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Announcing Delay Information to Improve Service in a Call Center With Repeat Customers

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ABSTRACT We study the model of predicting and announcing delays, including customer satisfaction and repeat the behavior. In a call center, anticipated delays affect the customer behaviors of balking and reneging; we characterize the level of satisfaction with delay information to modulate customer reactions. In reality, a customer reacts by repeating behavior upon entering the service with a full perception of the delay. In particular, customers may feel dissatisfied when entering service because they have experienced a delay that is longer than announced. That is how satisfaction with delay information and waiting time affects customers' repeat behavior. Generally, customers may arrive at a higher rate when they are satisfied with the anticipated delay and the waiting experience in a call center. We characterize such performance measures using an M/M/S+M queue model. The revenue of a call center is generated by serving customers, and each time a customer abandons a call, the system loses revenue. Interestingly, the model reveals the revenue from the repeat behavior of satisfied customers. The formula used to approximate the arrival process reveals that traditional research could systematically underestimate the total number of call-ins and revenue. We show how call center managers can determine the most economically optimal anticipated delay so that they can control the trade-off between revenue loss and revenue from satisfaction.

INDEX TERMS Behavioral queuing, call center, delay information, repeat behavior, satisfaction.

I. INTRODUCTION

In an invisible queue, informing customers of their anticipated waiting time has become a common use of technology, and such information can directly affect customers' behavior and influence their level of satisfaction. Here, we focus on the arriving customers' decision to wait for service and to repeat their behavior according to their levels of satisfaction with the delay information provided and their experiences waiting.

Making delay information available is especially important in call centers. Customers have no means of anticipating queue lengths, making the uncertainty involved in delay timing high. A maxim in the psychology of waiting is that ''uncertain waits feel longer than known finite waits'' [26], and uncertain wait times have been correlated with lower levels of satisfaction [29]. Delay information affects customers' reactions in terms of abandonment (balking and reneging behavior). Furthermore, when the announced length of a delay is longer than the actual delay, the customer may no longer call the center because of a lack of trust. Therefore, delay information can have a distinct role in increasing customers' patience by reducing the uncertainty of the waiting time in a queue.

A satisfied customer will be more likely to choose service from the same call center again than a dissatisfied customer. In the field of customer relationship management, Anderson and Sullivan [3] have shown that customer satisfaction is a good predictor of the likelihood of repeated purchases and revenue growth, and prior research has shown that customers react negatively to poor service by abandoning the firm [14]. In call center settings, the service encounter is unlike face-to-face service encounters at other service sites, such as restaurants, hotels, and banks. Therefore, the best means of providing and controlling customer satisfaction with a call center may be providing products and service efficiently and quickly.

Currently, more managers are beginning to emphasize the importance of providing delay information to improve

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customer satisfaction. First, it is a relatively inexpensive way to improve customer satisfaction. Second, satisfaction with the announced delay times affects customer' behavior. Managers would like to have repeat calls and more business from customers and therefore offer good customer service, provided they are able to maintain their revenue stream.

To the best of our knowledge, this is the first generalization of the delay information queuing model to incorporate customer satisfaction. Traditionally, queuing theory has modeled customer arrival at a call center as an external factor, as if arrivals follow a well-known distribution, without considering the potential impact on return, e.g., whether customers who are treated well might return to the firm or dissatisfied customers might not return. Little attention has been paid to repeat behavior with feedback about customer satisfaction or to feedback on satisfaction with the delay information provided. In particular, previous research usually ignored the role of satisfaction with delay announcements. In practice, customers may feel dissatisfied when they merely enter the service, thereby never choosing the firm because they do not trust the delay information provided.

The current study has been in part motivated by these trends in call centers for the retail service industry, including insurance companies, retail banks, and telephone booking companies. They sell products and services through the delivery channels of call centers, aiming for revenue. Changes have been taking place in the consumer/retail segment of these industries. As mature service delivery channels, call centers need to balance traditional efficiency and quality goals with the new emphasis on customer relationship management. That means instigating similar changes in how call centers function.

