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Demand Forecast for Bento by Machine Learning Using Product Popularity Based on Rating Systems

Kazuki Ota, and Hideki Katagiri

***Abstract*— “Bento” is widely known as a part of Japanese food culture. There are many companies in Japan that manufacture thousands of bento every day. The market for the food delivery industry is expanding in Japan. This study focuses on the catered bento industry, which delivers and manufactures bento. A method for estimating the popularity of a product is developed based on data on bento sales volume. The study proposes a demand forecasting model that takes into account the estimated popularity. To demonstrate the usefulness of the proposed prediction model, numerical experiments are conducted using real data provided by a company that delivers and manufactures bento. Numerical experiments show that the proposed model is superior to the conventional model.**

***Index Terms*—demand forecast, machine learning, MCMC sampling, rating system, time-series data.**

I. Introduction

In recent years, Japanese food culture has attracted worldwide attention. “Bento” is a part of Japanese food culture. There are many companies in Japan that manufacture and deliver bento to customers every day. In addition, the market for the food delivery industry is expanding in Japan. Food loss from the food services and food delivery industries has become a social problem. In this study, we focus on catered bento delivered to customers. Many of the companies in the bento catering business offer several types of bento, including daily bento, rice bowl bento, noodle bento, and so on.

In the Japanese bento manufacturers and sales companies, veteran workers forecast demand in order to reduce food loss. However, food loss occurs due to the difficulty of forecasting. Forecasting is dependent on individual skills. It takes time for an employee just starting out in the forecasting work to be able to forecast with the same accuracy as a veteran in the forecasting work.

It is required that demand forecasting models with high forecasting accuracy. The reason is that it influences the decision the number of materials to order and on the number of products to manufacture. When the sales volume is overestimated, food losses occur due to overproduction or over-ordering. If the sales volume is estimated to be low, additional production is required. Additional production puts a strain on the production line. Therefore, it is necessary to predict the bento sales volume with high accuracy.

There are several studies about demand forecasting [1], [2], [3], [4]. Conventional studies on demand forecasting for bento [1] have proposed state-space models that take into account temperature and product popularity. Other studies on demand forecasting have proposed methods using statistical models [2], deep learning [3], and machine learning [4].

The objective of this study is to develop a forecasting model that is more accurate than the conventional model [1]. There are two proposals in this study. The first is to propose a Markov Chain Monte Carlo (MCMC) method for estimating the popularity of a product. Second, we propose a model for predicting the bento sales volume that takes into account the estimated popularity. We conduct numerical experiments using real data provided by a company that delivers and manufactures bento. In order to verify the usefulness of the proposed model, we compare the prediction accuracy of the proposed model with that of the conventional model [1]. We also compare the predictions of the proposed model with those of veteran workers who have been in charge of demand forecast.

II. Catering bento and demand forecasting

Forecasting the demand for catering bento is difficult because demand fluctuates rapidly. Catering bento are manufactured and delivered every day. Therefore, sales data for catered bento are time-series data. Fig. 1 shows the time-series change in the sales volume of a particular bento. Factors that cause demand fluctuations are temperature, product popularity, customer schedules, and so on. These factors are changing on a daily basis. Therefore, it is difficult to make accurate predictions.

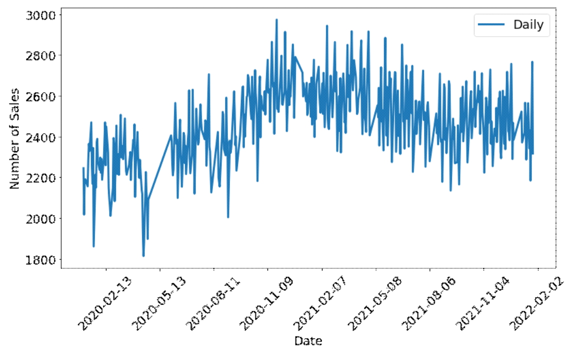

Fig. 1. Time variation in sales volume of bento

One factor that makes it difficult to forecast demand is the popularity of the product. The contents of some catered bento change daily. When the contents of the bento are popular, the sales volume of that bento is large. On the other hand, when the contents of the bento are unpopular, the sales volume is small. It is necessary to consider the popularity of products, in order to make accurate forecasts. However, it is difficult to account for the influence of popularity.

