

AI-based Optimization of Bike Relocation in Docomo Bike Share Service

X-Tech Development Department Shin Ishiguro Tomohiro Mimura

Satoshi Kawasaki

Service Innovation Department Yusuke Fukazawa^{†1}

Smart-life Planning Department Atsuko Murozumi^{†2}

The expanded use of bike-sharing services in recent years is not without its problems as reflected in particular by overflows or shortages of bikes at exclusive bike stations. In response to these issues, NTT DOCOMO has developed a bike-relocation optimization system for the pickup/drop-off trucks of the Docomo Bike Share service. This system predicts demand for bikes, optimizes the bike-relocation plan based on future predictions, and recommends relocation work to pickup/drop-off trucks. Using this system to relocate bikes is expected to alleviate overflows and shortages of bikes at each bike station and to maintain an easy-to-use bike-sharing environment for users.

1. Introduction

Bicycles are becoming increasingly popular in urban transportation or sightseeing as an easy means of traveling short distances from a train station to one's destination or between multiple destinations. In addition, the demand for bicycles has grown all

the more since the beginning of the COVID-19 pandemic as they are a type of individual transportation that makes it easy to avoid the “Three Cs” (closed spaces, crowded places, and close-contact settings). For individuals, however, owning a bicycle for use in an urban environment is generally difficult due to the need for periodic contracts to reserve

©2021 NTT DOCOMO, INC.

Copies of articles may be reproduced only for personal, noncommercial use, provided that the name NTT DOCOMO Technical Journal, the name(s) of the author(s), the title and date of the article appear in the copies.

All company names or names of products, software, and services appearing in this journal are trademarks or registered trademarks of their respective owners.

^{†1} Currently General Affairs Department

^{†2} Currently Human Resources Management Department

space in a bicycle parking lot, the need to carry one's bike onto a train if traveling between cities, etc. Against this background, bike sharing has been attracting attention and its use has been increasing.

DOCOMO BIKE SHARE, INC. has been rolling out its bike-sharing business called Docomo Bike Share with the support of NTT DOCOMO. In this service, exclusive bike stations are set up at various locations in the city so that users can select bike stations of their choice to rent and return bikes. This service allows rented bikes to be returned to any bike station, i.e., a user need not return to the bike station where the bike was rented, which makes this service highly convenient for traveling short distances. The use of Docomo Bike Share continues to grow. Annual number of rentals increased



Photo 1 Motor-assist bike in Docomo Bike Share service

dramatically from about 40,000 in FY2011 to about 10,000,000 in FY2019. In light of this demand, DOCOMO BIKE SHARE, INC. has come to provide about 830 bike stations and 8,300 bikes in Tokyo as of 2019.

The Docomo Bike Share service features motor-assist bicycles (**Photo 1** [1]), which means an easy-to-use service even with the many hills that make up Japan's urban landscape. In addition, since bike maintenance and battery charging are also part of the service, users can enjoy the use of bikes that are always well maintained.

Bike sharing as typified by the Docomo Bike Share service is designed so that a user can travel freely from a certain bike station to another bike station, which means that a bike lent out to a user may be returned to a bike station different from the bike station where it was rented. As a result, the allocation of bikes may become locally unbalanced depending on bike usage. This, in turn, means that certain bike stations may be short of bikes preventing users from renting bikes or may be overflowing with bikes preventing users from returning their bikes (**Photo 2**). How to go about alleviating



(a) Bike shortage



(b) Bike overflow

Photo 2 Unbalanced conditions in bike allocation

this imbalance in bike allocation has become a common problem in the operation of bike-sharing services. In particular, the Docomo Bike Share service allows for bike parking other than on a rack at a bike station, so there are cases in which many bikes are returned and parked outside the bike-station area causing an overflow of bikes that can be highly inconvenient to property owners and pedestrians (Photo 2 (b)).

To alleviate this imbalance and allocate an appropriate number of bikes, the Docomo Bike Share service performs bike relocation using pickup/drop-off trucks. This relocation process eliminates an imbalance in bike numbers by loading bikes from bike stations with an overflow of bikes and carrying them to bike stations with a shortage of bikes. Bike-share use, however, continues to increase, so there is a need to deal with this imbalance in bike allocation by efficiently operating a limited number of pickup/drop-off trucks.