In this paper, there is one behavioral mechanism by which customer satisfaction with delay information can affect the classical queuing model. We study the problem from the point of view of a firm that uses a call center. In dealing with satisfaction, this paper is based on the queue model with feedback [18]. We further capture situations in which the arrival rate, including repeat customers, depends on customer satisfaction with the delay information provided. The equilibrium arrival rate is calculated by the fixed points algorithm. We derive a closed-form formula in order allow the call center to maximize its profit.

In predicting delays for arriving customers, this paper builds on previous analytical studies, such as the work of Jouini *et al.* [20]. They analyze a call center with impatient customers and derive the influence of the delay announcement on the customers' balking and reneging behavior. In this paper, we refer to a model that addresses how the system's performance affects customer behavior. Customers strategically choose whether to return; thus, the equilibrium arrival rates of the queuing system are determined by the performance measures.

The rest of this is structured as follows. In the next section we discuss a brief review of literature. Section 3 formulates the queuing model with delay information that is embedded in the revenue maximization problem, and addresses two issues of delay information satisfaction and repeated behavior. The form is relevant for applications in service system with delay information, especially for call centers with very impatient customers. In Section 4, we conduct a numerical analysis for exploring for the effectiveness of the proposed delay announcements, then provide the analysis on how to make optimal delay information coverage probability in order to get optimal revenue. Section 5 provides the conclusion to the paper and discusses the future research directions.

II. LITERATURE REVIEW

There is an increasing number of studies of the impact of delay information on system performance in an invisible queue. One of the first representative papers is by Hassin [17], who studies the problem of revealing the queue length to arriving customers from the perspective of a revenue-maximizing manager. Whitt [33] models the effect of providing information on performance to customers of a call center, and shows how services can be improved by providing anticipating delay times to customers. Armony and Maglaras [5], [6] consider a system where the service manager provides the customers with an estimate of the delay, and a customer may balk or wait based on this information. Aksin *et al.* [4] combine modeling and empirical analysis in an analysis of delay announcements in a call center. Jouini *et al.* [21] propose a new framework making use of a news-vendor-like performance criterion to pick the value to announce from the estimated delay distribution.

It is a real phenomenon that customers decide to balk and renege after receiving delay information from a call center, which shows that delay information impacts customer abandonment. Armony *et al.* [7] study the performance impact of making delay announcements to arriving customers in a many-server queue setting with customer abandonment. Jouini *et al.* [20] study a model where customers react by hanging up immediately upon hearing the delay announcement if the announced waiting time is too long, and might subsequently renege because of impatience. Research has found that informing customers of delays is beneficial regardless of the model used, but the optimal amount of precision in the announcements varies from model to model. Guo and Zipkin [16] study a model in which customers are provided with delay information and make decisions based on their expected waiting times. They find that different information may hurt the utility of the service provider.

A number of authors, including Luo *et al.* [25], Carmon *et al.* [11], and Zhou and Soman [35] have paid attention to customer psychology in waiting situations. They focus on evaluating how waiting time affects customer satisfaction and how to minimize customer dissatisfaction with the waiting process, however, there are few papers that go one step further and analyze how waiting time impacts customer returns and referrals. Haxholdt *et al.* [18] and van Ackere *et al.* [31] present a queuing model with feedback, which exhibits the dependence of the arrival rate on the wait time. However, they make use of a simulation method with the service rate modeled as a decision variable. Recently, van Ackere *et al.* [30] have started to develop a behavioral model in which customers come and go based on waiting time with simulation method.

The relevance of this research is evident in the burgeoning practitioner literature on customer relationship management. Hui and Tse [19] and Kumar *et al.* [23] study the relationship between information and customer satisfaction. Some investigations show that customer satisfaction results in repeat business and increases the firm's profitability [8], [27]. Law *et al.* [24] focus on the effect of waiting time on repurchasing behavior and customer satisfaction in some service industries. Likewise, Chen [12] posits that the customer satisfaction level is an important factor that may affect the effectiveness of a loyalty program. In addition, customer satisfaction with waiting time affects customer loyalty [10]. For call centers, Dean [13] notes that service quality could affect customer loyalty to a call center, and he investigates real customers of an insurance company and a bank using call centers to validate his perspectives.

The current paper can be positioned in the literature above. A key characteristic of this paper is that we examine the metrics related to both customer satisfaction and arrival rates, and account for the characteristic that revenues are a direct function of delay announcements. This distinction will be discussed further below.

