PROCESS MANAGEMENT IN RESTAURANT SERVICE
--A case study of Japanese restaurant chain--

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Abstract
This paper discusses process management problems in restaurant services. First, it introduces an analysis on the customer behaviors using large-scale purchase data. Then it introduces a multi regression model which estimates the number of customers considering date and weather information. Then, it introduces an information sharing system that encourages the real-time sharing of order information among staff members.

Keywords: service engineering, restaurant, process management, multi-regression model, information sharing

1. INTRODUCTION

The market scale of service industries acquires approximately 70% of Japanese GDP. Additionally, the market share of restaurant industry is 6.9% of service industries, and market scale of restaurant is 25 trillion Yen. Therefore, restaurant industry is one of the most important key industries in Japan (METI, 2007). However, after 1990’s, restaurant industries have been in severe conditions according to the demographic change and escalating price competition due to the economic stagnation.

For the management of restaurants, one of the greatest challenges might be the prediction about their customers’ demands (Jensen and Hansen, 2007). In other words, how many and when their customers will come, and what they will order are crucial information for stock control and scheduling of employee attendance. On the other hand, customers are always free to choose a restaurant and order dishes by their own choice. It is essentially difficult to predict customer demands for restaurants. Additionally, servicing capacity of a restaurant is limited by both staffs' labor amount per unit time and store size.

Service engineering is a new and transdisciplinary research field that aims to support service industries (Takenaka, et al., 2010, Shimomura, et al. 2008). For this purpose, we must elucidate the nature of services using objective data acquired through actual services. Moreover, we must also focus on human factors such as customers’ values and employee’s service skills (Ueda, et al, 2009).

This paper introduces some challenges to support restaurant industries focusing on large-scale data of customers’ purchasing behaviors and staffs’ process management in a restaurant. Next, it discusses an analysis of the customers’ behavior using large-scale purchase data and introduces a prediction model of customers of a day in an actual restaurant.

2. ANALYSIS OF CUSTOMER BEHAVIOR IN RESTAURANT USING POS DATA

In Japan, the Point of Sale (POS) system was introduced to restaurant industries in 1980’s, and has been widely prevalent in restaurant chains (Stein, 2005). As it will be discussed in the next section, the restaurant POS system including a special kind of handy device for taking orders at table has greatly helped the accounting management in restaurants. Moreover, using this system, they became to be able to manage and provide many kinds of products. However, a large amount of POS data often has not been utilized enough for management because of the analysis cost. From the perspective of service engineering, we focus on the POS data to understand customer behaviors and needs. In this section, we introduce some of our analyses on customers’ visit to a restaurant using POS data of a restaurant chain.

2.1. Prediction of the Number of Customers for a Restaurant

As discussed in INTRODUCTION, although the prediction of customer demands is intrinsically difficult, restaurant managers should estimate the number of customers or sales of the day in some way for stock control and work...
scheduling. The authors interviewed some restaurant managers of a Japanese restaurant chain about their own estimation methods for the number of customers or sales of their products. Although they employ various empirical methods, one of the key factors might be the characteristics of date and weather conditions. Some of them, for instance, empirically estimate that the number of customer will drop by 10 to 20% on a rainy day. As for date characteristics, the relationships among weekday, weekend and public holidays according to the calendar might impact dynamically on the number of customers. Moreover, seasonal and local events, such as year-end party, festivals, or events in nearby area might also affect on the customer coming. Considering those managers’ knowledge, we examined the possible parameters on the number of customers using POS data of about 10 restaurants for over 2 years.

Fig.1 shows the impact of the total amount of rainfall on the number of customers of a restaurant (located at Osaka, 4 floors with 350 seats, POS data from Jan. 1st, 2008 to Aug. 31st, 2010 is analyzed). A one-way analysis of variance shows significant difference in groups (F(6,967)=3.756, p<0.01). However, the Levine’s test for equality of variance shows that the data does not meet the assumption of homoscedasticity. We only found the significant difference between “0 mm” and “21-30 mm” by Dunnett’s T3 test. As for this restaurant, small rain might not affect on the customers’ visit. In fact, the restaurant is located at a big arcade of downtown.

![Fig. 1 Averaged number of customers according to the total amount of rainfall in a day. Error bar shows each condition’s Standard Error.](image)

Thorough those analyses, we have tested dozens of parameters that could impact on the customer coming or sales. After those analyses, we constructed a multiple regression model for the prediction of the number of customers and sales. In this model, we prepared 30 different parameters; date characteristics, seasonal events, local events, and weather information including total rainfall (0-10mm, 11-30mm, over 31mm) and daily maximum temperature (6 scale according to occurrence ratio). To select those parameters, we have tested collinearity and partial correlation among parameters and excluded some parameters that have strong collinearity with major parameters. Additionally, in this model, we employed the stepwise selection of parameters (Pin(0.05), Pout(0.1)).