To meet this need, NTT DOCOMO developed a relocation optimization system that collects data on bike-share usage and local population statistics in real time and predicts the demand for renting

and returning bikes at each bike station (**Figure 1**). In this way, the system can select which bike stations should be targeted for relocation work to alleviate future overflows or shortages and advise pickup/drop-off truck drivers the order in which those bike stations should be visited and the number of bikes that should be picked up and relocated. In this article, we describe our work in optimizing the bike relocation process in the Docomo Bike Share service.

2. Design of Docomo Bike Share Service and Rebalancing Problem

Each bike station provided by Docomo Bike Share includes racks for docking bikes, but a rack itself is not equipped with a rental/return function but rather with a beacon for detecting bike location in the immediate vicinity. Specifically, short-range communication between the beacon and bike makes it possible to determine the state of bike return near the bike station. In this way, the service has been designed to enable bike status to be detected by a beacon so that the number of racks

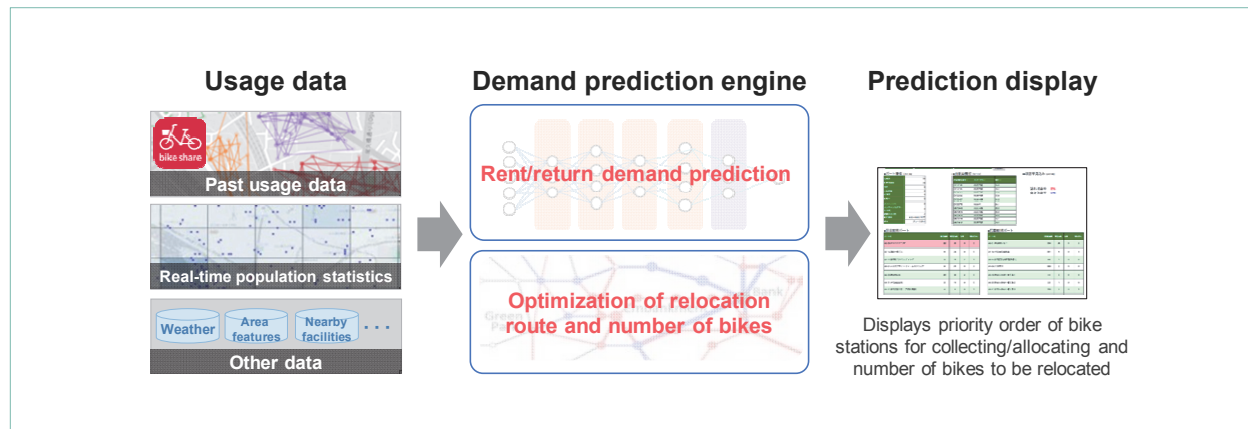


Figure 1 Overview of relocation optimization system

does not restrict the maximum number of bikes located at a bike station. In other words, the design is such that the number of bikes exceeding the number of racks cannot be physically limited. This design makes effective use of the space occupied by the bike station and enables many bikes to be parked, but if a large number of bikes happen to be returned, it can also result in a situation in which bikes overflow the parking area.

To evaluate bike overflow conditions at a bike station in the Docomo Bike Share service, the number of bikes that constitute an overflow limit is determined at each bike station on the basis of a threshold value that depends on the time period. This value serves as an indicator of an overflow situation.

In addition, if it is predicted that demand will exceed the number of available bikes at a bike station, opportunities for using the service may be lost. To evaluate such lost opportunities, the number of bikes that constitute a shortage limit is determined at each bike station for use as an indicator of a shortage situation. At most typical bike stations, the existence of demand for bike rentals in a state

in which no bike is available is considered to be a lost opportunity, so this bike shortage limit is set to zero.

Here, a number of bikes at a bike station that is under the bike overflow limit and above the bike shortage limit is defined as an appropriate number of allocated bikes.

Renting or returning bikes in excess of these limits results in a state of bike overflow or shortage at a bike station as shown by the diagram in **Figure 2**.

Up to now, pickup/drop-off truck drivers in the Docomo Bike Share service have been performing bike relocation by judging future demand on their own based on past usage and weather forecasts. However, in the case of bike demand that can change from hour to hour, a manually prepared work plan cannot necessarily achieve optimal relocation.