Companies that manufacture and deliver catered bento need a demand forecasting model that takes into account the

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popularity of products. In catered bento companies, veteran workers forecast demand by taking into account factors such as product popularity, temperature, and so on. For those just starting out in the forecasting work, it is difficult to make forecasts that take into account product popularity.

III. Related Study

Conventional research in our study can be divided into two fields. One is a group of studies in the field of demand forecasting. The other is a group of studies in the field of rating and ranking systems that inspired the construction of a popularity estimation model.

In the field of demand forecasting, there are studies using deep learning and statistical models [1], [2], [3], [4]. Demand forecasting is required to be highly accurate because it influences the ordering of ingredients and manufacturing volume.

Inspired by studies of rating and ranking systems [5], [6], [7], [8], we build a model to estimate the popularity of products. As far as we can see, there are no studies that estimate popularity. Since popularity is a major factor in demand fluctuation, it is necessary to consider popularity.

The studies on general demand forecasting are explained in Section III-A. The study of demand forecasting for bento is described in Section III-B. Research on rating and ranking system, which was used as a reference for proposing the popularity estimation model, is described in Section III-C.

A. Research on General Demand Forecasting

One of the popular forecasting methods is statistical modeling. Huber et al. [2] proposed a method using ARIMAX (Autoregressive Integrated Moving Average with Explanatory Variable) that focuses on the hierarchical organizational structure found in the retail industry. The relationship between the sales volume and demand factors is often nonlinear. Statistical models have limitations in representing nonlinear relationships.

Recently, attention has focused on methods that use machine learning and deep learning to view the forecasting problem as a regression problem. Punia et al. [4] developed a method using LSTM (Long Short Term Memory) which is a type of deep learning method. The prediction accuracy was shown to be better than that of general machine learning methods. Anipov et al. [3] proposed a human-interpretable method using gradient boosting which is one of the machine learning methods. As a result of comparative experiments with multiple machine learning methods, it was shown that the proposed method had the best accuracy.

Based on the results of previous studies, we construct a prediction model using gradient boosting. The reason for not employing a statistical model is that the bento sales volume and the demand variation factors are likely to have a nonlinear relationship. In addition, deep learning is not used because of the small amount of data available.

B. Research on Demand Forecasting for Bento

Kano et al. [1] proposed a demand forecasting model for catered bento using a state-space model that takes into account the popularity of products and temperature. Similar to their study, we build a demand forecasting model for catered bento. Their study assumed that there are two types of bento. The first type is a daily bento in which the dishes inside are changed every day. The second type is bento in which the same dish is served regularly (e.g., rice bowl bento, noodle bento).

We see two problems with their study. The first problem is the incorrect estimation of the popularity. New products are introduced irregularly in the catered bento market. Some products are offered infrequently in catered bento. Few data are available for new products and products that are offered infrequently. Therefore, it is necessary to be able to estimate popularity appropriately even with a small amount of data. The second problem is the lack of consideration for the popularity of several types of bento offered at the same time. In general, catered bento companies offer not only a daily bento but also several types of bento (e.g., rice bowl bento, noodle bento). The customer selects one bento from a daily bento and several types of bento. The number of each type of bento sold then depends on the popularity of each type of bento. Therefore, it is necessary to consider the popularity of each type of bento.

C. Research on Popularity Estimation Method to be Incorporated in This Study

There are several studies on ranking and rating systems. Peiris et al. [5] developed the Elo rating system using Bayesian methods. Their model is capable of computing sequential rankings. Guo et al. [6] extended TrueSkill to learn from wins, losses, and draws as well as score information. The new TrueSkill classified wins and losses with higher accuracy than the previous TureSkill. Motegi et al. [7] considered sports ranking systems from a network viewpoint. They proposed a model in which defeating a famous player in the peak performance is more valuable than defeating the same player in other periods. Glickman et al. [8] proposed a Bayesian space-state framework for a ranking logit model considering the player's ability to change with time. They made an estimation by MCMC sampling.

Inspired by these studies, we construct a model to estimate the product popularity of bento. We employ an estimation method based on MCMC sampling.

IV. Proposed Popularity Estimation Model

This section describes the proposed popularity estimation model. The calculation method of popularity estimation is developed by applying the techniques in the study field of rating and ranking systems. In addition, we create product groups to estimate the popularity of new products and products that are offered infrequently.

