Mobile Ticket Dispenser System with Waiting Time Prediction

Yun-Wei Lin[1] and Yi-Bing Lin[2], *Fellow*, *IEEE*
[1]Institute of Information Science, Academia Sinica, Taiwan
e-mail: jyneda@gmail.com
[2]Department of Computer Science, National Chiao Tung University, Taiwan
e-mail: liny@csie.nctu.edu.tw

***Abstract*—A ticket dispenser (TD) is used to assist customers for the waiting process in, e.g., a shop. This paper deploys a mobile ticket dispenser system (MTDS) with waiting time prediction to enhance user experience in waiting. For example, the MTDS for a restaurant allows a customer to remotely draw a ticket for meal order anywhere through a smart phone before she/he arrives at the restaurant and therefore reduces her/his waiting time. We propose an output indicator and develop a discrete event simulation model to investigate the performance of the MTDS. Our study indicates that the waiting times can be more accurately predicted without consuming much wireless network resources and power consumption of mobile devices.**

***Index Terms*—ticket dispenser, user experience, wireless communication, waiting time prediction, queueing analysis**

I. Introduction

Ticket dispensers (TD) are used in supermarkets, retail shops, post offices or anywhere that large groups need to be assisted in the ordering process. When a customer draws a number from the ticket dispenser, the number represents the customer's order in the waiting queue. Traditional TDs require a customer to be physically presents in, for example, a restaurant to draw the ticket, and then waits for her/his turn to get the meal she/he ordered. A popular restaurant always has a long queue of customers. Therefore, it is typical that people spend long times waiting in the queue before their orders are complete, and user experience is not good. This issue can be resolved by wireless and mobile technologies. Specifically, a mobile ticket dispenser system (MTDS) allows a customer to remotely draw a ticket for meal order anywhere through a smart phone. With the MTDS, a customer can order before arriving at the restaurant, and the waiting time can be significantly reduced. However, the customer may arrive later than her/his order is complete by the restaurant, and receives a "cold" meal. Therefore, how to advise customers with precise predicted waiting times is essential to improve user experience.

Y. W. Lin is with the Institute of Information Science, Academia Sinica, Taipei 11529, Taiwan, R.O.C. (e-mail: jyneda@gmail.com).
Y. B. Lin is with the Department of Computer Science, National Chiao Tung University, Hsinchu 30010, Taiwan, R.O.C. and also with the Institute of Information Science, Academia Sinica, Taipei 11529, Taiwan, R.O.C. (e-mail: liny@csie.nctu.edu.tw).

Existing studies [1-4] on remote reservation and booking focus on the user interface designing, the customer list management, and the booking service. Waiting time prediction is seldom investigated. This paper develops an MTDS with waiting time prediction based on the client-server architecture. Through wireless connectivity, before a customer arrives at the restaurant, the MTDS can accurately predict the waiting times via the message exchange between the MTDS server and the MTDS client to improve user experience.

This paper is organized as follows. Section II introduces the proposed mobile ticket dispenser system (MTDS). Section III investigates the waiting time prediction mechanism. Section IV proposes an analytic model for the MTDS and investigates the performance of the MTDS by numerical examples, and the conclusions are given in Section V.

II. A Mobile Ticket Dispenser System

A mobile TD system (MTDS) consists of the MTDS server (Fig. 1 (a)) and the MTDS client (Fig. 1 (b)). We have implemented the MTDS server in an open service platform called "BuddySquare" [5]. The MTDS can be connected to a mobile network such as 3G or LTE (Figs. 1 (c) and (d)) [6-7]. Alternatively, it can be connected to the Wi-Fi network (Fig. 1 (e)). The MTDS follows the client-server model where an MTDS client is downloaded from an app store and installed in a smart phone, or is implemented in a web site that can be directly accessed by a smart phone. The MTDS application can also work with a feature phone, where tickets are delivered by Short Message Service (SMS). A customer can use the MTDS client to send an order request to the MTDS server through the Internet (Fig. 1 (f)). The communication path is established between the MTDS client and the MTDS server through (b)-(c)-(d)-(f)-(a) for 3G/LTE service or (b)-(e)-(f)-(a) for