III. BASIC MODEL

In this section, we develop a model in which the service process contains two stages with feedback and the service provider announces the anticipated wait time to an arriving customer immediately. A customer's experience while using the call center consists of two parts: one part is waiting for service and service in the queue; the other part is deciding what to do, including repeat and queuing behavior. Behavior in the queue will be analyzed, and then we will focus on customers' equilibrium arrivals when they are satisfied with the delay information provided. The objective of the model is to maximize call center's revenue.

A. THE QUEUING SYSTEM WITH DELAY INFORMATION

We consider a firm that offers a homogenous product through a call center, such as a telephone booking system or any retail telemarketing firm. When the queuing process takes abandonment into account, this model can be viewed as an M/M/S+M queuing system with balking and reneging. The model doesn't differentiate the first call from customer return with the loyalty, and customers are served on FCFS without any priority. Especially, abandonment is not allowed once a customer starts service. Performance measures are derived, and system optimization is established.

System Parameters:

- λ_e : The equilibrium arrival rate
- μ : The service rate($1/\mu$ is the average service time)
- s : The number of servers (the decision variable)
- n : The number of customers waiting in the queue($n \geq 0$)
- T : The initial random patience threshold of the customers
- γ : An exponential distribution rate for the customer patience threshold
- ρ : The load on the system($\rho = \lambda_e / s\mu$)

On arriving, a new customer could get service immediately if the number of customers in the system is less than s. If all of the agents are busy, the customers have a probability α_0 of balking before any delay information is provided. This features models a portion of extremely impatient customers who call with the idea to hang up at once while they need to wait of service. The remaining customers may decide to balk due to the delay information or to accept the announced delay. We denote the distribution of a customer's virtual delay after hearing the information by D_n, where n is the number of waiting customers ahead of her or him and virtual waiting is defined as the waiting time of each customer who does not abandon the call. Let d_n denote the announced delay and $p^B(n)$ denote the probability of balking when the random patience threshold exceeds the delay d_n. We assume that the balking behavior of customers is independent,

$$p^B(n) = P(T < d_n) = 1 - e^{-\gamma d_n}. \tag{1}$$

If a customer who waits in the queue after hearing the delay information, it means the customer is willing to wait in queue only a certain amount of time. We continue to model another behavior of reneging. If the service has not begun by this certain amount of time, reneging would happen. Make her updated patience threshold is still exponentially distributed with rate γ'. Let $g_n(t)$ and $G_n(t)$ denote the probability density function of D_n and the cumulative distribution function of D_n. Jouini *et al.* [20] drive the expression,

$$g_n(t) = \sum_{i=0}^{n} \left(\prod_{j=0, j\neq i}^{n} \frac{s\mu + j\gamma'}{(j-i)\gamma'} \right) (s\mu + i\gamma') e^{-(s\mu + i\gamma')t}, \tag{2}$$

$$G_n(t) = 1 - \sum_{i=0}^{n} \left(\prod_{j=0, j\neq i}^{n} \frac{s\mu + j\gamma'}{(j-i)\gamma'} \right) e^{-(s\mu + i\gamma')t}, \quad t \geq 0. \tag{3}$$

In this model, we announce to the customer the delay d_n discussed and reviewed in Jouini *et al.* [20], where d_n corresponds to a given coverage probability β. The virtual delay of a new customer cannot exceed the anticipated delay with this probability. The announced delay is given by

$$d_n = G_n^{-1}(\beta) \tag{4}$$

Let t_k denote the initial patience threshold of the kth customer. In such a system, customers will update their patience threshold according to d_n and the initial random patience threshold t_k to the value $\theta t_k + (1-\theta) d_n$, where $\theta > 0$, upon hearing the delay information. In previous research,

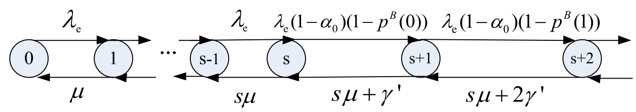

FIGURE 1. Birth-death processes in the model.

the coefficient of the new patience threshold, θ, was modeled as a fixed value. In addition, we assume that θ is a random variable with a distribution.