In Section IV-A, the concept of the popularity estimation is presented. The model for estimating popularity by MCMC sampling is described in Section IV-B.

A. Game Models for the Product of each Bento

We assume that the product popularity of bento is related to the percentage of the bento sales volume. The percentage of the bento sales volume is calculated by Eq. (1).

$$R_j = \frac{N_j}{\sum_{j \in J} N_j}, \tag{1}$$

where N_j is the sales volume of bento j. R_j represents the percentage of sales of bento j. $|J|$ is the number of types of bento offered. The denominator is the total bento sales volume that day.

The comparison of bento sales volume in percentage is regarded as a game. The product with the larger sales volume percentage is the winner of the game. The product with the smaller sales volume percentage is the loser of the game. Then, we assume that the winner's product is more popular than the loser's product. The use of sales percentage eliminates the effect of total sales volume. In our study, we believe that fluctuations in total sales have nothing to do with the popularity of bento.

The following is an example of a comparison of the two types over the following two days, $M1$ and $M2$. The first type is a comparison of sales volume. The second type is a comparison of sales volume percentages. Assume that the total sales volume on dates $M1$ and $M2$ are 4,000 and 3,500, respectively. The volume of bento sold on date $M1$ is 2,500, and the sales volume percentage is 62.5%. The volume of bento sold on date $M2$ is 2,300, and the sales volume percentage is 65.7%. Consider the first type of comparison, the comparison of sales volume ($M1$: 2,500, $M2$: 2,300). The winner is the bento on date $M1$ because the sales volume on date $M1$ is larger than that on date $M2$ when compared with 2,500 on date $M1$ and 2,300 on date $M2$. This result may have been influenced by the total sales volume. Then, consider the comparison of the percentage of sales ($M1$: 62.5%, $M2$: 65.7%). The winner is the bento on the date $M2$ because the sales volume percentage on date $M2$ is larger than that on date $M1$ when compared with 62.5% on date $M1$ and 65.7% on date $M2$.

Popularity estimation from the group of bento offered is done in order of sales volume. In our study, we assume that the order of sales volume is 1: Daily bento, 2: Rice bowl bento, and 3: Noodle bento, in that order. The popularity estimation is performed in the following order: 1: Daily bento, 2: Rice bowl bento, and 3: Noodle bento. For new products and products that are offered infrequently, it may not be possible to properly estimate the popularity of products. The reason why popularity cannot be properly estimated is that the comparison game has been conducted only a few times. Therefore, in our study, products are grouped according to their appearance and cooking methods. Popularity is estimated through playing a game based on past sales data.

The game model of the daily bento product is explained in Section IV-A1. The game model of the rice bowl/ noodle bento product is described in Section IV-A2.

1) Estimated Product Popularity of Daily Bento:

The popularity estimation of the daily bento is performed by a comparison game between the sales volume percentage of the daily bento on the t-th date and that on the $(t+m)$-th date. In order to eliminate the influence of the bento other than the daily bento, a comparison game is played with the daily bento products on these two dates. In general, catered bento companies offer the same products on a cyclical basis, with the exception of the daily bento.

Table I is used to explain why the comparison game is played on the t-th date and the $(t+m)$-th date. Table I shows the percentage of sales and the products offered for the daily bento. Table I also includes rice bowl and noodle bento products. In Table I, three bento (daily bento, rice bowl bento, and noodle bento) are offered on the same day for each of them. Assume that a comparison game is played on a product on the tth date and the $(t+m)$th date. The percentage of daily bento sales on the t-th date is 65.0%, and that on the $(t+m)$-th date is 62.0%. The winner is the Daily A offered on the t-th date because the sales volume percentage 65.7% of daily bento on the t-th date is larger than 62.5% that on the $(t+m)$-th date. The fact that the winner is Daily A makes us consider Daily A to be more popular than Daily G. The reason why we consider the Daily A to be more popular is that the comparison is conducted between the same date for the rice bowl and noodle bento products (Bowl B, Noodle C). Suppose the game is played on a random two-day products (the t-th date and the $(t+1)$-th date). The percentage of daily bento sales on the t-th date is 65.0%, and that on the $(t+1)$-th date is 60.0%. The winner is the Daily A offered on the t-th date. In this case, however, the fact that the winner is Daily A does not make us consider Daily A to be more popular than Daily D. The reason why we do not consider Daily A to be more popular is that we are comparing daily bento on dates when the rice bowl and noodle bento products are different (the t-th date: Bowl B, Noodle C; the $(t+1)$-th date: Bowl E, Noodle F).