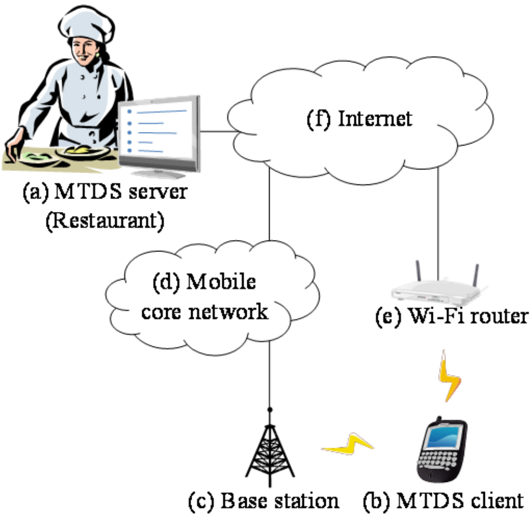

Fig. 1: The MTDS system architecture.

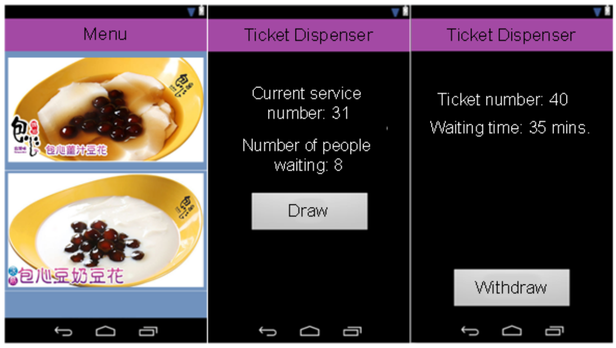

Fig. 2: The user interface of the MTDS client.

Wi-Fi service. Fig. 2 illustrates the user interface of the MTDS client we implemented.

Without loss of generality, consider a to-go restaurant that allows customers to order meals through the MTDS. When a customer uses the MTDS client to make a meal order at time t_0, if there are n-1 orders in the waiting queue of the restaurant, then we denote the customer as C_n. Customer C_n will receive a pair of ticket numbers (n_a, n_a+n) from the MTDS server, where n_a is the ticket number of the order being served by the cook at t_0 or the number of the order completed by t_0 if the cook is idle, and n_a+n is the dispensed ticket number for C_n. Without loss of generality, assume that there is one cook in the restaurant (our model can be directly extended for multiple cooks). For n>1, when C_n draws the ticket, the cook is working on an order, n-1 orders are in the waiting queue, and C_n's order will be the n-th order in the waiting queue. If n=1, then either the cook is idle or is working on an order, and C_n's order will be the only one in the waiting queue. When C_n arrives at the restaurant, if the (i+n_a)-th order is in service, where $i \leq n$, then C_n should wait.

The MTDS works with the following steps:

Step 1. A customer uses the MTDS client to order a meal from the to-go restaurant.

Step 2. The order request is sent to the MTDS server. The MTDS server issues a pair of ticket numbers (n_a, n_a+n) to the customer. Denote the customer as C_n. The MTDS server also suggests the predicted waiting time t when C_n's ticket is issued (i.e., at t_0). We will elaborate more on t later.

Step 3. The restaurant handles the meal orders following the FIFO (first in first out) discipline.

Step 4. Before arriving at the restaurant, C_n may be informed of "adjusted waiting times" several times; In other words, the MTDS dynamically adjusts the predicted waiting time for better accuracy. The details will be given in Section 5.

Step 5. C_n arrives at the restaurant and shows the ticket number (in the MTDS client) to get the ordered meal when it is ready.