With this in mind, we developed a relocation optimization system for making relocation work more efficient based on demand prediction. The aim of this system is to alleviate extreme bike overflow or shortage at bike stations by predicting future

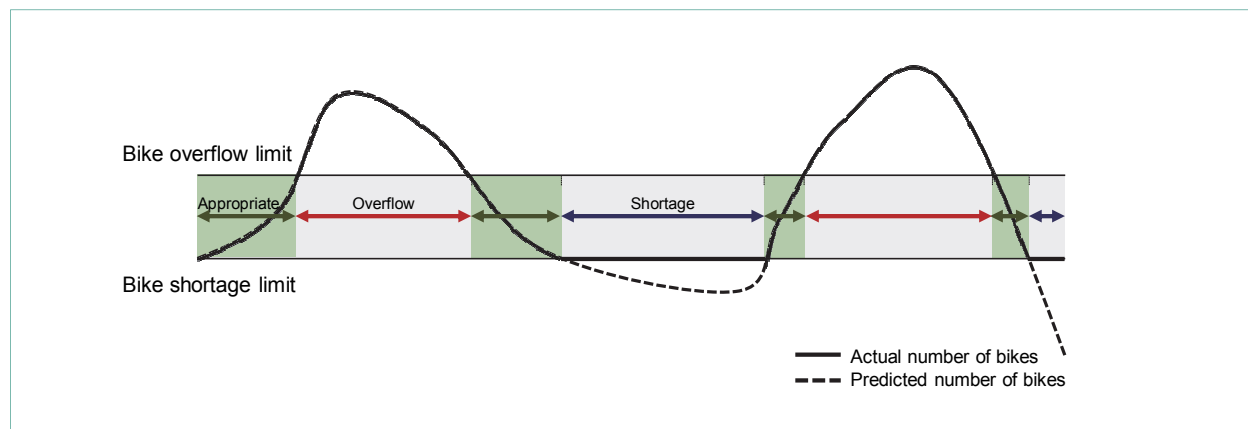


Figure 2 Diagram of bike overflow and shortage at bike station

overflow and shortage at each bike station, planning a procedure for allocating and collecting bikes so as to balance out the number of bikes at each bike station, and conveying that information to pickup/drop-off truck drivers as a basis for performing relocation work.

3. Overview of Relocation Optimization System

3.1 Demand Prediction Function

The renting and returning of bikes in a bike sharing service are affected by a variety of factors such as the number of people moving about, time of day, day of the week, weather, and the holding of events. We therefore created a model of demand prediction to reflect such ever-changing demand. For this model, we used, in particular, eXtreme Gradient

Boosting (XGBoost)^{*1} and an extension of a time-series deep learning technique^{*2} [2].

An overview of the demand prediction function is shown in **Figure 3**. This function predicts as objective variables the number of rented bikes and number of returned bikes that occur over a period of one hour for each of the next 24 hours. It creates hourly models equivalent to a period of 24 hours for both rentals and returns resulting in a total of 48 models and calculates the number of rented bikes and number of returned bikes for each time period as prediction results. Consequently, by determining the difference between the number of rented bikes and the number of returned bikes in each hour, it becomes possible to calculate the amount of change in the number of available bikes at that time. This change in the number of available bikes can then be used to calculate the predicted values