We derive some related steady state probabilities by making use of PASTA property (Wolff.1982). Birth and death rates are both state-dependent as shown in Figure 1.$p(i)$ denotes the probability that a number i of customers are present in the system at a random instant ($i > 0$) in the steady state. Let $L(t)$ denote the system state representing the number of customers in the call center at $t \geq 0$, where $\{L(t), t \geq 0\}$ is a Markov birth-and-death process. When the system reaches a steady state, new and repeat customers enter the call center at the rate λ_e. If $i < s$, all of the arriving customers can enter the system immediately; thus, the birth rates are λ_e, and their departures signal service completion. Otherwise, if $i \geq s$, an arriving customer will immediately balk upon hearing the announced delay; thus, the birth rates are $\lambda_e(1-\alpha_0)\left(1-p^B(n)\right)$ according to the analysis above. In this case, the departures represent service completion or customer abandonment, making the death rates equal to $s\mu + (i-s)\gamma'$.

In the stationary regime, the steady-state probabilities are given by

$$p(i) = \frac{\lambda_e^i}{i!\mu^i}p(0) \quad \textit{for } 1 \leq i \leq s,$$
$$p(i) = \frac{\lambda_e^i}{s!\mu^s}\left(\prod_{j=1}^{i-s}\frac{1-p^B(j-1)}{s\mu+j\gamma'}\right)p(0) \quad \textit{for } i > s, \tag{5}$$

and

$$p(0) = \left(\sum_{i=0}^{s}\frac{\lambda_e^i}{i!\mu^i} + \sum_{i=s+1}^{\infty}\frac{\lambda_e^i}{s!\mu^s}\left(\prod_{j=1}^{i-s}\frac{1-p^B(j-1)}{s\mu+j\gamma'}\right)\right)^{-1}. \tag{6}$$

Given these, it is straightforward to derive the probability of immediate service P^I: $P^I = \sum_{i=0}^{s-1} p(i)$. Thus, the mean number of customers in queue L_q is $L_q = \sum_{i=1}^{\infty} ip(s+i)$.

Jouini *et al.* [20] derive the performance of the conditional probability that a customer will renege, $r_n(\theta)$:

$$r_n(\theta) = 1-\beta-\sum_{i=0}^{n}\left(\prod_{j=0,j\neq i}^{n}\frac{s\mu+j\gamma'}{(j-i)\gamma'}\right) \times\frac{s\mu+i\gamma'}{s\mu+\frac{\gamma}{\theta}+i\gamma'}e^{-(s\mu+i\gamma')d_n}, \tag{7}$$

In what follows, we assume that the new patience threshold θ is a random variable. We calculate the conditional probability $r_n(\theta)$ as the expected value, assuming the new patience threshold θ is uniformly distributed and rescaled within the range $[a, b]$. Returning to Equation (7), we have

$$\begin{aligned} r_n(\theta) &= \frac{1}{b-a}\int_a^b (1-\beta\text{-}\sum_{i=0}^{n}\left(\prod_{j=0,j\neq i}^{n}\frac{s\mu+j\gamma'}{(j-i)\gamma'}\right) \\ &\quad \times\frac{s\mu+i\gamma'}{s\mu+\frac{\gamma}{\theta}+i\gamma'}e^{-(s\mu+i\gamma')d_n})d\theta \\ &= 1-\beta-\sum_{i=0}^{n}\left(\prod_{j=0,j\neq i}^{n}\frac{s\mu+j\gamma'}{(j-i)\gamma'}\right) \\ &\quad \times\frac{s\mu+i\gamma'}{s\mu+\frac{\gamma}{\theta}+i\gamma'}e^{-(s\mu+i\gamma')d_n} \\ &\quad \cdot\left(1-\frac{\gamma}{(b-a)\cdot(s\mu+i\gamma')}\right. \\ &\quad \left.\cdot\ln\left(\left((b-a)\cdot(s\mu+i\gamma')+\gamma\right)/\gamma\right)\right) \end{aligned} \tag{8}$$

In particular, the special scenario in which $a = b = 0$ is the complete update case, which represents all customers updating their initial patience threshold to the announced delay. The quantity $r_n^0(\theta)$ is

$$r_n^0(\theta) = P(d_n < D_n | T > d_n). \tag{9}$$

Because the initial patience threshold T and D_n are independent, we can state

$$r_n^0(\theta) = P(d_n < D_n) = 1-\beta. \tag{10}$$

With an intuitive understanding of the conditional probability $r_n^0(\theta)$: once a customer is in the queue, she or he abandons it if and only if the announced delay is shorter than the actual delay.