In Step 2, we assume that the restaurant always handles the meal orders following the FIFO discipline no matter when the corresponding customer arrives at the restaurant. In other words, the ordered meal may be prepared before the customer arrives. In this scenario, both the cook and customers are "patient". The restaurant may exercise a prepaid mechanism to guarantee that the money is always received even if the customer does not show up. On the other hand, the customer always comes to pick up her/his order so that the prepaid money will not be wasted. We will address the scenario for impatient customers and/or the cook (who will drop the orders) in a separate paper and will not be elaborated here.

III. The Waiting Time Prediction Mechanism

The waiting time of C_n is the summation of services times for the orders ahead of C_n when her/his MTDS ticket is issued. Suppose that C_n requests the MTDS ticket at time t_0. Let τ_i be the service time of order i in the waiting queue, where i=0 to n. That is, τ_n is the service time for C_n. If the cook is not idle at t_0, then let $\bar{\tau}_0$ be the residual service time of the order being handled by the cook at t_0 (i.e. between the arrival of C_n's order and when the service for the first order is complete). Let τ be the actual order-ready time for C_n. Then

$$\tau = \begin{cases} \tau_1 & \text{, the cook is idle at } t_0 \\ \bar{\tau}_0 + \sum_{i=1}^{n} \tau_i & \text{, the cook is busy at } t_0 \end{cases} \quad (1)$$

From (1), a simple equation to predict the waiting time by using the means of $\bar{\tau}_0$ and τ_i can be expressed

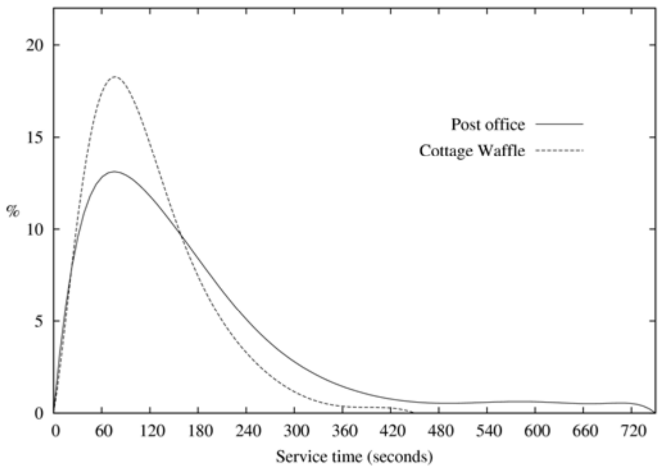

Fig. 3: The service time measured for post office and Cottage Waffle.

$$t = \begin{cases} E[\tau_1] & \text{, the cook is idle at } t_0 \\ E[\bar{\tau}_0] + \sum_{i=1}^{n} E[\tau_i] & \text{, the cook is busy at } t_0 \end{cases} \quad (2)$$

From the residual life theorem [8], $E\left[\bar{\tau}_0\right]$ in (2) is expressed as

$$E[\bar{\tau}_0] = \frac{V + (E[\tau_0])^2}{2E[\tau_0]}$$

where V is the variance of the service times τ_i, for $i \geq 0$. In (2), the τ_i distribution depends on the service behavior of the cook in the restaurant (or the clerk of the post office). In this study, we actually measured the service times for two service examples during January, 2014. The first example is the post office in National Chiao Tung University. The second example is a bake shop called "Cottage Waffle" which provides freshly baked waffles. Fig. 3 shows the service time distributions of the post office and Cottage Waffle. In the first example, the mean service time of the post office is $E[\tau_i]$=158.3 seconds and variance V=23805.9=0.95$E[\tau_i]^2$. In the second example, the mean service time of Cottage Waffle is $E[\tau_i]$=112.8 seconds and variance V=10051.8=0.79$E[\tau_i]^2$. A Gamma distribution is used to fit the sampled service times. The Gamma distribution is selected because it can be shaped to represent many distributions as well as measured data [9-10]. A Gamma density function with the shape parameter γ and the scale parameter λ is

$$f(\tau_i) = \frac{\lambda^\gamma \tau_i^{\gamma-1} e^{-\lambda \tau_i}}{\Gamma(\gamma)} \quad (3)$$

where $\Gamma(\gamma) = \int_{\tau=0}^{\infty} e^{-\tau} \tau^{\gamma-1} d\tau$, and $\gamma > 0$.