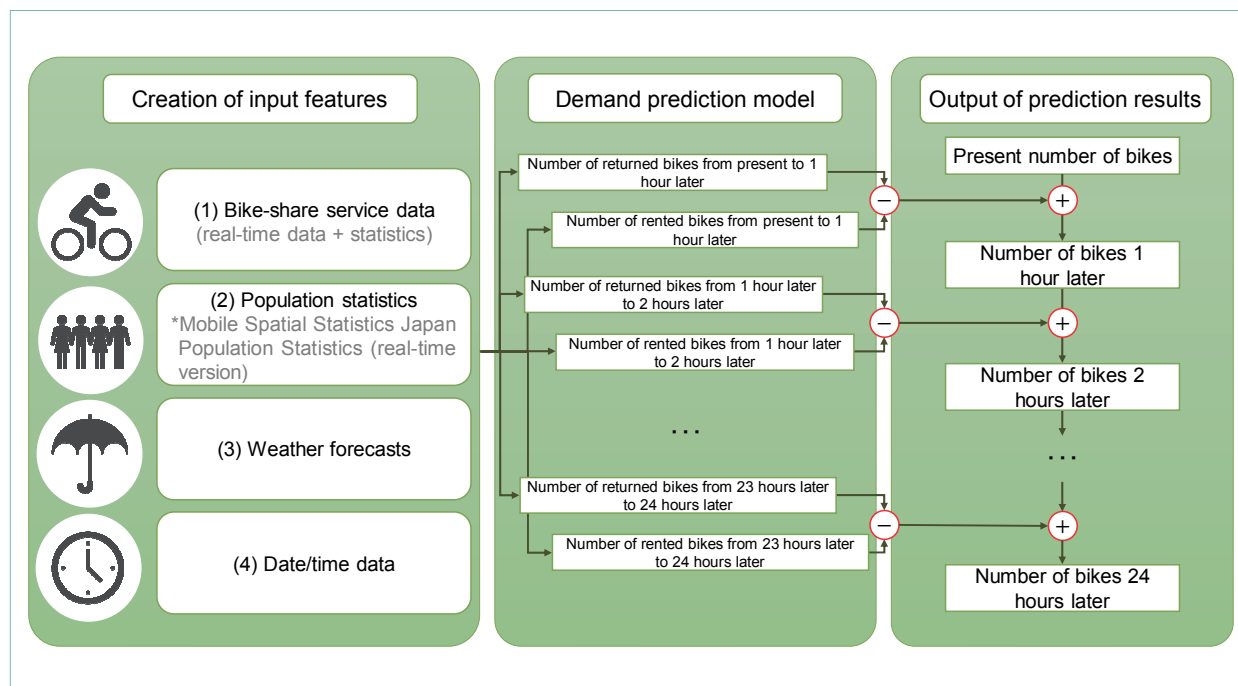


Figure 3 Overview of demand prediction function

^{*1} XGBoost: A machine learning technique that achieves high-accuracy regressive prediction by taking a majority vote based on a prediction model using different decision trees.

^{*2} Deep learning technique: A machine learning technique that achieves regressive prediction taking time-series changes into account through a recurrent neural network.

for the number of available bikes in each hour by determining the cumulative sum of available bikes taking the number at the present time as the initial value.

The input features used for learning are (1) bike-share service data, (2) population statistics, (3) weather forecasts, and (4) data/time data. Using these features in model learning should make it possible to mechanically determine any correlation between change in future demand and population, weather, and past bike-share usage and to achieve more accurate predictions of future demand.

- (1) Bike-share service data includes the number of rented bikes and number of returned bikes up to that hour at each bike station and the amount of change in those values. It also includes the average values for the number of rented bikes and number of returned bikes for the same day of the week and time period in the past as well as the average value of that change as statistical quantities.
- (2) Population statistics refers to the population within 500 m of each bike station and amount of change. We expect the use of real-time data here to enable change in human movement to be grasped particularly in predictions targeting the next one to two hours.
- (3) Weather forecasts consist of the latest weather data on rainfall, wind, temperature, humidity, and atmospheric pressure for the hour targeted for prediction.
- (4) Date/time data consists of the time, year, month, date, and day of the week for the hour targeted for prediction.

3.2 Relocation Planning Function

The relocation planning function shown in **Figure 4** is described in detail below.

1) Inference of Bike Overflow/shortage Based on Prediction Results

A future prediction value of the number of available bikes can be obtained by the demand prediction function described above. The number of available bikes for each hour as determined by this function is the cumulative sum of the change in the number of available bikes, and as shown in Fig. 2, the prediction value may take on a negative value. Now, if the prediction value of the number of bikes for each hour at each bike station should rise above the bike overflow limit established for each bike station, it could be inferred that the bike station is overflowing by the number of bikes exceeding that limit. Conversely, if the prediction value should drop below the bike shortage limit, it could be inferred that the bike station is short by the number of bikes exceeding that limit.

