Inventory Management Based on Demand Forecasting Using Ryokan’s Beer Sales Data

Hironobu Kawamura¹, Keisuke Nomoto², and Enchih Kuo²

¹ Faculty of Engineering, Information and Systems, University of Tsukuba, Japan
² Department of Policy and Planning Sciences, University of Tsukuba, Japan

Abstract: Though service sector in Japan has developed, number of traditional inns (ryokan) has declined over the last 30 years. One of the reasons for this decline is that many ryokan managers tend to rely more on experience and intuition than on data analysis. Moreover, few studies have focused on hotel inventory control. Therefore, considering that safety stock levels and inventory costs have become crucial factors in the hotel industry, this study proposes methods for determining an appropriate level of safety stock using demand forecasting that considers the peculiarities of the hotel business. It applies multiple regression analysis and neural networks to forecast beer demand based on sales data from company A, a traditional Japanese inn. This study also compares the proposed safety stock level with that of company A. Furthermore, it provides an empirical analysis of inventory management in the hotel business. The results not only demonstrate that the reorder criteria determined by the multiple regression analysis and ANN are superior to the method currently used by company A but also verify the efficacy of the proposed methods.

Key Words: Case study, multiple regression model, neural network model, safety stock

1. Introduction

The conditions under which Japan’s service industry operates have changed drastically in recent years. According to Ref.1, owing to the increase in Japan’s elderly population, the service industry has gained more importance. Ref.2 has also recognized the importance of the service industry in improving Japan’s economic growth, claiming that the “service sector’s share of the gross domestic product (GDP), about 70% in Japan, is the key to improving economic growth.” Service industries include financial, education, information, medical, and food services as well as lodging businesses such as hotels and inns, which boast the biggest share of Japan’s total tourism revenue.

Hotels and ryokans (traditional Japanese inns) are types of lodging. Ref.3 indicated that ryokan room numbers have declined in recent years as illustrated in Figure 1.

Ref.4 indicated the management ambiguities of family-run businesses as one of the main reasons for this decline. Many ryokan managers tend to rely more on experience and intuition than on data analysis. The reasons for such an approach could be many. It is possible that the managers have known their own judgment to be more or less favorable as a result of years of experience. Because of the family business format, it is likely that the management is resistant to changing its approach as their current method poses no difficulties. They are likely to think that there is no need to change a process if it is working satisfactorily. Moreover, family-run businesses are not bound by strict processes; therefore, they favor running things as per tradition rather than adopting a new system altogether. Because a hotel’s food services constitute a high proportion of sales, inventory management of food and beverages needs to be done scientifically. However, few studies have focused on this issue. This study focuses on beer inventory management in company A, a traditional Japanese inn that aims to obtain an appropriate beer stock and improve its cash flow while maintaining the service levels.

This study fills that knowledge gap by presenting two new approaches for setting appropriate safety stock levels using real data and considering the hotel industry’s peculiarities. The methods are then evaluated for their effectiveness. The analyses in this study are run in IBM SPSS (Ver. 22).

2. Literature Review

It is well known that an accurate forecast of customers’ demand patterns is vital to ensure the highest level of service
delivery. This is particularly true for the food and beverage departments of hotels and inns. This is mainly due to the perishable nature of food and beverages as well as banquet needs. Ref. 5 presented a forecasting method that combines a time series analysis by exponential smoothing and multiple regressions for a two-stage model. Ref. 6 indicated that numerical demand forecasting methods focus either on time series or on causal relationships. The multiple regression approach focuses on causal relationships.

The other method used in this study for demand forecasting is the neural network model. Many researchers, such as Ref. 7 and Ref. 8, have provided empirical results for the comparison between the ANN model and other forecasting models. Ref. 7 compared a traditional forecasting method with the neural network model for both monthly and quarterly time series and demonstrated that the neural network model performs better than traditional methods and is particularly effective under a discontinuous time series. Ref. 8 also applied a supervised feed-forward neural network model to forecast Japanese tourist arrivals in Hong Kong and showed the neural network model to be more effective forecasting arrivals than the multiple regression model. Refs. 5–8 discussed forecasting methods but did not discuss the relationship between inventories and forecasting.