In our observation, most stores with skillful services can

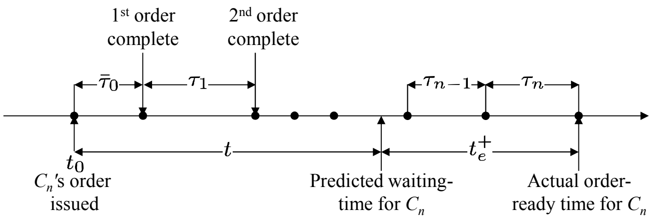

Fig. 4: The timing diagram.

control the service time variances such that $V \leq E[\tau_i]^2$. If γ=1 in (3), i.e., V=$E[\tau_i]^2$, then both $\bar{\tau}_0$ and τ_i are exponentially distributed, and the waiting time τ of C_n has an Erlang distribution. In this scenario we can consider another waiting time prediction equation based on exponential service times with the mean $E[\tau_i]$=1/λ. That is, the predicted waiting time t has the Erlang density function with the shape parameter n and the scale parameter λ:

$$f(t) = \frac{\lambda^n t^{n-1} e^{-\lambda t}}{(n-1)!} \quad (4)$$

For the two service examples we observed in January, 2014, the variances V of the service times in one month are 0.95$E[\tau_i]^2$ and 0.79$E[\tau_i]^2$, respectively.

IV. The Analytic Model

Suppose that C_n makes a meal order at time t_0 through a smart phone, and the MTDS server suggests a predicted waiting time t at Step 2 of Section 2. The predicted waiting time t described in Section 3 can be considered as a random variable. Suppose that random variable t has the density function $f(t)$. Fig. 4 illustrates the timing diagram for C_n's order, where τ_i is the service time of order i, and $\bar{\tau}_0$ is the residual service time of the order being handled by the cook at time t_0 (when C_n's MTDS ticket is issued). The actual order-ready time for C_n is expressed in (1).

Assume that $\tau_0, \tau_1, ..., \tau_n$ are independent and identically distributed (i.i.d.) random variables. The predicted waiting time t is used to predict τ for C_n, and its accuracy can be estimated by

$$t_e = |\tau - t| \quad (5)$$

which is the error between the actual order-ready time τ and the predicted waiting time t. That is, the prediction is accurate if t_e is small. If τ_i has the density functions $g_i(\tau_i)$ and the Laplace transforms $g_i^*(s)$, then τ is also a random variable, and its density function $g(\tau)$ and Laplace transform $g^*(s)$ can be derived as follows. Suppose that $\bar{\tau}_0$ has the density function

$r_0(\tau_0)$ with Laplace transform $r_0^*(s)$. If $g_0(\tau_i)$ is nonlattice, then from the residual life theorem [5], we have

$$r_0^*(s) = \frac{1-g_0^*(s)}{sE[\tau_0]}$$

From the convolution of the Laplace transforms, $g^*(s)$ is expressed as

$$g^*(s) = \begin{cases} g_1^*(s) & \text{, the cook is idle at } t_0 \\ r_0^*(s)\prod_{i=1}^{n} g_i^*(s) & \text{, the cook is busy at } t_0 \end{cases} \quad (6)$$

Since τ_i are i.i.d. random variables, $g_i(\tau_i) = g_j(\tau_j)$, where $0 \le i, j \le n$, and (6) is re-written as

$$g^*(s) = \begin{cases} g_i^*(s) & \text{, the cook is idle at } t_0 \\ r_i^*(s)[g_i^*(s)]^n & \text{, the cook is busy at } t_0 \end{cases} \quad (7)$$