Fig. 2 shows actual number of customers and estimated number by the constructed model for the restaurant. We constructed a multiple regression model using POS data from 1st, 2008 to Aug. 31st, 2010. In this case, we input 24 parameters to the model and 16 parameters were selected by the stepwise method. The correlation coefficient (r) of this model is 0.8546541, and the coefficient of determination, (r^2) is 0.7304337.

Then, we calculate this model’s accuracy to the actual numbers by the following formula (1).

\[ p = \frac{a - \hat{a}}{a} \]  

(1)

The accuracy of the model p is defined as a proportion of estimated number of customers \( \hat{a} \) to the actual number of customers a. The averaged accuracy of this model for the same period (975 days) is 87.745%.

![Fig. 2 Comparison of number of customers between actual and estimated numbers by the constructed model. The last year’s data is shown.](image)

| Table 1 Selected Parameters and their Coefficient of the Multiple Regression Model |
|-------------------------------------------------|--------|-------|------|--------|
| Parameters                                      | Coeff-| SE    | t    | Probabili- |
| Constant term                                   | 471.11| 8.39  | 56.1 | 0.0000  |
| Sunday                                          | 419.84| 12.44 | 33.7 | 0.0000  |
| Saturday                                        | 396.12| 12.45 | 31.9 | 0.0000  |
| Holiday (except weekend)                        | 424.04| 27.08 | 15.6 | 0.0000  |
| Holiday (weekend)                               | 162.45| 19.03 | 9.59 | 0.0000  |
| End-Year Party Season                           | 402.29| 44.33 | 9.08 | 0.0000  |
| New-Year’s Holidays                             | 146.78| 12.33 | 11.90| 0.0000  |
| Max. Temp. 1: Under11 degree C                  | 100.76| 10.84 | 9.30 | 0.0000  |
| Max. Temp. 2: 11-16 degree C                   | 76.61 | 11.37 | 6.74 | 0.0000  |
| New-Year Party Season                           | 192.31| 35.77 | 5.38 | 0.0000  |
| Season (week of early January)                  | -62.21| 11.14 | -5.59| 0.0000  |
| Max. Temp: 3:16-21 degree C                    | 47.94 | 10.66 | 4.50 | 0.0000  |
| Max. Temp: 4:17-22 degree C                    | 81.40 | 12.39 | 6.55 | 0.0000  |
| Weekday before Holiday                          | 126.89| 35.50 | 3.57 | 0.0004  |
| Thursday                                        | 40.47 | 12.36 | 3.27 | 0.0011  |
| Farewell Party season                           | 68.19 | 21.10 | 3.23 | 0.0013  |
| The last day of holidays                        | -98.62| 34.82 | -2.83| 0.0047  |
Table 1 shows selected parameters and their coefficient of the constructed model. For example, the model calculates the number of customers of a rainy Friday on December with maximum temperature at 8 degrees C is approx. 837 (471.11+182.45+146.78+100.76-62.21-836.88).

We hope that such a simple model will help less-experienced managers to learn the tendency of their restaurant easily. However, this model is limited because it cannot account mutual interaction of parameters. Therefore, we are constructing a correction algorithm for days that are far off the model (or outlier), using other methods like Bayesian network.

We cannot go into the details in this paper, but we constructed the same models for other 70 restaurants of the same restaurant chain. In those models, various combinations of parameters are selected by the same stepwise method, and the accuracies also varied from approx. 66% to 92% according to their locations and store sizes. Now we plan to develop a supporting system for managers to understand and to predict the customers’ behaviors.

3. OPERATION MANAGEMENT IN RESTAURANT

After estimating the number of customers of a day, the manager must arrange work schedule of employees. However, it is not easy to find proper relationships between employee behavior and actual processes of restaurants. In this section, it discusses actual operations by staff members in restaurants and how an information system can improve them. Before the POS system was introduced to restaurant businesses, service staff members memorize a customer order after receiving it and then give the information to the kitchen staff verbally. However, because the capacity of human memory is restricted, staff often mistake or forget orders, especially when a restaurant becomes busy. Consequently, the scale of restaurant deeply depends on capacity of human skills. In early 20th century, order sheet is introduced to the restaurant business to improve information sharing among staffs. However, because order sheets do not record the order-received time, kitchen staff cannot distinguish the sequence of orders.

In 1980’s, POS system is introduced to restaurant industry to resolve shortcoming of order sheet system (Swart, 1986, Muller, 1999). When a staff receives an order from customer, he/she inputs the order information with table number using a portable device, and transmits it to the POS terminal. Accordingly, hall staffs members do not need to deliver order sheets to the kitchen. Additionally, POS terminal adds order-received time and price information, and transmit to kitchen printer. Then kitchen staffs start to cook dishes by referring the printed order sheet.