2) Recommended Work Based on Evaluation Values

The next step is to formulate a work plan for collecting and allocating bikes for these amounts of overflow and shortage and to then dispatch pickup/drop-off trucks to do this work. At this time, the picking up of excess bikes for relocation and the dropping off of bikes at a bike station having a shortage of bikes constitute a sequence of tasks, so bike collecting and bike allocating are an inseparable pair of tasks. Additionally, since the truck moves during the relocation process, the distance from the truck's present location to the bike station targeted for collecting bikes and the distance from that bike station to the bike station targeted for allocating bikes can be calculated. Taking

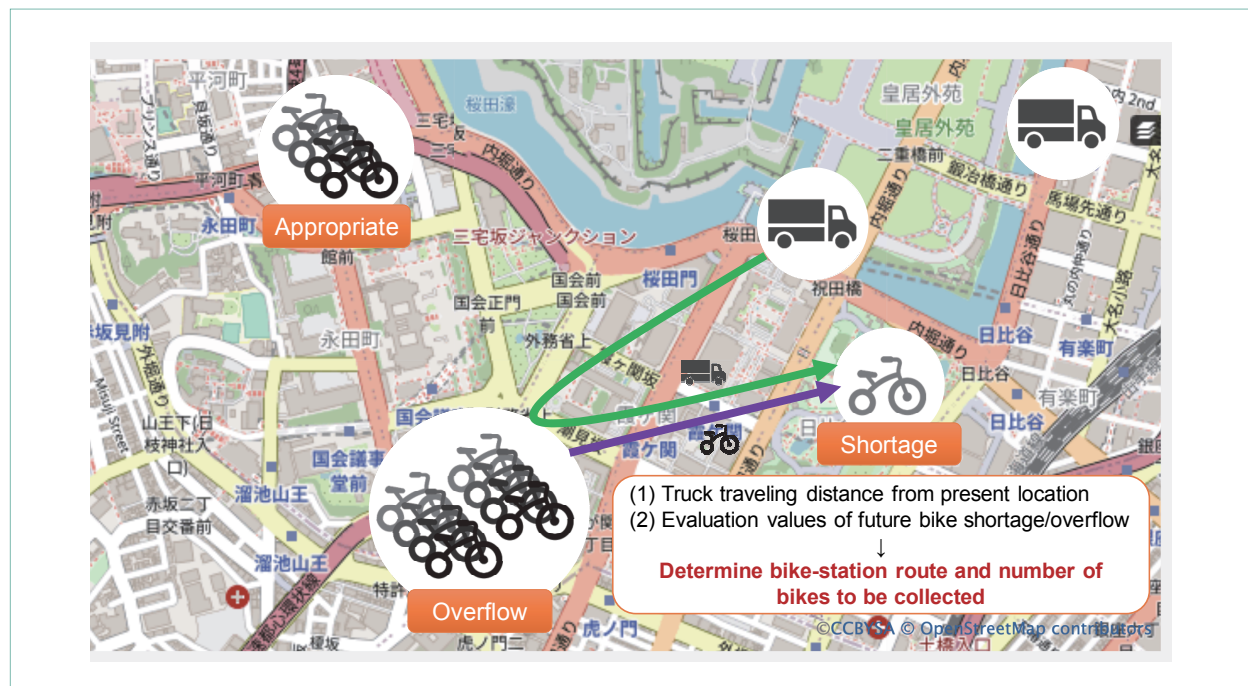


Figure 4 Overview of relocation planning function

these distances into account, an overflow evaluation value and a shortage evaluation value can be calculated for each bike station. The overflow evaluation value takes on a larger value as the number of excess bikes becomes larger and the distance becomes shorter. In such a case, the bike station would be evaluated as having high collection priority. The shortage evaluation value, in turn, takes on a larger value as the number of deficient bikes becomes larger and the distance becomes shorter. In this case, the bike station would be evaluated as having high allocation priority. Each of these evaluation values can change from hour to hour due to the time taken up by relocation work and truck movement and to fluctuation in the supply and demand for bicycles. These evaluation values can therefore be recalculated based on a request received from the truck on completing its work.

At this time, the bike station receiving the highest evaluation value is given priority and the next order of tasks is determined.

3) Determining the Number of Bikes to be Collected/allocated Based on Evaluation Values

The number of bikes to be collected or allocated at a bike station selected on the basis of the corresponding evaluation value is as follows. In collection work, as many bikes as needed to bring the number of available bikes below the bike overflow limit will be picked up, and in relocation work, as many bikes as needed to bring the number of available bikes above the bike shortage limit will be allocated.