If C_n actually arrives at the restaurant at the predicted waiting time t, and the (i+n_a)-th order is in service, where $i \le n$, then $\tau > t$, and C_n should wait for the period $\tau - t$. In contrast, if $i > n$, then $\tau < t$ and C_n may get a cold meal. The probability that $\tau > t$ can be expressed as

$$Pr[\tau > t] = \int_{\tau=0}^{\infty}\int_{t=0}^{\tau} f(t)g(\tau)dtd\tau$$

From (5), let $t_e^+ = E[t_e|\tau > t]Pr[\tau > t]$ be the error of the predicted waiting time when $i \le n$ and $t_e^- = E[t_e|\tau < t]Pr[\tau < t]$ be the error when $i > n$. Then t_e^+ is derived as

$$\begin{aligned} t_e^+ &= E[t_e|\tau > t]Pr[\tau > t] \\ &= \int_{\tau=0}^{\infty}\int_{t=0}^{\tau} (\tau - t)f(t)g(\tau)dtd\tau \\ &= \int_{\tau=0}^{\infty}\int_{t=0}^{\tau} \tau f(t)g(\tau)dtd\tau - \int_{\tau=0}^{\infty}\int_{t=0}^{\tau} tf(t)g(\tau)dtd\tau \\ &= A - B \end{aligned} \quad (8)$$

Suppose that t has an Erlang distribution with parameters n and λ (i.e. the prediction equation (4) is used), then the first term of (8) is

$$\begin{aligned} A &= \int_{\tau=0}^{\infty}\int_{t=0}^{\tau} \tau g(\tau)\left[\frac{\lambda^n t^{n-1}e^{-\lambda t}}{(n-1)!}\right]dtd\tau \\ &= \int_{\tau=0}^{\infty} \tau g(\tau)\left\{1 - \sum\nolimits_{j=0}^{n-1}\left[\frac{(\lambda\tau)^j}{j!}\right]e^{-\lambda\tau}\right\}d\tau \\ &= E[\tau] - \sum\nolimits_{j=0}^{n-1}\left(\frac{\lambda^j}{j!}\right)\int_{\tau=0}^{\infty}\tau^{j+1}g(\tau)e^{-\lambda\tau}d\tau \\ &= E[\tau] + \sum\nolimits_{j=0}^{n-1}\left[\frac{(-\lambda)^j}{j!}\right]\left[\frac{d^{j+1}}{ds^{j+1}}g^*(s)\right]\Bigg|_{s=\lambda} \end{aligned} \quad (9)$$

The second term of (8) is

$$\begin{aligned} B &= \int_{\tau=0}^{\infty}\int_{t=0}^{\tau} t\left[\frac{\lambda^n t^{n-1}e^{-\lambda t}}{(n-1)!}\right]g(\tau)dtd\tau \\ &= \int_{\tau=0}^{\infty} g(\tau)\left(\frac{n}{\lambda}\right)\left[1 - \sum\nolimits_{j=0}^{n}\left(\frac{\lambda^j}{j!}\right)\tau^j e^{-\lambda\tau}\right]d\tau \\ &= \left(\frac{n}{\lambda}\right)\left\{1 - \sum\nolimits_{j=0}^{n}\left[\frac{(-\lambda)^j}{j!}\right]\left[\frac{d^j}{ds^j}g^*(s)\right]\Bigg|_{s=\lambda}\right\} \end{aligned} \quad (10)$$

If τ_i has a Gamma distribution with mean $1/\lambda$ and variance V, then the Laplace transform of $g_i(\tau_i)$ is

$$g_i^*(s) = \left(\frac{1}{Vs\lambda + 1}\right)^{\frac{1}{V\lambda^2}}$$

In (7), if the cook is idle, the term $\frac{d^j}{ds^j}g^*(s)$ in (10) is expressed as

$$\frac{d^j}{ds^j}g^*(s) = (-V\lambda)^j\left(\frac{1}{Vs\lambda+1}\right)^{\frac{1}{V\lambda^2}+j}\left[\prod_{l=1}^{j}\left(\frac{1}{V\lambda^2} + l - 1\right)\right] \quad (11)$$