At the same time, the new reneging rate γ' is calculated by applying the fixed point algorithm.

$$\gamma' = \frac{\lambda}{L_q}\sum_{n=0}^{\infty}(1-p^B(n))p(s+n)r_n. \tag{11}$$

We define the satisfaction index P_c as the service level at which customers react to announced delays upon entering service. It is true in practice that these customers will feel dissatisfied even if they enter the service because they have experienced a delay that they perceived to be longer than the initially announced delay. Satisfaction with the delay information provided has no influence on these customers' experience this time. However, P_c determines whether a customer will return later or choose to leave forever. We can write this measure of satisfaction with the delay information provided as

$$P_c = P\left(\frac{\text{virtual delay}}{\text{announced delay}} \leq 1 \,|\text{entering the service}\right). \tag{12}$$

Next, we derive an expression for a customer's satisfaction with the delay information, P_c, which is the conditional probability that a customer is satisfied with the announced delay upon experiencing service in the system, given that the customer's initial patience threshold exceeds the announced delay. We assume that customers who receive immediate service are satisfied with the delay information; therefore P_c is given in two parts, P_{c1} and P^I.

$$P_c = P^I + P_{c1}. \tag{13}$$

Because the customers entering the service do not balk when $d_n < T$, we obtain

$$\begin{aligned} &P(D_n \leq d_n | \theta t_k + (1-\theta) d_n \geq D_n) \\ &\quad = P(D_n \leq d_n) \\ &\quad = \beta \end{aligned} \tag{14}$$

Next, we can state that

$$\begin{aligned} P_c &= P^I + \beta \cdot \sum_{n=0}^{\infty} (1-\alpha_0)(1-p^B(n)) p(s+n) \\ &= P^I + \beta(1-\alpha_0) \cdot \sum_{n=0}^{\infty} e^{-\gamma d_n} p(s+n). \end{aligned} \tag{15}$$

Finally, the probability of a new arrival balking is denoted by p^B, the probability of reneging by p^R, the probability of entering service by p^S, and the probability of entering service dissatisfied by P'_c:

$$\begin{aligned} &p^B = \sum_{n=0}^{\infty} p^B(n) p(s+n), \quad p^R = \frac{\gamma' L_q}{\lambda_e} \\ &p^S = 1 - p^B - p^R, \quad P'_c = p^S - P_c \end{aligned} \tag{16}$$

B. ANALYSIS OF REPEAT CUSTOMER BEHAVIOR

Consider a firm selling a good or service through a call center to customers who purchase the good or service repeatedly, for example the booking ticket system in telephone networks. Customers gain more value from a higher quality level and incur a cost due to wait time; these customers choose the call center based on the expected value of the service. Furthermore, they may repeat the purchase, depending on the quality experienced and perceived. As one of customers satisfaction issue, delay announcements impact the behaviors of customers in a complicated way by Yu *et al.* [34]. It may also be that customers would appreciate cheap talk more than accurate delay information, see Allon *et al.* [2]. In this paper, we mainly address the issue that customers will be dissatisfied when their experienced delay exceed the delay information provided. Thus, we make the assumption that two major variables impacting repeated behavior are wait time and satisfaction with delay information.

Following Gandomi and Zolfaghari [15], we address the problem with the assumption that only a certain proportion of the customers who purchased a product in the last period will purchase again in the current period. In the queue model-handling method, we refer to more details on analysis of call centers with retrials by Aguir *et al.* [1] and Pustova [28].