TABLE I
EXAMPLE OF A DAILY BENTO PRODUCT GAME

Sales Date	Percentage of daily bento served[%]	Daily bento	Rice bowl bento	Noodel bento
t	65.0	Daily A	Bowl B	Noodel C
$t+1$	60.0	Daily D	Bowl E	Noodel F
⋮	⋮	⋮	⋮	⋮
$t+m$	62.0	Daily G	Bowl B	Noodel C

The percentage of daily bento used to estimate the popularity is calculated by Eq. (2).

$$DR = \frac{DN}{DN + BN + NN}, \tag{2}$$

where DR is the ratio of the daily bento sales volume, DN is the daily bento sales volume, BN is the rice bowl bento sales volume, and NN is the noodle bento sales volume.

2) Estimated Product Popularity of Rice Bowl and Noodle Bento:

The following two conditions must be satisfied on the dates when the comparison game is played for the bowl and noodle bento (e.g., the t-th date and the $(t+i_1)$-th date, the t-th date and the $(t+i_2)$-th date, etc.). The first condition is that each date of comparison of the percentage of product sales must be within $|I|$ days of each other. The second condition is that the comparison game is played with products within a certain range of product popularity $|v|$ for each daily bento. In addition, the estimation of the product popularity of the rice bowl and noodle bento is done after the estimation of the product popularity of the daily bento.

Table II is used to explain why the comparison game is played on the t-th date and the $(t+i_1)$-th date. Table II shows the products and the percentage of sales of rice bowl bento. Table II also shows the daily bento products and the popularity of the daily bento. Assume that a comparison game is played on the t-th dated product and the $(t+i_1)$-th dated product. In this case, all the bento products offered

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on the t-th date and the $(t+i_1)$-th date are different. The percentages of the sales volume of the rice bowl bento on t-th date and on $(t+i_1)$-th date are 21.0% and 27.0%, respectively. The winner is Bowl J on the $(t+i_1)$-th date because the sales volume percentage 27.0% of bowl bento on the $(t+i_1)$-th date is larger than 21.0% on the t-th date. The fact that the winner is Bowl J makes us consider Bowl B to be more popular than Bowl J.

TABLE II
EXAMPLE OF A GAME OF RICE BOWL BENTO PRODUCT

Sales Date	Percentage of Rice bowl bento served[%]	Popularity of daily bento	Daily bento	Rice bowl bento
t	21.0	0.2	Daily A	Bowl B
$t+1$	57.0	-0.5	Daily D	Bowl E
⋮	⋮	⋮	⋮	⋮
$t+i_1$	27.0	0.1	Daily I	Bowl J

In order to remove the influence of the noodle bento, the ratio of the number of bowl bento used for estimation is calculated by Eq. (3).

$$BR = \frac{BN}{DN+BN}, \tag{3}$$

where BR is the ratio of the rice bowl bento sales volume. The product popularity of noodle bento is also considered and estimated in the same way as for rice bowl bento.

B. MCMC sampling to Estimate Product Popularity

In our study, the popularity of each bento product is considered a random variable. The distribution of the popularity of each bento product is approximated by MCMC sampling. The model equations for MCMC sampling used in this study are defined below.

$$P[t,1] \sim \mathcal{N}(\mu[W[t]], \sigma[W[t]]^2), \quad t \in T, \tag{4}$$
$$P[t,2] \sim \mathcal{N}(\mu[L[t]], \sigma[L[t]]^2), \quad t \in T, \tag{5}$$
$$P[t,1] > P[t,2], \quad t \in T, \tag{6}$$
$$\mu[n] \sim \mathcal{N}(0, \sigma_\mu^2), \quad n \in N, \tag{7}$$
$$\sigma[n] \sim Gamma(\alpha, \beta), \quad n \in N, \tag{8}$$