In (7), if the cook is busy at t_0, the term $\frac{d^j}{ds^j}g^*(s)$ in (10) is expressed as

$$\frac{d^j}{ds^j}g^*(s) = \left(\frac{1}{E[\tau_i]}\right)\sum\nolimits_{l=0}^{j}\begin{pmatrix} j \\ l \end{pmatrix}\left[\frac{(-1)^l l!}{s^{l+1}}\right] \times\left\{\frac{d^{j-l}}{ds^{j-l}}[g_i^*(s)]^n - \frac{d^{j-l}}{ds^{j-l}}[g_i^*(s)]^{n+1}\right\} \quad (12)$$

In (12),

$$\frac{d^{j-l}}{ds^{j-l}}[g_i^*(s)]^n = \begin{cases} [g_i^*(s)]^n & \text{, for } j-l=0 \\ n\left\{\sum_{k=0}^{j-l-1}\begin{pmatrix} j-l-1 \\ k \end{pmatrix}\times\left\{\frac{d^k}{ds^k}\{[g_i^*(s)]^{n-1}\}\right\}\left[\frac{d^{j-l-k}}{ds^{j-l-k}}g_i^*(s)\right]\right\} & \text{, for } j-l=1,2,...,j \end{cases}$$

For Gamma τ_i distribution, if the cook is idle at t_0, then from (9), (10), and (11), (8) is expressed as

$$t_e^+ = \left(\frac{1}{\lambda}\right)\left(\frac{1}{V\lambda^2+1}\right)^{\frac{1}{V\lambda^2}} \quad (13)$$

If the cook is busy at t_0, then from (9), (10), and (12), (8) is expressed as

$$t_e^+ = E[\tau] - \left(\frac{n}{\lambda}\right) + \lambda\left\{\sum\nolimits_{j=0}^{n-1}\sum\nolimits_{l=0}^{j+1}\begin{pmatrix} j+1 \\ l \end{pmatrix}\left[\frac{(-\lambda)^j}{j!}\right]\left[\frac{(-1)^l l!}{\lambda^{l+1}}\right]\right.$$

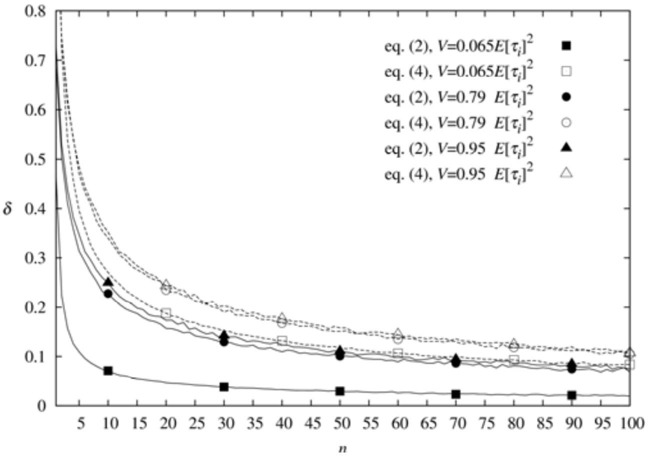

Fig. 5: Accuracy of prediction equations (2) and (4) against *n*.

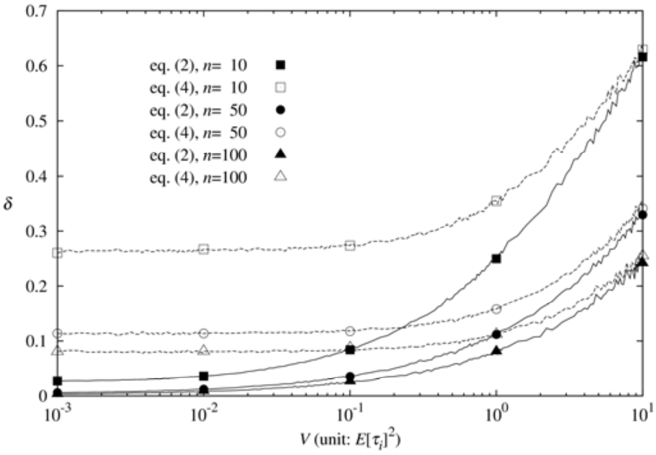

Fig. 6: Accuracy of prediction equations (2) and (4) against *V*.