This proportion is modeled by the parameter c_i. c_i is the probability that a customer becomes a repeat customer in the next period. $(1 - c_i)$ is the proportion of customers who fail to proceed to the call center. The potential probability of repeat behavior c_i depends greatly on the specific industry of the call center. For example, c_i is expected to be relatively high for a call center providing a ticket booking service because the service frequency is sufficiently high that people would prefer a higher-quality service. We consider different levels of repeat behavior $c_i \in [0, 1]$. The parameter i determines the repeat property of customer queue behavior. Customers who have reneged have experienced longer delays, leading them to leave with lower satisfaction levels than balking customers, thus the parameter c_3 representing the probability of balking repeatedly is higher than the parameter c_4 representing the probability of reneging repeatedly. In addition, customers entering the service have different perceptions of the delay information due to comparisons between the announced delay and the virtual delay. It is true in practice that a customer who will experience a delay longer than announced may lose trust in the call center, thus the value of c_1 is larger than the value of c_2. Let λ_{new} be the original customer arrival rate. We assume that λ_{new} depends strongly on the size of the call center. We can directly derive the equilibrium arrival rate λ_e,

$$\lambda_e = \lambda_{new} + \left(c_1 P_c + c_2 P'_c + c_3 p^B + c_4 p^R\right) \lambda_e. \tag{17}$$

This equilibrium model falls into the class of product form networks described by Baskett *et al.* [9]; therefore, the stationary behavior of the queuing model will not depend on the distribution of repeated behavior delays. Then they can be ignored.

C. PROVIDING OPTIMAL DELAY INFORMATION

In our model, the revenue of the system generated by serving a customer is denoted by *TR*. If a customer is lost, the call center will incur a revenue loss. The current setting of the coverage probability assumes this revenue loss occurs, and controls the trade-off between abandonment behavior and repeat behavior. Therefore, the service provider needs to solve the following unconstrained problem:

$$TR = \max_{\beta} \left\{ p^S \cdot \lambda_e(\beta) \right\}. \tag{18}$$

For the case of a loss in the system, the objective function takes this simple form because this type of loss can be expressed by the equilibrium rate of customers entering the service. It would be straightforward to incorporate the costs of maintaining customer satisfaction with the delay and the delay information provided in the form of technological anticipation.

The problem formulated above is easy to solve because the abandonment probability and equilibrium rate are embedded in the revenue expression. This paper uses an algorithm to obtain the equilibrium arrival rate λ_e and an enumeration method to obtain the desired economically optimal coverage probability solution.

Then, the solution of the equilibrium arrival rate becomes calculating the root of equation (17). The intermediate variable λ_e can be obtained using a fixed-point algorithm (see, for example, Karamardian and Garcia [22]), which is described as follows:

Fixed Point Algorithm

Initialization: $\lambda_e^{(0)} \leftarrow \lambda_0, i \leftarrow 0, \varepsilon$

Do

$i \leftarrow i + 1$

$\lambda_e^{(i)} \leftarrow \lambda_{new} + \left(c_1 P_c + c_2 \left(p^S - P_c\right) + c_3 p^B + c_4 p^R\right) \lambda_e^{(i-1)}$

While $\left|\dfrac{\lambda_e^{(i)} - \lambda_e^{(i-1)}}{\lambda_e^{(i-1)}}\right| > \varepsilon$

$\lambda_e \leftarrow \lambda_e^{(i)}$

End Algorithm

IV. NUMERICAL EXPERIMENTS

In this section, we first measure the performance of the model, including customer satisfaction with delay information and abandonment behavior, when various system parameters, including announcement coverage and customer patience, are varied. Then, we show the effect of different repeat behavior on the call center upon customer satisfaction and compare system revenue without repeat behavior with heavy repeat behavior and with light repeat behavior. Finally we explore the optimal announcement behavior and optimal system revenue. The global parameters are $\alpha_0 = 0.05$, $\gamma = 0.5$, and $\mu = 1$.

A. THE EFFECT OF ANNOUNCEMENT COVERAGE β ON SATISFACTION WITH DELAY INFORMATION

To illustrate the performance of customer satisfaction with delay information, we first consider the six performance parameters p^R, p^B, P_{c1}, P^I, P'_c and p^S as functions of the system size. To observe the performance of customer behavior in the role of coverage probability clearly, we remove repeat behavior by making $c_1 = c_2 = c_3 = c_4 = 0$, which means the system is in the efficiency- and quality-driven regime. These performances are for each $\lambda_{new} \in \{5, 10, 20, 50\}$ and the patience update interval value (a, b) is $(0, 1/3)$.