Moreover, due to the work of collecting and allocating bikes, the number of bikes currently loaded on the truck changes. For this reason, the following values are used as upper limits to the number

of bikes to be collected and the number of bikes to be allocated.

Bikes to be collected = min (number of excess bikes, max. number of loadable bikes – current number of loaded bikes)

Bikes to be allocated = min (number of deficient bikes, current number of loaded bikes)

4) Determining a Bike Relocation Plan

This step determines work priority for each time period based on the evaluation values calculated for each bike station and the number of bikes required for collection and allocation. It extracts the bike-station pair having the highest evaluation values for collection and allocation work and creates a plan for collecting and allocating bikes between those bike stations with the maximum number of bikes that can presently be loaded on the truck. Moreover, in the case that the number of bikes to be collected and the number of bikes to be allocated differ (that is, either the number of bikes to be collected or the number of bikes to be allocated is smaller), collection and allocation work will continue for two more bike stations to maintain a balance between the number of bikes collected and allocated. When relocating bikes using multiple pickup/drop-off trucks, the possibility arises that the same bike station will be selected as a target for bike relocation in the same time period. To avoid this situation, a relocation plan for multiple trucks will be created when one truck is already working by selecting other bike-station pairs for other trucks.

4. Trial

We conducted a trial to assess the effectiveness of the demand-prediction and relocation-planning

system described above. For this trial, we created a web application that presents the number of bikes to collect and relocate from one bike station to another in each time period via a tablet-type user interface and promoted its use by pickup/drop-off truck drivers. The target districts selected for the trial were Koto city, Minato city, Chuo city, Shinjuku city, and Shinagawa city in the Tokyo area. The trial was conducted in each of these wards for the periods listed in **Table 1**. Each of the pickup/drop-off trucks used in the experiment could load up to 30 bikes. Considering that the relocation of bikes throughout the Tokyo area could be quite complex, we decided to use a different number of trucks in each ward and performed relocation planning within each ward for that number of trucks. The number of trucks used in each ward is listed in **Table 2**. For learning data, we used bike-share service data, Mobile Spatial Statistics Japan Population Statistics (real-time version)^{*3}, and Meso-Scale Model (MSM)^{*4} Grid Point Value (GPV) data of the Japan

Table 1 Trial period in each ward

Ward	Period
Koto, Minato	2019/11/1~15
Chuo, Shinjuku, Shinagawa	2019/11/1~20 2019/12/3~6

Table 2 Number of trucks used in each ward

Ward	Number of Trucks
Koto	3
Minato	2
Chuo	1
Shinjuku	1
Shinagawa	1

^{*3} Mobile Spatial Statistics® Japan Population Distribution Statistics (real-time version): Data obtained by calculating population distribution throughout Japan at 500 m and 10 minute intervals for up to 1 hour to 30 minutes before through statistical analysis using mobile data. Mobile Spatial Statistics is a registered trademark of NTT DOCOMO, Inc.

^{*4} MSM: A weather forecasting model introduced by the Japan Meteorological Agency (JMA) that makes predictions once every 3 hours, 39 hours into the future.

Meteorological Business Support Center and set the learning period from October 2017 to March 2019. Details on these data are given in **Table 3**.

For relocation by the proposed system, **Figure 5** shows the results of comparing evaluation values for the number of deficient bikes (shortage) and number of excess bikes (overflow) in periods before and after the trial. Before the trial, relocation was performed based on the judgment of the pickup/drop-off truck drivers, and in the period after the trial, it was performed based on the instructions received from this system. It was found that applying this system could improve shortage and overflow conditions in all of the five Tokyo wards targeted by this trial. It could also be seen that percentage improvements in shortage and overflow conditions differed from one ward to another.

In Shinjuku city, the improvement effect with respect to the number of excess bikes was only 0.4%. In this regard, work based on pickup/drop-off

trucks is often efficient if more bikes than usual can be moved in one relocation operation. Shinjuku city, however, features many small-scale bike stations each of which allocate only a small number of bikes, so achieving an improvement in overflow requires the patrolling of many bike stations in the relocation process. We consider that this is why the efficiency-improvement effect by this system turned out to be small for relocation by pickup/drop-off trucks in this ward.