where N is the set of products, and T is the set of sales dates. $P[t,1]$ and $P[t,2]$ in Eq. (4) and Eq. (5) represent the performance of the winner and loser in the game on sales day t, respectively. $P[t,1]$ and $P[t,2]$ are assumed to follow a normal distribution. $\mathcal{N}(a, b^2)$ denotes the normal distribution with mean a and variance b^2. $\mu[n]$ and $\sigma[n]$ denote the mean and variance of the popularity of product n, respectively. The larger the value of $\mu[n]$, the more popular the product n is. $W[t]$ and $L[t]$ are the indices of the winners and losers, respectively. Eq. (6) means that the performance of the winners is greater than that of the losers. Eq. (7) represents that the popularity of product n follows a normal distribution with mean 0 and variance σ_μ^2. Eq. (8) indicates that the variation in the popularity of product n follows a gamma distribution with α and β as parameters.

V. SALES VOLUME FORECASTING MODEL PROPOSAL AND EVALUATION INDEX

We propose a sales volume forecasting model with gradient boosting that takes into account the product popularity of each bento. The mean μ of the product popularity of each bento estimated in Section IV-B is used as the features. We use four types of features to forecast sales volume. The first type of feature is the predicted total sales volume of the products offered on the forecast date. The second one is the product popularity of each bento offered on the forecast date. The third one is the past sales volume of each bento. The fourth one is the past product popularity of each bento. For past sales volume and product popularity, values from 2, 4, and 6 weeks ago are used.

Two types of evaluation indices are developed to validate the usefulness of the proposed model. The first type is the mean forecast error (ME^+), and the standard deviation of the error (SD^+) when the forecast value is predicted above the actual value. The second type is the mean forecast error (ME^-), and the standard deviation of the error (SD^-) when the forecast value is predicted below the actual value. The ME^+, SD^+, ME^-, and SD^- are calculated by Eqs. (9), (10), (11), and (12), respectively.

$$ME^+ = \frac{1}{T}\sum_{t=1}^{T} d_t^+, \quad t \in T, \tag{9}$$

$$SD^+ = \sqrt{\frac{1}{T}\sum_{t=1}^{T} (s_t^+)^2}, \quad t \in T, \tag{10}$$

$$ME^- = \frac{1}{T}\sum_{t=1}^{T} d_t^-, \quad t \in T, \tag{11}$$

$$SD^- = \sqrt{\frac{1}{T}\sum_{t=1}^{T} (s_t^-)^2}, \quad t \in T, \tag{12}$$

where d_t^+, s_t^+, d_t^-, and s_t^- are computed by Eqs. (13), (14), (15), and (16), respectively.

$$d_t^+ = \begin{cases} 0 & (f_t - y_t \leq 0) \\ f_t - y_t & (f_t - y_t > 0) \end{cases}, \quad t \in T, \tag{13}$$

$$s_t^+ = \begin{cases} 0 & (f_t - y_t \leq 0) \\ f_t - \bar{f} & (f_t - y_t > 0) \end{cases}, \quad t \in T, \tag{14}$$

$$d_t^- = \begin{cases} f_t - y_t & (f_t - y_t < 0) \\ 0 & (f_t - y_t \geq 0) \end{cases}, \quad t \in T, \tag{15}$$

$$s_t^- = \begin{cases} f_t - \bar{f} & (f_t - y_t < 0) \\ 0 & (f_t - y_t \geq 0) \end{cases} \quad t \in T, \tag{16}$$

where the number of data is T, the predicted value is f_t, the mean of the predicted value is $\bar{f}$, and the observed value is y_t. Then, the $f_t - y_t$ represent the prediction error and $f_t - \bar{f}$ represent the deviation.

Eqs. (13) and (14) are set to 0 when the prediction error is less than 0 in order to consider the case where the predicted value is larger than the actual measured value. Eqs. (15) and (16) are set to 0 when the prediction error is greater than 0 in order to consider the case where the predicted value is smaller than the measured value.

ME^+ represents the mean of the amount of food loss, and SD^+ represents the variation in the amount of food loss. In the catering bento industry, which is sensitive to food loss, ME^+ needs to be smaller. ME^- represents the average shortfall, and SD^- represents the variation of the

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shortage. Catering bento can compensate for shortages to some extent. However, if ME^- is too large, replenishing the shortage causes a burden on the production site, thus ME^- must be small.

VI. Numerical experiment

We confirm the usefulness of the proposed method in this research. Actual sales data of catered bento are used to validate the usefulness. The actual data was provided by a company in Kanagawa Prefecture, Japan that delivers and manufactures 13,000 catered lunches per day.