Ref. 9 presented the current status and future prospects of the liquor industry (in Japanese) and examined possible explanatory variables such as gender, season, and health consciousness for beer demand. In this study, the variables that are not covered in previous studies are discussed and used. For determining safety stock levels, Ref. 10 indicated that in many cases, lead times vary; thus, they proposed a method for setting safety stock levels and ordering points that considers the distribution of lead times. Ref. 11 indicated that the distribution of sales data may not be sufficient, such as in the consumer electronics industry, where technology changes very fast and businesses face an intermittent demand. Their study also showed the way of determining the order point under the constraint of limited demand information. Ref. 10 and Ref. 11 considered safety stock under constrained demand information and the variation of lead time, respectively, but there was no discussion of the prediction methods used.

### 3. Demand forecasting

#### 3.1 Data and variables

This study presents two approaches for setting safety stock levels and compares their performances with real data obtained from company A, a traditional Japanese inn. The managers of company A tend to make decisions about inventory based on experience and intuition, and often experience shortages. Scientific inventory management for hotels and inns applies to a number of specific items. As beer often goes out of stock, beer sales are used as the dependent variable to forecast demand. Beer sales from August 1, 2012 to May 31, 2014 are considered in this study.

Explanatory variables include the following:

| Variables                                    | Time |
|----------------------------------------------|------|
| Unit sales of beer                           |      |
| Number of guests                             |      |
| Season                                       |      |
| Days of the week                             |      |
| Gender                                       |      |
| Age groups                                   |      |
| Weather                                      |      |
| Purpose                                      |      |
| Bottomless/Non-bottomless drinks             |      |

The main variables affecting beer sales in inns are seasons and days of the week. Seasonal fluctuations are caused by increases and decreases in tourism; likewise, customer flow on weekends (Saturdays and Sundays) is greater than that on weekdays. The gender and age variables are also important. Refs. 11 and 12 suggested that significant differences in the volumes and types of liquor consumed exist between different genders and ages. For example, older people drink not only beer but also sake and shochu, which may reduce beer consumption.

Beer consumption may also depend on the levels of health consciousness in each age group. Climate and purpose are also key variables. Purpose can be divided into several types, such as excursion, family trip, or hot-spring cure. The consumption of alcoholic beverages in hotels and inns is likely to increase when guests come for an excursion and decrease when health-conscious guests come for the hot-spring cure. Furthermore, whether bottomless drinks are offered will also affect beer consumption rates. Inn service includes many types of the drinks, including soft drinks. In company A, the all-you-can-drink service charges a set price for a period of two hours, whereas non-bottomless drinks are charged individually.

For the variables discussed in the previous section, the data available in this study provided by company A are shown in Table 1.

Data about the unit sales of beer can be divided into bottomless and non-bottomless drinks. These data are available from August 1, 2012 to May 31, 2014. The number of guests can be divided into four patterns by gender and type of use during a one-day trip (these data can also be divided into bottomless/non-bottomless drinks, but data are available only from October 1, 2012).

For the explanatory variables mentioned in the previous section, seasons can be adjudged by date. Gender and bottomless/non-bottomless drinks can be identified by the number of guests, but age and purpose cannot be identified. Furthermore, the inn sells three beer brands; however, this study’s beer sales data do not distinguish among them. The fixed lead time for a beer order is one day. The data for guests on one-day trips represent the total number of food reservations made in advance. The number of unpredictable guests, such as hot-springs visitors, was not included as the changes in unit sales of beer caused by unpredictable guests were negligible. The deterioration rates of food and drink are not considered in this study because the expiration date of beer is longer than that of fresh food. The upper limit of storage space for...
beer was not taken into consideration since the space for beer storage is sufficient.

3.2 Basic analysis
Explanations of each variable are shown in Table 2.

Table 2: Explanations of variables

| Data group     | Explanatory variable | Explanation                                      |
|----------------|----------------------|--------------------------------------------------|
| Guest          | Male total           | The total number of daily male guests             |
|                | Female total         | The total number of daily female guests           |
|                | Male lodging         | The total number of daily male lodging guests     |
|                | Female lodging       | The total number of daily female lodging guests   |
|                | Male one-day trip    | The total number of daily male one-day trip guests|
|                | Female one-day trip  | The total number of daily female one-day trip guests|
| Drinks         | Bottomless drinks orders | The total number of daily bottomless drinks |
|                | Non-bottomless drinks orders | The total number of daily non-bottomless drinks. |
|                | Unit of beer sales   | The total number of daily beer sales              |
|                | Unit of sales: Bottomless drinks | The total number of daily beer sales for bottomless drinks |
|                | Unit of sales: non-Bottomless drinks | The total number of daily beer sales for non-bottomless drinks |

A basic analysis of the variables for the correlation between the unit of sales and the total number of daily male guests reveals a strong positive correlation. A strong positive correlation also appears between unit sales and total number of daily bottomless drinks for male guests.