Other wards, however, include large-scale bike stations that can allocate many bikes. This made it possible to perform bike relocation making good use of the features of pickup/drop-off trucks and to achieve improvement effects in overflow and shortage conditions.

We next describe an experiment related to prediction accuracy at the time of an event. In bike sharing, most usage is periodic in nature corresponding to the days of the week in which people

Table 3 Details of input features

Name of Data	Details
Bike-share service data	Approx. 5,900 bikes
	Bike stations: Approx. 580
	Approx. 7,300,000 bike rentals
	Each of these figures represent total amounts for all Tokyo areas as of March 2019
Population statistics *Mobile Spatial Statistics Japan Population Statistics (real-time version)	Mobile phones Approx. 78,450,000 (excluding corporate and MVNO phones)
	Total number of phones for all of Japan as of March 2019. Uses statistics tabulated in mesh form
	500 m mesh, once every 10 min
Weather forecasts *Meso-Scale Model (MSM) GPV	Rainfall, temperature, humidity, wind, wind direction, atmospheric pressure, and cloudiness
	Issues forecasts once every 3 hours, 39 hours into the future
	1,000 m mesh

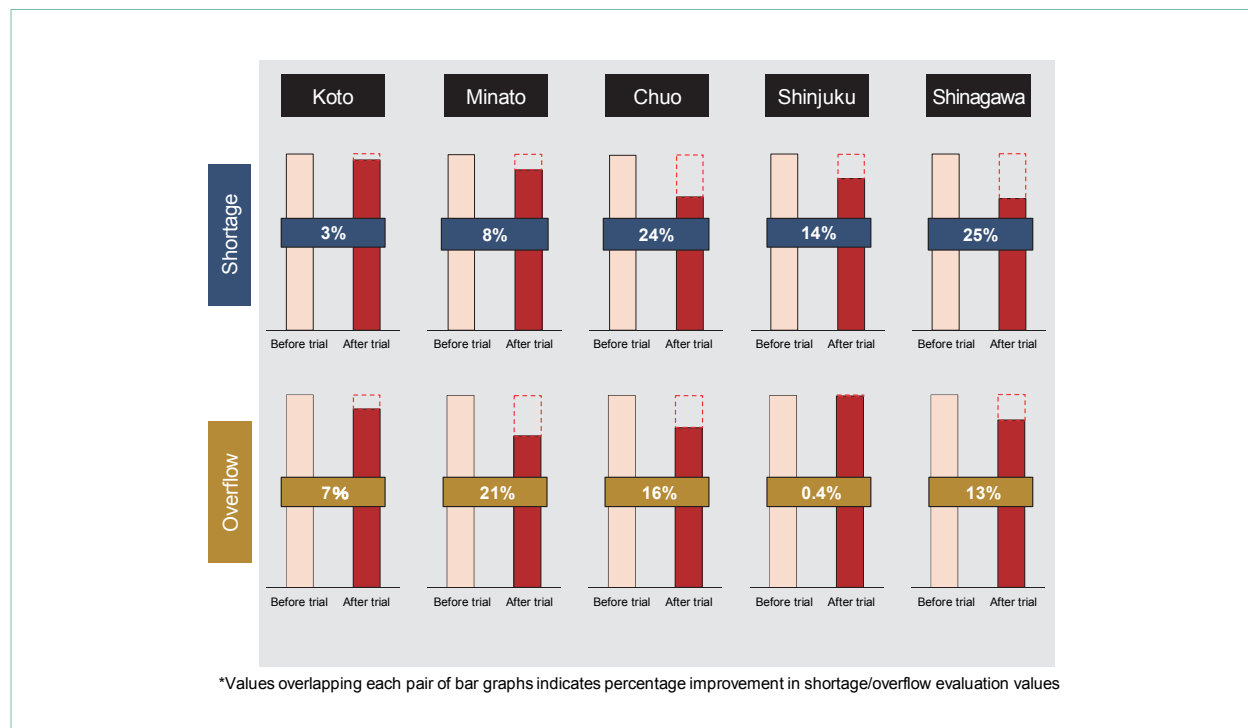


Figure 5 Comparing improvement effect in shortage and overflow of bikes before and after trial