Although POS improves the handing-over processes of customer orders, some problems remain. The kitchen staff members often calculate the total number of identical dishes irrespective of the table and cook them collectively because this batch method is more efficient. Moreover, it is still difficult for them to grasp the elapsed time of each order.

3.1 Information Sharing System for Restaurants

To resolve those problems, Ganko Food Service Co. Ltd. developed a new information sharing system (ISS) and introduces it to their full-service restaurants from 2008. In this paper, we present a brief overview of ISS and discuss the effectiveness in actual restaurants (Shimmura, et al. 2010).

![Fig. 3 Layout for order checking system of ISS.](image)

The ISS especially targets temporal aspects of process management and information sharing among staff. Figure 3 presents a sample display of the order checking system at a certain kitchen area. The horizontal axis of Fig. 3 shows the passage of time by table. The total number of orders is shown to the left of each dish in this display. When kitchen staff members start preparation, they can know the total number of each dish needed. The square moves to the right every 2 min and the color changes at every 10 min (blue–yellow–red). When elapsed time get over 20 min, alarm sounds to notify delay to staff. Kitchen staff members usually check and grasp condition of process.

3.2 Introduction of ISS to restaurants

To test system effectiveness of ISS, we introduced it to four restaurants owned by Ganko Food Service Co. Ltd. (Osaka, Japan) from September 2008 to April 2009. Restaurant A has 232 sheets (2 floors), B has 246 sheets (2 floors), C has 245 sheets (1 floor), and D has 76 sheets (1 floor). Restaurant A, B and C are large restaurants that have 200 dishes on their menu. Meanwhile, C is a smaller restaurant that provides 50 dishes.

To grasp the operation speed and load using conventional POS, serving time of a dish from taking the order to finish preparation of it are checked at those restaurants for a week before the ISS was introduced. After ISS is introduced, staffs receive operational training to master operation method of ISS functions. Objectives of this study keep secret to them to avoid their prejudice and behavioral noise. Order-received time and dish served time is measured by same
method. (Restaurant A: from September 28, 2009, B: from February 12, 2010, C: from May 12, 2010, D: from May 10, 2010). Data on the customers who made reservation were excluded for analysis. To compare effectiveness of two systems, we used the same number of orders for analysis (A=967, B=1074, C= 327, D=940 orders using POS and ISS). Fig. 4 shows the frequency distribution of preparation time of a dish from order-receipt to preparation finish using conventional POS and ISS.

Fig. 4 Frequency distribution of preparation time (min.) of a dish from order-receipt to preparation finish.

Using ISS, the averaged serving time of all dishes from taking the order to finish preparation was significantly improved in restaurant A and B (A: from 8.98 min. (POS) to 8.34 min (ISS). F(1, 2136)=8.399, p<0.05, B: from 7.66 min. (POS) to 6.60 min. (ISS), F(1,1930)=24.130, p<0.01). On the other hand, there is no significant difference in that between POS and ISS in restaurant C and D (C: from 10.06 min. (POS) to 9.88 min. (ISS), D: 7.56 min. (POS) to 7.63 min. (ISS)). The authors suppose the reason for those results as follows.

Restaurant A and B are large restaurants, and received many orders at the same time. Therefore, the order checking display might help staff members to check the number of orders and elapsed time of each order. Especially for orders of lunch sets, nabe, sashimi, and sushi, we found improvement in averaged preparation time. However, we could not find improvement in other categories such as dessert, boiled dish, soup, baked dish, dinner set, fried dish, and simmered dish. One simple reason is that production capacities of those categories are limited. The staffs cannot be helped when they have many orders at once.

As for restaurant C, we could not find significant improvements in the preparation time although restaurant C is as large as restaurant A and B. This result might be because of reservation rate. The reservation rate of restaurant C is approximately 70%, is much higher than other restaurants (A: 38%, B: 23%). Therefore, this result needs to be further investigated.

As for restaurant D, the averaged preparation time of lunch sets seemed to get worse (approx. 7.7 min. (POS) to 8.5 min. (ISS)). Because this restaurant mainly provides fried dishes for lunch sets, production capacity could be limited by the availability of cooking equipment. As for other categories, we could not find big difference between POS and ISS. Although we still have some problems to be solved, we explore a new function of ISS to support communications and collaborations among staff members according to those results.

4 Conclusions
This study discusses process management problems of restaurants, introducing our challenges to elucidate the customer behaviors using POS data and to promote information sharing among staffs using a new POS system. We hope those challenges of service engineering will help not only restaurant businesses but also other service industries.

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References