The monthly time series variation of beer sales is shown in Fig. 2.

![Fig. 2 Monthly time series variation of beer sales](image)

In this study, two forecasting methods are used for beer demand forecasting, which are listed in Table 3.

Table 3: Methods for demand forecasting

| Method                              | Neural network model |
|-------------------------------------|----------------------|
| 1. Multiple regression analysis    | ANN                  |
| 2. Multiple regression analysis    |                      |
| considering the number of all-you-can-drink users (Model A). |           |
| considering seasonal fluctuations. (using a dummy variable / using busy season data (stratified) (Model B).) |   |

Table 4: Variables used in multiple regression analysis considering the number of all-you-can-drink users

| Variable                              | Contents                                      |
|---------------------------------------|-----------------------------------------------|
| Total unit sales of beer              | Total sales; number of beers                  |
| Month (dummy variable)                | From Feb. to Dec.                            |
| Day of the week (dummy variable)      | From Tues. to Sun.                           |
| Bottomless drink orders               | Total bottomless drink users                  |
| Non-bottomless drink orders           | Total non-bottomless drink users              |
| Male total                            | Total number of male users                   |

Table 5: Summary of the multiple regression model considering the number of bottomless drink orders

| R  | R² | Adjusted R² | Std. Error of the Estimate |
|----|----|-------------|----------------------------|
| 0.857 | 0.734 | 0.729 | 25.294 |

Predictors: (constant), bottomless drink orders, non-bottomless drink orders, August, Friday, November, December

The results in Table 5 indicate that 72.9% of the unit sales of bottled beer are explained by the bottomless drink orders, non-bottomless drink orders, Friday, August, November, and December variables. As Table 6 shows, the model is statistically significant at the 1% level. Table 7 indicates that the effects of all explanatory variables are significant at the 1% level.

For examining residuals, each of the residual plots displays a random pattern, which confirms no significant residual problem. A histogram of the residual is also shown in Fig. 3. The shape near residual = 0 can be observed in normal distribution; although it is qualitative, the assumption of a normal distribution is reasonable. The regression analysis result is shown as equation (1).

\[
\hat{y} = -1.587 + 1.264 \times \text{(bottomless drinks)} \\
+ 0.33 \times \text{(non-bottom less drinks)} \\
- 18.263 \times \text{(August)} + 13.322 \times \text{(Friday)} \\
+ 16.966 \times \text{(November)} + 14.538 \times \text{(December)}
\]

(1)

3.4 Multiple regression analysis considering seasonal fluctuations
This section discusses a multiple regression analysis that considers the busy season and off season in detail. The
Table 6  ANOVA of the multiple regression model considering the number of bottomless drink orders

| Sum of Squares | df  | Mean Square | F       | Sig |
|----------------|-----|-------------|---------|-----|
| Regression     | 631014.437 | 6           | 105169.073 | 164.378 | 0 |
| Residual       | 229048.615  | 358         | 639.801  |       |   |
| Total          | 860063.052  | 364         |          |       |   |

Dependent Variable: Total sales of beer
Predictors: (constant), bottomless drink orders, non-bottomless drink orders, August, Friday, November, December

Table 7  Partial regression coefficients

| Unstandardized Coefficients | Standardized Coefficients | t       | Sig | Conlinearity Statistics |
|-----------------------------|---------------------------|---------|-----|-------------------------|
| B                           | Std. Error                | B       | t   | Sig                     |
| (Constant)                  | -1.587                    | 2.323   | -0.683 | .495                    |
| Bottomless                  | .264                      | .049    | .745 | 25.538                  | .000 | .873 | 1.145 |
| Non-bottomless drinks       | .330                      | .030    | .310 | 10.959                  | .000 | .950 | 1.054 |
| August                      | -18.263                   | 4.900   | -3.727 | .000                    |
| Friday                      | 13.322                    | 3.882   | .346 | .952                    | .001 | .952 | 1.050 |
| November                    | 16.966                    | 4.904   | .346 | .956                    | .001 | .956 | 1.035 |
| December                    | 14.538                    | 4.995   | .346 | .954                    | .001 | .954 | 1.035 |