commute by train, time of day, etc. This type of demand can be predicted with sufficient accuracy by statistically analyzing bike-share service data. On the other hand, the occurrence of special demand due to a major event cannot be explained simply by analyzing the periodicity of bike-share usage and is consequently difficult to predict. For this reason, adding population statistics to input data enables the system to obtain changes in the neighboring population and to predict change in usage demand at the time of an event. The results of predicting change in bike usage at a bike station in the neighborhood of a certain event venue are shown in **Figure 6**. These results show that using population statistics could improve the accuracy of predictions in relation to times of peak demand for some bike stations. They also show

that real-time population statistics can serve to explain changes in demand due to an increase/decrease in the neighboring population at places such as event venues where amount and time of people movement can easily change depending on the day. We therefore consider that real-time population statistics can help improve prediction accuracy.

5. Conclusion

This article described our efforts in optimizing the relocation of bikes for improving operation of the Docomo Bike Share service. We developed, in particular, a system that combines a demand prediction function and a relocation planning function to predict imbalance in future demand and supply and to propose bike relocation according to current

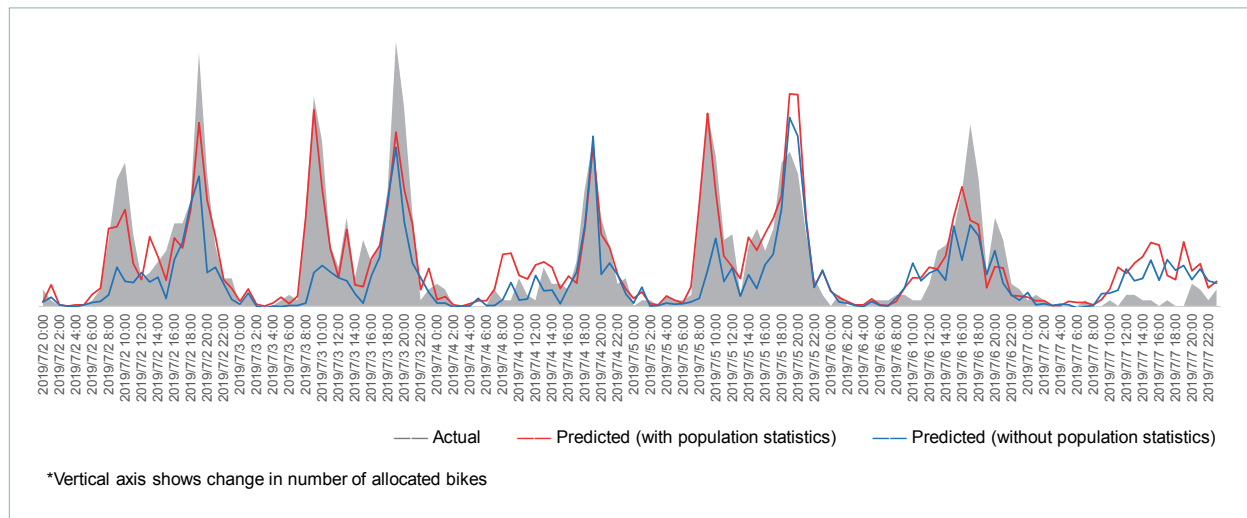


Figure 6 Example of bike station with improved prediction (July 2 – July 7, 2019)

conditions. We showed that relocating bikes with this system reduced the number of bike stations in an overflow or shortage state and made the work of relocation more efficient in five districts within the Tokyo area. We also found that the use of population statistics makes it possible to estimate fluctuations in demand and improve the accuracy of predictions at locations such as event venues where making predictions solely on the basis of past bike share usage is difficult. Going forward, we plan to study the use of this bike relocation optimization system throughout Japan and

the optimization of other means of transportation by applying the know-how obtained in the development of this system.

REFERENCES

- [1] NTT DOCOMO Bike Share Service.
<https://docomo-cycle.jp/?lang=en>
- [2] T. Mimura, S. Ishiguro, S. Kawasaki and Y. Fukazawa: "Bike-share demand prediction using attention based sequence to sequence and conditional variational autoencoder," In Proc. of the 3rd ACM SIGSPATIAL International Workshop on Prediction of Human Mobility, pp.41–44, Nov. 2019.