About 80% of the company's customers are factory workers. Interviews with this company revealed the following about the popularity of their products. Customers prefer products made with meat to those made with vegetables and fish. Products with a good filling are more popular than those with a poor filling.

Section VI-A shows the results of product popularity estimation for each bento. The results of the sales volume are explained in Section VI-B.

A. Results of Product Popularity Estimation for each Bento

The data used were the sales days $|T| = 305$, the number of daily bento products $|N| = 23$, and the number of bowl bento products $|N| = 9$. Each parameter was set to $I = 14$ and $v = 1$.

Some of the results of the estimated mean μ of the product popularity of the daily bento are displayed in Table III. Table III shows that "Hamburger steak" and "Fried

TABLE III
Popular and unpopular items for daily bento

Rank	Products	Estimated value(μ)	Rank	Products	Estimated value(μ)
1	Hamburger steak	7.98	19	Ham	-2.60
2	Fried chicken with vinegar and tartar sauce	6.59	20	Egg	-4.17
3	Tatsutaage	6.27	21	Fish	-4.22
4	Pork cutlet	5.84	22	Chinese style sauteed vegetables	-5.23
5	Mix fly	4.89	23	Japanese style sauteed vegetables	-7.46

chicken with vinegar and tartar sauce" are popular, with a large mean μ of popularity. In addition, "Japanese-style sauteed vegetables" and "Chinese-style sauteed vegetables" are unpopular because the mean μ of popularity is small. The results in Table III can be regarded as reasonable because they are consistent with the results of interviews with the company.

Some of the results of the estimated mean μ of the product popularity of the rice bowl bento are displayed in Table IV. Table IV shows that "Stir-fry pork with ginger &Fried chicken" and "Pork cutlet bowl" are popular. In addition, "Beef bowl", "Japanese curry", and "Chicken and egg bowl" are unpopular because the mean μ of popularity is small. The μ value switches from positive to negative between the 6th-ranked "Salt pork bowl" and the 7th-ranked "Beef bowl". Consider the reasons why "Beef bowl", "Japanese curry", and "Chicken and egg bowl" are unpopular. The reason for the low popularity of "Beef bowl" and "Japanese curry" may be that there are many chain restaurants in Japan that serve

TABLE IV
Popular and unpopular items for rice bowl bento

Rank	Products	Estimated value(μ)	Rank	Products	Estimated value(μ)
1	Stir-fry pork with ginger &Fried chicken	10.67	6	Salt pork bowl	0.04
2	Pork cutlet bowl	5.31	7	Beef bowl	-8.40
3	Fried chicken bowl	5.01	8	Japanese curry	-9.13
4	Grilled meat bowl	4.82	9	Chicken and egg bowl	-11.36
5	Tempura bowl	2.95			

both. "Beef bowl" and "Japanese curry" are not an option for customers because they are readily available at any time. The reason for the low popularity of "Chicken and egg bowl" may be that customers have grown tired of it. Catering bento, which are sensitive to customer boredom, regularly improve their products. However, the interviews revealed that only "Chicken and egg bowl" had not been improved.

Tables III and IV show that products which are difficult to cook at home tend to be popular. This is likely due to customers' psychological desire to eat foods that they rarely have the opportunity to eat.

B. Machine Learning Prediction Results for Number of Sales

The prediction period was from June 15, 2020, to October 30, 2020. The study period was limited to one period prior to the forecast date. First, we compare the prediction accuracy of the proposed model with that of the conventional model [1]. Second, we also compare the predictions of the proposed model with those of veteran workers who have been in charge of demand forecast. According to an interview with a forecaster at a company that delivers and manufactures catered lunches, the permissible replenishment amount is about 3% of the actual sales volume. Each bento can be replenished with 50 daily bento and 20 rice bowl and noodle bento each.

Fig. 2 shows the measured values of the daily bento, the predictions of the proposed model, and the predictions of the conventional model. The vertical axis indicates the sales volume. The horizontal axis is the date of sale. The results of calculating the evaluation indices defined in Eqs. (9) - (12) for the daily bento forecasts of the proposed model, the conventional model, and the forecaster are shown in Table V. From Fig. 2, it is difficult to determine whether the proposed model or the conventional model is superior. Table V shows that the proposed model improved ME^+ and SD^+ compared to the conventional model. On the other hand, ME^- worsened.