Table 8  Definitions of busy season and off season

| Month/Year       | Bottomless Drink Orders | Busy/Off Season |
|------------------|-------------------------|-----------------|
| October 2012     | 563                     | Busy            |
| November 2012    | 639                     | Busy            |
| December 2012    | 1,279                   | Busy            |
| January 2013     | 406                     | Busy            |
| February 2013    | 610                     | Busy            |
| March 2013       | 342                     | Off             |
| April 2013       | 285                     | Off             |
| May 2013         | 242                     | Off             |
| June 2013        | 299                     | Off             |
| July 2013        | 228                     | Off             |
| August 2013      | 214                     | Off             |
| September 2013   | 456                     | Off             |

Table 9  Summary of the multiple regression model (busy season)

| R    | R-square | Adjusted R-square | Std. Error of the Estimate |
|------|----------|-------------------|---------------------------|
| .705 | .497     | .497              | 18.6314                   |

Predictors: (constant), non-bottomless drink orders, male lodging

The results in Table 9 indicate that the numbers of non-bottomless drinks and male lodgings explain 49.7% of beer sales. Table 10 reveals that the model is statistically significant at 1% and the VIF value is less than 10. The histogram of the residual is shown in Fig. 4 and the result of the regression analysis is shown as equation (2).

$$\hat{y} = -1.376 + 0.297 \times (\text{non-bottomless}) + 0.265 \times (\text{male lodging})$$  (2)

busy and off seasons are defined in Table 8, with 500 orders as the criterion. The definitions of the busy season and off-season were established as a result of meetings with inn managers. Customers come mainly in the winter, at the end of the year. Although orders in January were below 500, it is considered as part of the busy season at company A.

(1) Multiple regression analysis using a dummy variable

The multiple regression analysis using the stepwise method (the model using the busy and off seasons as dummy variables) is not adopted because the adjusted R-square is less than 0.4.

(2) Multiple regression analysis using busy season data (stratified)

The result of multiple regression using dummy variables is not preferred. Thus, to compare the busy and off seasons, multiple regression analysis has been studied after their stratification. The busy season results are shown in Tables 9 and 10 and in Fig. 4.

The results in Table 9 indicate that the numbers of non-bottomless drinks and male lodgings explain 49.7% of beer sales. Table 10 reveals that the model is statistically significant at 1% and the VIF value is less than 10. The histogram of the residual is shown in Fig. 4 and the result of the regression analysis is shown as equation (2).
Table 10 Partial regression coefficients (busy season)

|                         | Unstandardized Coefficients | Standardized Coefficients | Conlinearity Statistics |
|-------------------------|----------------------------|---------------------------|-------------------------|
|                         | B  | Std. Error  | B            | t   | Sig | Tolerance | VIF |
| (Constant)              | -1.376 | 2.621   | 0.525 | -0.525 | 0.600 |
| Non-bottomless drinks   | 0.297 | 0.044   | 0.468 | 6.822 | 0.000 | 0.722 | 1.385 |
| Male lodging            | 0.265 | 0.054   | 0.335 | 4.875 | 0.000 | 0.722 | 1.385 |

a. Dependent Variable: Total unit sales of beer

Table 11 Summary of the multiple regression model (off season)

|                         | R  | R-square | Adjusted R-square | Std. Error of the Estimate |
|-------------------------|----|----------|-------------------|----------------------------|
|                         | 0.477 | 0.467   | 16.9231           |                            |

Predictors: (constant), male one-day trip, male lodging, Saturday, Friday Dependent variable: total unit sales of beer

Table 12 ANOVA of the multiple regression model (off season)

|                         | Sum of Squares | df | Mean Square | F  | Sig   | Sig   |
|-------------------------|----------------|----|-------------|----|-------|-------|
| Regression              | 54529.109      | 4  | 13632.277   | 47.6 | .000  |       |
| Residual                | 59855.900      | 209| 286.392     |      |       |       |
| total                   | 114385.009     | 213|             |      |       |       |

Dependent variable: Total unit sales of beer
Predictors: (constant): male one-day trip, male lodging, Saturday, Friday