In terms of abandonment behavior, we obtain a conclusion similar to Jouini's conclusion [20], shown in Table 1. The coverage probability β controls the trade-off between balking and reneging behavior. The abandonment behavior rule under the given coverage probability is consistent even when taking account of the uniform distribution of the updated patience threshold parameter θ. We also show the probability of entering service p^S, which is increased with β until it reaches its maximum, then is gradually decreased.

TABLE 1. Performance measures for different coverage probabilities β.

β	p^R	p^B	P_c: P_{c1}	P_c: P^I	P_c'	p^S
$s = \lambda_{new} = 5$						
0.1	0.186	0.035	0.041	0.554	0.184	0.779
0.2	0.167	0.046	0.084	0.534	0.169	0.787
0.3	0.146	0.058	0.129	0.513	0.154	0.796
0.4	0.124	0.071	0.175	0.491	0.138	0.804
0.5	0.1	0.087	0.222	0.469	0.122	0.813
0.6	0.073	0.105	0.269	0.448	0.105	0.822
0.7	0.045	0.125	0.311	0.431	0.088	0.83
0.8	0.021	0.148	0.34	0.428	0.064	0.832
0.9	0.01	0.17	0.338	0.454	0.028	0.82
$s = \lambda_{new} = 10$						
0.1	0.134	0.027	0.038	0.589	0.212	0.839
0.2	0.12	0.034	0.08	0.564	0.202	0.846
0.3	0.105	0.041	0.127	0.536	0.191	0.854
0.4	0.087	0.05	0.178	0.505	0.18	0.863
0.5	0.065	0.061	0.234	0.471	0.169	0.874
0.6	0.04	0.073	0.294	0.438	0.155	0.887
0.7	0.018	0.085	0.348	0.418	0.131	0.897
0.8	0.012	0.096	0.38	0.429	0.084	0.893
0.9	0.006	0.11	0.395	0.451	0.038	0.884
$s = \lambda_{new} = 20$						
0.1	0.094	0.023	0.036	0.617	0.231	0.884
0.2	0.083	0.027	0.078	0.584	0.228	0.89
0.3	0.068	0.032	0.126	0.547	0.226	0.899
0.4	0.05	0.039	0.182	0.506	0.223	0.911
0.5	0.026	0.046	0.246	0.463	0.219	0.928
0.6	0.013	0.051	0.301	0.447	0.188	0.936
0.7	0.009	0.056	0.346	0.451	0.138	0.935
0.8	0.006	0.061	0.385	0.458	0.089	0.932
0.9	0.003	0.07	0.413	0.472	0.042	0.927
$s = \lambda_{new} = 50$						
0.1	0.054	0.019	0.033	0.648	0.246	0.927
0.2	0.041	0.022	0.075	0.605	0.256	0.936
0.3	0. 017	0.025	0.12	0.576	0.262	0.958
0.4	0.008	0.029	0.177	0.527	0.259	0.963
0.5	0.007	0.031	0.221	0.527	0.215	0.963
0.6	0.005	0.032	0.264	0.528	0.171	0.963
0.7	0.004	0.034	0.306	0.529	0.128	0.963
0.8	0.003	0.036	0.346	0.532	0.084	0.962
0.9	0.001	0.039	0.381	0.538	0.041	0.96

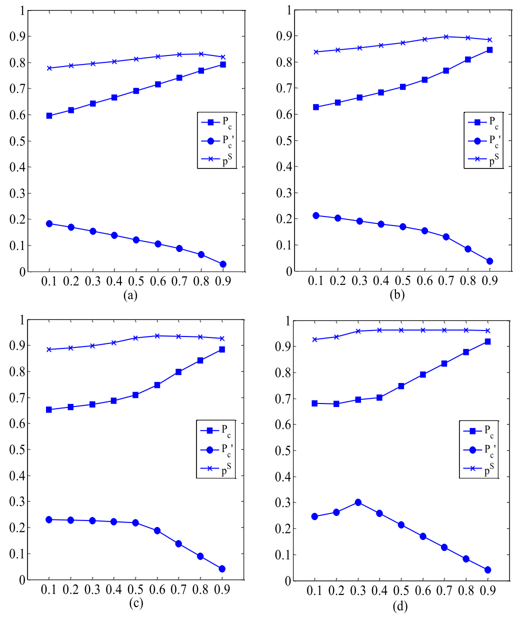

FIGURE 2. Impact of β on delay information satisfaction and dissatisfaction. (a) s=λ=5. (b) s=λ=510. (c) s=λ=20. (d) s=λ=50.