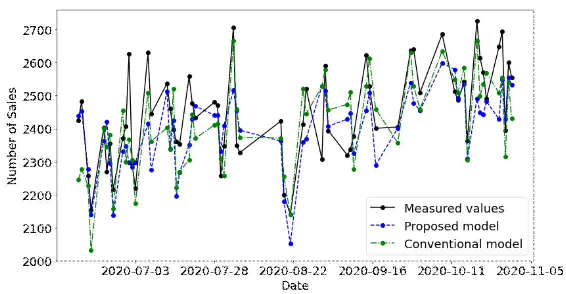

Fig. 2. Comparison of daily bento predictions

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TABLE V
EVALUATION OF THE ACCURACY OF DAILY BENTO PREDICTIONS

	Proposed model	Conventional model	Field worker
ME^+	**16.2**	38.2	33.2
SD^+	**77.1**	100.5	91.9
ME^-	-52.7	-40.2	**-34.0**
SD^-	**83.9**	91.9	91.2

Fig. 3 shows the measured values of the rice bowl bento, the predictions of the proposed model, and the predictions of the conventional model. The vertical axis indicates the sales volume. The horizontal axis is the date of sale. The results of calculating the evaluation indices defined in Eqs. (9) - (12) for the rice bowl bento forecasts of the proposed model, the conventional model, and the forecaster are shown in Table VI. Fig. 3 shows that the proposed model is superior to the conventional model because it takes values closer to the measured values. Table VI shows that the proposed model improved on all indicators compared to the conventional model.

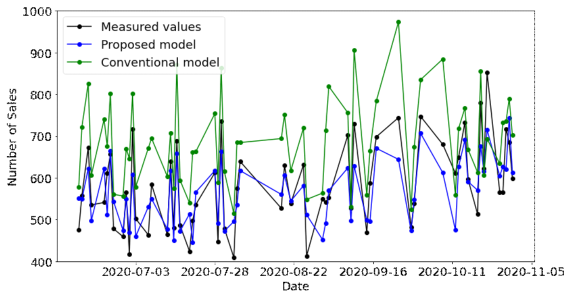

Fig. 3. Comparison of rice bowl bento predictions

TABLE VI
EVALUATION OF THE ACCURACY OF RICE BOWL BENTO PREDICTIONS

	Proposed model	Conventional model	Field worker
ME^+	21.2	37.5	**11.5**
SD^+	**66.6**	92.0	86.0
ME^-	**-18.4**	-18.9	-26.1
SD^-	**67.3**	84.1	77.1

Judging from all the indicators in Tables V and VI, the proposed model can predict less food loss than the conventional model for all bento. In addition, the amount of additional production required is acceptable. Furthermore, the proposed model gave a prediction result with little variation.

Next, a comparison of accuracy with the prediction of field employees is conducted. In the case of the daily bento, ME^+ in the proposed model is smaller than the field prediction. The ME^- of the proposed model slightly exceeds the allowable quantity of 50. Thus, the ME^- of the proposed model is worse than the field forecast. Therefore, we think that the accuracy of the proposed model and the field prediction are comparable. In the case of the rice bowl bento, $ME-$ in the proposed model is smaller than the field prediction. On the other hand, ME^+ is larger than the field worker's prediction. The larger ME^+ of the proposed model indicates that the proposed model generates more food loss than the field prediction by veteran workers. Therefore, we conclude that the accuracy of the proposed model and the field prediction are comparable.

VII. CONCLUSION

In our study, we have constructed an estimation method for the product popularity of catered bento by MCMC sampling. Moreover, we have proposed a demand forecast model for catered bento by machine learning. We also conducted a numerical experiment using actual sales data of companies that deliver and manufacture bento. The experimental results showed an advantage over the conventional method. Although some of the indicators values are better than the predictions of the field employees, they are not improvement of forecasting accuracy is needed.

We plan to do two things in the future. The first is to consider the effect of temperature. Since temperatures change every day, the impact of temperature on the volume of bento sold also changes every day. By considering the effect of temperature, we can expect to improve the accuracy of the forecast. The second is to automate the creation of product groups when estimating popularity. We plan to apply natural language processing techniques to automate the creation of product groups.

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