Table 13 Partial regression coefficients (off season)

|                         | Unstandardized Coefficients | Standardized Coefficients | Conlinearity Statistics |
|-------------------------|----------------------------|---------------------------|-------------------------|
|                         | B  | Std. Error  | B            | t   | Sig | Tolerance | VIF |
| (Constant)              | 1.186 | 1.84   | 0.645 | 0.52 | 0.987 | 1.013 |
| Male one day trip       | 0.484 | 0.039   | 0.632 | 12.554 | 0.000 | 0.855 | 1.169 |
| Male lodging            | 0.091 | 0.034   | 0.144 | 2.656 | 0.008 | 0.846 | 1.183 |
| Saturday                | 9.575 | 3.574   | 0.146 | 2.679 | 0.008 | 0.846 | 1.183 |
| Friday                  | 8.91  | 3.427   | 0.136 | 2.6 | 0.01 | 0.92 | 1.087 |

Fig. 4 Histogram of residual (busy season)

Fig. 5 Histogram of residual (Off season)

The predictions calculated for beer sales from October 2013 to May 2014 are compared with real sales data. Let the multiple regression model shown in Section 3.3 be Model A and let the multiple regression model shown in Section 3.4 be Model B. Comparisons between Models A and B in terms of the mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute deviation (MAD) are shown in Table 13. Mean absolute percentage error (MAPE) expresses the accuracy as a percentage of the error and is shown as equation (4):

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \frac{|y_i - \hat{y}_i|}{y_i}$$

where

$y_i$: measured value
$\hat{y}_i$: prediction
$N$: data number

The RMSE indicates how far the prediction is from the correct answer. The value is better the closer it is to 0. It can be calculated by equation (5):

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$$

The results in Table 11 indicate that 47.7% of beer sales are explained by the number of male one-day trips, male lodgings, Saturday, and Friday. Tables 12 and 13 also reveal that the model is statistically significant at the 1% level and a VIF value of less than 10 is confirmed. The result of the regression analysis is shown as equation (3):

$$\hat{Y} = 1.186 + 0.484 \times (\text{male one-day trip}) + 0.091 \times (\text{male lodging}) + 9.575 \times (\text{Saturday}) + 8.910 \times (\text{Friday})$$
where

\( y_i \): measured value

\( \hat{y}_i \): prediction

\( N \): data number

The MAD gives the amount of error and is shown as equation 6:

\[
MAD = \frac{\sum_{i=1}^{N} |y_i - \hat{y}_i|}{N}
\]

Although Model B seems better at MAPE overall, this is not the case on a monthly basis, where Model A is superior at the RMSE and MAD. As Model A provides better predictions overall, it is the adopted model. Figure 6 shows real beer sales data and predicted values. The continuous line represents the real data on beer sales while the dotted line is the prediction by model A. The demand predictions concur very well with the actual beer sales data.

3.5 Demand forecasting based on neural networks

Neural network models are usually referred to as “artificial neural networks” (ANN) (Ref.14), whereby a learning algorithm of a hierarchical network model is drawn from conventional data analysis. ANN are formed by formal neurons. The information processing model of formal neurons is shown in Figure 9. It expresses the transmission of information between neurons. The “combination function” is defined as a weighted sum of the input signals and can be expressed by mathematical models (equation 7). The excitement will be transmitted to another neuron when \( x_i \) is equal to or greater than the threshold. This function is called activation function. According to Ref.15, there are several types of transfer functions, including step, linear, and sigmoid functions.

\[
x_i = \sum_{j=1}^{n} w_{ij} s_j
\]

where

\( s_j \): The output signal of the cell \( j \), taking 0 or 1 value.

\( w_{ij} \): The coefficient of synaptic weights representing the synaptic connections from \( j \) to \( i \).

The structure is determined in the form of binding neurons and is called the “neural network model.” One of the most typical is a hierarchical network constructed as an input layer, hidden layer, and output layer. In statistics, the input layer comprises independent variables, the explanatory variables, and the output layer is the dependent variable. Therefore the number of neurons in the input layer and output layer would be determined by the learning task. The learning algorithm of a hierarchical network model is drawn using a conventional data analysis method, which involves applying stimulation and obtaining the correct reaction. As the correct reaction cannot be obtained the first time, the correct reaction is called the “teacher stimulation.” In the hierarchical network model, sequential learning involves calculating the weight of the inputs until a satisfying result is obtained.