$$\times\left\{\left[\frac{d^{j-l+1}}{ds^{j-l+1}}\left(\frac{1}{Vs\lambda+1}\right)^{\frac{n}{V\lambda^2}}\right]\Bigg|_{s=\lambda}-\left[\frac{d^{j-l+1}}{ds^{j-l+1}}\left(\frac{1}{Vs\lambda+1}\right)^{\frac{n+1}{V\lambda^2}}\right]\Bigg|_{s=\lambda}\right\}\Bigg\}$$
$$+n\left\{\sum_{j=0}^{n}\sum_{l=0}^{j}\binom{j}{l}\left[\frac{(-\lambda)^j}{j!}\right]\left[\frac{(-1)^l l!}{\lambda^{l+1}}\right]\right.$$
$$\left.\times\left\{\left[\frac{d^{j-l}}{ds^{j-l}}\left(\frac{1}{Vs\lambda+1}\right)^{\frac{n}{V\lambda^2}}\right]\Bigg|_{s=\lambda}-\left[\frac{d^{j-l}}{ds^{j-l}}\left(\frac{1}{Vs\lambda+1}\right)^{\frac{n+1}{V\lambda^2}}\right]\Bigg|_{s=\lambda}\right\}\right\} \tag{14}$$

Similarly, t_e^- is derived as

$$\begin{aligned} t_e^- &= E[t_e|\tau<t]\Pr[\tau<t] \\ &= \int_{\tau=0}^{\infty}\int_{t=\tau}^{\infty}(t-\tau)f(t)g(\tau)dtd\tau \\ &= \int_{\tau=0}^{\infty}\int_{t=\tau}^{\infty}tf(t)g(\tau)dtd\tau-\int_{\tau=0}^{\infty}\int_{t=\tau}^{\infty}\tau f(t)g(\tau)dtd\tau \\ &= C-D \end{aligned} \tag{15}$$

The first term of (15) is

$$\begin{aligned} C &= \int_{\tau=0}^{\infty}\int_{t=\tau}^{\infty}tg(\tau)\left[\frac{\lambda^n t^{n-1}e^{-\lambda t}}{(n-1)!}\right]dtd\tau \\ &= \left(\frac{n}{\lambda}\right)\sum_{j=0}^{n}\left[\frac{(-\lambda)^j}{j!}\right]\left[\frac{d^j}{ds^j}g^*(s)\right]\Bigg|_{s=\lambda} \end{aligned} \tag{16}$$

The second term of (15) is

$$\begin{aligned} D &= \int_{\tau=0}^{\infty}\int_{t=\tau}^{\infty}\tau g(\tau)\left[\frac{\lambda^n t^{n-1}e^{-\lambda t}}{(n-1)!}\right]dtd\tau \\ &= -\sum_{j=0}^{n-1}\left[\frac{(-\lambda)^j}{j!}\right]\left[\frac{d^{j+1}}{ds^{j+1}}g^*(s)\right]\Bigg|_{s=\lambda} \end{aligned} \tag{17}$$

For Gamma τ_i distribution, if the cook is idle at t_0, substitute (16) and (17) into (15) to yield

$$t_e^- = \left(\frac{1}{\lambda}\right)\left(\frac{1}{V\lambda^2+1}\right)^{\frac{1}{V\lambda^2}} \tag{18}$$

