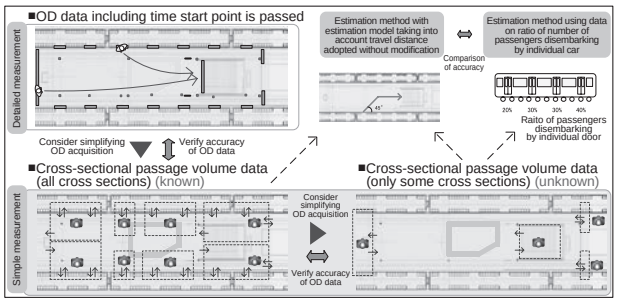

Fig. 14 Overview of Evaluating Accuracy of OD Estimation by Difference in Number of Measurement Locations

Data type and estimation model \ Evaluation index	Line No. 2 Correlation coefficient	Line No. 1 Correlation coefficient
(Known) Estimation model taking into account travel distance	0.986	0.987
(Unknown) Adopt data on ratio of weight by individual car	0.605	0.759
(Unknown) Estimation model taking into account travel distance	0.863	0.866

	Correlation coefficient
Fiscal 2010 research for station E (known) Estimation model taking into account travel distance	0.986

Known: When cross-sectional passage volume through train doors data is known
Unknown: When cross-sectional passage volume through train doors data is not known (only some cross sections)

$$N_{ij} = N_{i*} N_{*j} A_i B_j \exp\left[-\lambda d_{ij}\right]$$ Estimation model taking into account travel distance when "known"

$$N_{ij} = N_{*j} \exp\left[-\lambda d_{ij}\right]$$ Estimation model taking into account travel distance when "unknown"

Fig. 15 Estimation Model and Results of OD Estimation

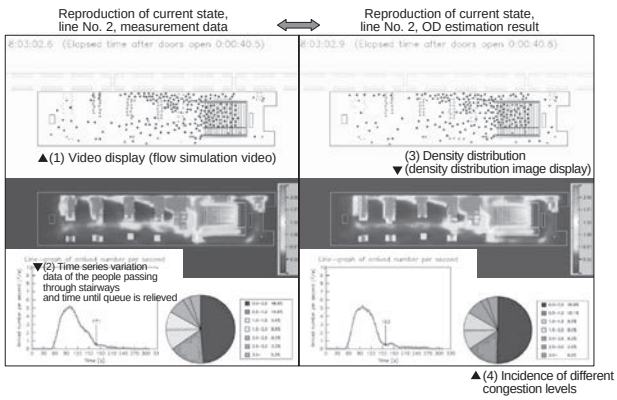

Fig. 16 Four Display Methods for Comparing Measurement Data and Results of Simulating OD Estimation

greater Tokyo area. Fig. 18 shows the size of the temporary enclosures. One of the temporary enclosures had to be set up approx. 2 m from the stairway, so it was necessary to predict and verify passenger flow at the morning rush in detail by simulation.

First, we measured the number of people passing through a cross section of the stairway area at the morning rush before and after renovation by the OD data acquisition method discussed in section 5. As a result of implementing the simplified parameter tuning of section 4, we gained 92.1% reproducibility of the current situation as shown in Fig. 12, meaning we were able to secure reproducibility greater than 90%. After confirming reproducibility of individual parameters of the simulator, we compared and considered prediction proposals for the temporary enclosure setup proposals in Fig. 19 and 20. With the type at the top of Fig. 19, we predicted queue to be relived 1 min. 48 sec. after opening of train doors, and relief of congestion before the next train arrives (within 3 min.) was predicted (Table 2).

Measurements on the day the temporary enclosure was set up showed that queue was actually relieved in 1 min. 49 sec., proving that predictions could be made with high accuracy. Result of prediction for the platform of line No. 1 was 2 min. 15 sec., while actual time was 2 min. 21 sec., showing that the differences from actual time were within 6 sec. These results proved that simulation accuracy was increased to a level that can be used in actual work.

8 Improvement of Model for Entire Platform and Development of Graphic User Interface

Through research, we were able to verify accuracy of reproducibility for use in actual work and create tools for visualizing prediction results. In light of those successes, we are working to further broaden the range of applicability (improvement of model for entire platform), develop a graphic user interface, and increase the calculation speed of parameter tuning, all with use by personnel in actual work in mind. Development is thus underway toward practical use of those in actual work.

9 Conclusion and Outlook for the Future

Development is underway for practical use so as to build a system that can verify time until queue is relieved and congestion on station platforms when installing equipment there or changing wiring. In development up to this point, we have confirmed improvement in reproducibility of simulations using error automatic compensation by comparing with actual phenomena measurement data, reaching a level where use in actual work is possible. In the future, we will continue with development for practical use to build a system based on actual work, while increasing examples of application, so as to meet a variety of needs when planning equipment.

Fig. 17 Location of Temporary Enclosure at Station C

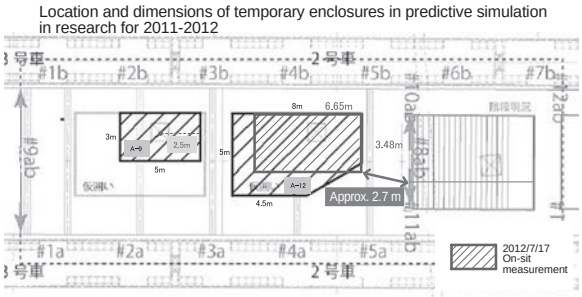

Fig. 18 Study of Proposal for Setup of Temporary Enclosures at Station C

Fig. 19 Prediction of Proposal for Setup of Temporary Enclosures at Station C

Table 2 Comparison of Times to Relief of Queue

	Line No. 2, reproduction of current state	Line No. 2, prediction improvement (temporary enclosure: A-12 only)	Line No. 2, prediction improvement (temporary enclosure: A-9 and A-12)
a. Time to relief of queue	1 min. 54 sec. from opening of door	1 min. 48 sec. from opening of door	1 min. 45 sec. from opening of door
b. Incidence of congestion level (60 sec. from opening of door)	16.6%	16.7%	20.0%
c. Incidence of congestion level (120 sec. from opening of door)	6.0%	10.6%	13.5%

*Incidence of congestion level is total value at 2.0 people/m^2 or greater.

Reference:

1) Hideki Ozumi, Kiyoshi Sakamoto, "Survey Research on Flow of Passengers on Platforms Using Laser Technology," *JR EAST Technical Review*, No.18 (2010)

2) Shiro Kase, Kiyoshi Sakamoto, "Homujo ni okeru saigennsei no takai ryokyaku ryudo simulation no kaihatsu [in Japanese]," *Railway Architecture* (March 2012): 27 - 29

3) Shiro Kase, Kiyoshi Sakamoto, Takeshi Yamada, Jinya Nakamura, Kazuaki Ohnishi, Junji Innami, Kazuo Ishima, "A Study about the accurate simulation for the passenger flow on the railway station, Part 4-Part 6," *Architectural Institute of Japan Technical Lecture Digest E-1, Architectural Planning I* (2012)