To build a model using ANN, we use variables as in Table 4 as the variables are measured using different data for each unit. As the unit of each variable used in this study is different, Ref.13 has recommended normalizing units for each variable in estimating the model by ANN to increase generalizability. Therefore, this study compresses the observed values of the explanatory variables from 0 to 1 using the following equation (8):

\[
x^*_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}
\]

where

\( x^*_i \): compressed value

The analysis of the ANN model uses Weka used by Witten et al. (2011) (Ref.14). The initial values are set to the initial Weka setting, and the number of neurons in the intermediate layer is considered. Predictions have been examined based on the intermediate layer with 1, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, and 75 neurons, and the number of neurons in the intermediate layer is 14 as determined by the prediction error for MAPE, RMSE, and MAD. The results are shown in Figs. 7, 8, and 9.

3.6 The prediction result

The time series graph of the prediction by ANN and the real data on beer sales from October 2013 to May 2014 are given in Fig. 10. The continuous line represents the real data on beer sales, and the dotted line is the prediction by ANN. The demand predictions concur with the actual beer sales data.
Table 14 Comparison of MAPE, RMSE, and MAD

|                  | MAPE         | RMSE         | MAD          |
|------------------|--------------|--------------|--------------|
|                  | Model A      | Model B      | Model A      | Model B      | Model A | Model B |
| Total period     | 126.90%      | 104.6        | 27.372       | 46.902       | 16.829  | 27.823  |
| Oct.             | 36.70%       | 59.1%        | 13.834       | 36.646       | 9.951   | 21.997  |
| Nov.             | 290.8%       | 133.1%       | 37.6         | 46.707       | 31.722  | 33.951  |
| Dec.             | 36.1%        | 59.6%        | 42.684       | 79.295       | 24.204  | 50.508  |
| Jan.             | 40.3%        | 68.8%        | 17.064       | 57.045       | 10.701  | 35.593  |
| Feb.             | 145.6%       | 146.4%       | 16.005       | 37.68        | 11.284  | 22.741  |
| Mar.             | 151.9%       | 161.9%       | 26.547       | 42.223       | 16.184  | 25.405  |
| Apr.             | 92.6%        | 83.3%        | 24.365       | 26.369       | 14.385  | 16.911  |
| May              | 285.5%       | 129.2%       | 26.257       | 22.559       | 16.069  | 14.831  |

Fig. 8 Number of neurons and RMSE

Fig. 9 Number of neurons and MAPE

Fig. 10 Number of neurons and MAD

4. Safety Stock

This section discusses the inventory management of beer based on a reorder point policy. The values for safety stock were calculated using the formula given by equation (9):

\[
\text{Safety stock} = \text{SD of the prediction error} \times k \times \sqrt{\text{Leadtime}}
\]

(9)

When the distribution of the prediction error is not a normal distribution, the safety coefficient must be adjusted by trial and error. The distribution of the prediction error by multiple regression analysis and ANN are confirmed in Figs. 11 and 12. As can be seen in the figures, the shape of the distribution, which becomes convex around the prediction error = 0, shows a normal distribution.

Fig. 11 Estimation result of ANN and beer sales data

Fig. 12 Multiple regression analysis

Therefore, the safety stock for the multiple regression analysis and ANN are calculated by equation (9), as shown in Table 15.

|                  | Std. Error of Prediction Error | Safety Stock (permissible stock out rates of 1%) | Safety Stock (permissible stock out rates of 5%) |
|------------------|--------------------------------|-----------------------------------------------|-----------------------------------------------|
|                  | Std. Error of Prediction Error | Safety Stock (permissible stock out rates of 1%) | Safety Stock (permissible stock out rates of 5%) |
| Multiple regression analysis | 27.37                          | 63.78                                         | 45.16                                         |
| ANN              | 27.06                          | 63.06                                         | 44.65                                         |
Table 16  Comparison at permissible stock out rate of 1%

|                  | Company A | Multiple regression analysis | ANN  |
|------------------|-----------|------------------------------|------|
| Shortage occurrence dates | 51(100%) | 9(17.62%)                    | 8(15.69%) |
| ♦ Dates of excessive inventory surplus of stock |          |                              |      |
| Average of surplus | 50.44     | 67.2                         | 63.81|
| Maximum of surplus | 80        | 143.64                       | 134.9|
| Minimum of surplus | 5         | 10.31                        | 2.28 |
| ♦ Dates of stock out |          |                              |      |
| The sum of stock out | 2313     | 241.06                       | 83.96|
| Average of stock out | 45.35    | 26.78                        | 10.5 |
| Maximum of stock out | 223      | 96.48                        | 18.55|
| Minimum of stock out | 1        | 0.42                         | 2.2  |