If the cook is busy at t_0, then (15) is expressed as

$$t_e^- = n\left\{\sum_{j=0}^{n}\sum_{l=0}^{j}\binom{j}{l}\left[\frac{(-\lambda)^j}{j!}\right]\left[\frac{(-1)^l l!}{\lambda^{l+1}}\right]\right.$$
$$\left.\times\left\{\left[\frac{d^{j-l}}{ds^{j-l}}\left(\frac{1}{Vs\lambda+1}\right)^{\frac{n}{V\lambda^2}}\right]\Bigg|_{s=\lambda}-\left[\frac{d^{j-l}}{ds^{j-l}}\left(\frac{1}{Vs\lambda+1}\right)^{\frac{n+1}{V\lambda^2}}\right]\Bigg|_{s=\lambda}\right\}\right\}$$
$$+\lambda\left\{\sum_{j=0}^{n-1}\sum_{l=0}^{j+1}\binom{j+1}{l}\left[\frac{(-\lambda)^j}{j!}\right]\left[\frac{(-1)^l l!}{\lambda^{l+1}}\right]\right.$$
$$\left.\times\left\{\left[\frac{d^{j-l+1}}{ds^{j-l+1}}\left(\frac{1}{Vs\lambda+1}\right)^{\frac{n}{V\lambda^2}}\right]\Bigg|_{s=\lambda}-\left[\frac{d^{j-l+1}}{ds^{j-l+1}}\left(\frac{1}{Vs\lambda+1}\right)^{\frac{n+1}{V\lambda^2}}\right]\Bigg|_{s=\lambda}\right\}\right\} \tag{19}$$

We have developed a discrete-event simulation model to compute $E[\tau]$, $E[t]$, t_e^+, and t_e^- for prediction equation (4). The approach is similar to the one in [11]. Equations (13), (14), (18) and (19) are used to validate against simulation experiments, where the errors between the analytic model and the simulation experiments are within 1%. Then we extend the simulation model to accommodate the prediction equations (2). Define δ as the accuracy indicator expressed as

$$\delta = \frac{|\tau - t|}{\tau} = \frac{t_e}{\tau}$$

where t is computed by prediction equations (2) and (4). As we mentioned, the smaller the δ value, the better the prediction. Based on the experiments, we make the following observations.

Effect of *n*: Fig. 5 illustrates the δ curves for prediction equations (2) and (4), where V=0.065$E[\tau_i]^2$, 0.79$E[\tau_i]^2$, and 0.95$E[\tau_i]^2$, respectively. The figure indicates that δ decreases as n increases. In other word, both equations (2) and (4) are more accurate as n increases. Prediction equation (2) is more accurate than (4) for a small n. For large n and V, both equations have similar accuracy performance.

Effect of service times' variance V: Fig. 6 plots the δ values against V for equations (2) and (4), where n = 10, 50, and 100. The figure shows that the predictions are more accurate for small V or large n. The figure also indicates that (2) is more accurate than (4) for small V. Both equations have same accuracy when V is large. Although (4) assumes $V=E[\tau_i]^2$ and was expected to fit better for τ_i with large V, Figs. 4 and 5 indicate that (2) always outperforms (4). In the remainder of this paper, we only consider (2) for waiting time prediction.

Figs. 5 and 6 show that accuracy of the prediction is highly affected by the variance V of service times and the number n of orders in the waiting queue. The accuracy indicator δ is large (i.e., the error t_e is large) when V is large. Based on the above discussion, the waiting time prediction is accurate when n is large and V is small for both prediction equations (2) and (4).

V. Conclusion

This paper developed a mobile ticket dispenser system (MTDS) with waiting time prediction that enhances user experience in the ordering process. We investigated the impact of the queue length n and the variance of the service times V on accuracy of predicted waiting time. An analytic model was proposed to model the waiting time prediction. The analytic results were used to validate against the simulation experiments. We define the indicator δ to evaluate the MTDS performance. The accuracy indicator δ describes the error rate between the actual order-ready time and the predicted waiting time. Our study indicated that δ decreases as V decreases or n increases; that is, the MTDS can effectively assist the ordering process for a popular restaurant that is crowded (with large waiting queue length n) and the cook prepares meals with good management on controlling the service times with small variance V.

In summary, we have developed an MTDS system and provided guidelines to predict the waiting time. Specifically, we showed how to predict the waiting time by the MTDS for good user experience.

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