Table 17  Comparison at permissible stock-out rate of 5%

|                  | Company A | Multiple regression analysis | ANN  |
|------------------|-----------|------------------------------|------|
| Shortage occurrence dates | 51(100%) | 12(23.53%)                   | 16(31.37%) |
| ♦ Dates of excessive inventory surplus of stock |          |                              |      |
| Average of surplus | 50.44     | 49.31                        | 47.24|
| Maximum of surplus | 80        | 125.03                       | 116.49|
| Minimum of surplus | 5         | 1.06                         | 2.65 |
| ♦ Dates of stock out |          |                              |      |
| The sum of stock out | 2313     | 429.49                       | 284.55|
| Average of stock out | 45.35    | 35.79                        | 17.78|
| Maximum of stock out | 223      | 115.09                       | 36.96|
| Minimum of stock out | 1        | 6.21                         | 0.63 |

5. Discussion

In this section, the time series graphs for “sales data,” “reorder point determined by company A,” “reorder point determined by multiple regression analysis,” and “reorder point determined by ANN” are shown at permissible stock-out rates of 1% and 5%. It should be noticed here that “reorder point determined by company A” reflects an inventory of 80 bottles (4 cases) for the busy season and 60 bottles (3 cases) for the off season.

(1) Permissible stock-out rate of 1%

A summary of the indicators at a permissible stock-out rate of 1% appears in Table 16. The brackets next to shortage occurrence dates mean the difference (%) with respect to company A.

The comparison in Table 16 shows that not only the stock-out days but also the shortages are much less in the multiple regression analysis and ANN than for company A in reality. The reorder points determined by the multiple regression analysis and ANN are superior to company A’s criteria. Moreover, the ANN value seems greater than the multiple regression analysis value in average stock out and surplus.

(2) Permissible stock-out rate of 5%

The stock-out days in the multiple regression analysis and ANN both increased over those of the permissible stock-out rate of 5 but the days increased more in ANN than in multiple regression analysis. The brackets next to value of shortage occurrence dates means the difference (%) with respect to company A.

6. Conclusion

This study discussed the issue of beer inventory management in Japanese ryokans based on demand forecasting. Keeping the hotel industry in mind, models and methods have been proposed to forecast and determine the appropriate safety stock levels. The findings show that the reorder criteria determined by the multiple regression analysis and ANN are superior to that of company A.

Comparisons between the multiple regression analysis and ANN reveal that ANN could reduce average shortages through both inventory stock surpluses and 1% and 5% permissible stock out rates. However, ANN had more shortage days than the multiple regression analysis at a permissible stock out rate of 5%. Such a small difference between these two methods can be attributed to coincidence.

The ANN model is sometimes criticized for being a “black box.” However, it can approximate a wide range of non-linear functions when the relationships between the variables are not well understood. Therefore, the multiple regression analysis is easier to deal with as long as there is no significant difference in the results.

This study empirically analyzed demand forecasting through multiple regression analysis and ANN using beer sales data. The results indicated setting safety stock seems...
appropriate for combining demand forecasting with customer information and management experience. It should be noted that this study does not refute the qualitative aspects of managers’ experience and intuition, but it shows that inventory control in traditional hotels is more efficient when conducted through scientific management techniques.

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Hironobu Kawamura is an assistant professor at the Information and Systems, Faculty of Engineering, University of Tsukuba, Japan. He holds a PhD in Industrial Management Engineering from the Nagoya Institute of Technology. His current research interests are in quality control and service management.

Keisuke Nomoto is Associate Director of General Planning, The Nippon Foundation. He joined the Nippon Foundation in 2015 and had been involved in establishing the Nippon Foundation Paralympic Support Center. He has a Bachelor’s degree in Policy and Planning Science from University of Tsukuba, Japan.

Enchih Kuo is now a master course student of Department of Policy and Planning Sciences, University of Tsukuba, Japan. He received bachelor degree from Soochow University, Taiwan, in 2011. He is studying in the field of inventory control.