The system size determines the maximum value of the probability of service p^S. This rule shows that a manager attempting to maximize revenue should choose a value for β because of its role in customer behavior.

P_{c1} and P^I are performance measures for customer satisfaction with the delay information provided. Note that β plays both roles in satisfaction with the delay information in this analysis. The higher β values in all system sizes show that P_{c1} always increases, and P_{c1} varies considerably with β. That means that more customers in the queue and entering the service are satisfied with the delay information with β, and at the same time, P_{c1} is insensitive to the system size so that it does tend to vary with the system size. A manager could choose an optimal value for β more carefully by considering the delay information satisfaction objective.

We also provide the probability of immediate service. P^I always decreases with β no matter what the system size is. There is no doubt that customers who receive immediate service have the highest satisfaction level. However, the performance measure of P^I does not vary much with β; this would make an optimal choice of β less critical for satisfying customers who receive immediate service. The flow framework assumes that a customer who is satisfied with the delay information provided is equivalent to a customer who enters the service without waiting, which is not necessarily true in practice because a customer may experience frustration due to waiting.

In figures 2(a)-2(d), we show a comprehensive analysis of delay information satisfaction and dissatisfaction as functions of β.The changes of P_c and P_c' are particularly apparent, but the pooling effect is absent. Delay information satisfaction P_c does vary with β with apparently increasing regularity, in contrast, delay information dissatisfaction P_c' decreases irregularly. Consistent with the previously presented analysis of p^S,this figure shows the probability of a customer entering service according to her or his satisfaction level.

TABLE 2. Impact of patience reaction on performance measures.

(a,b)	p^R	p^B	P_c: P_{c1}	P_c: P^I	P_c'	p^S
β=20%						
(0,0)	0.142	0.011	0.036	0.811	0	0.847
(0,1/3)	0.083	0.027	0.078	0.584	0.228	0.89
(0,2/3)	0.06	0.032	0.09	0.516	0.302	0.908
(0,1)	0.044	0.035	0.098	0.477	0.346	0.921
(0,5/3)	0.008	0.04	0.11	0.412	0.431	0.952
β=40%						
(0,0)	0.129	0.016	0.086	0.769	0	0.855
(0,1/3)	0.05	0.039	0.182	0.506	0.223	0.911
(0,2/3)	0.012	0.045	0.21	0.431	0.302	0.943
(0,1)	0.009	0.045	0.212	0.425	0.309	0.946
(0,5/3)	0.006	0.046	0.214	0.42	0.314	0.948
β=60%						
(0,0)	0.108	0.025	0.162	0.705	0	0.867
(0,1/3)	0.013	0.051	0.301	0.447	0.188	0.936
(0,2/3)	0.008	0.052	0.306	0.438	0.196	0.94
(0,1)	0.006	0.052	0.308	0.435	0.199	0.942
(0,5/3)	0.004	0.053	0.309	0.432	0.202	0.943
β=80%						
(0,0)	0.071	0.043	0.282	0.604	0	0.886
(0,1/3)	0.006	0.061	0.385	0.458	0.089	0.932
(0,2/3)	0.004	0.062	0.388	0.454	0.093	0.935
(0,1)	0.003	0.062	0.389	0.452	0.094	0.935
(0,5/3)	0.002	0.062	0.39	0.45	0.096	0.936

B. THE EFFECT OF PATIENCE PARAMETER VARIATION ON DELAY INFORMATION SATISFACTION

In the previous section, we analyzed system performance as a function of the coverage probability β when the patience variation (a, b) is given. In the section, we explore the effect of varying the patience parameter with the parameter settings $s = 20$, $\lambda_{new} = 20$, and $c_1 = c_2 = c_3 = c_4 = 0$, for five values of (a, b): (0,0), (0,1/3), (0,2/3), (0,1), (0,5/3). The

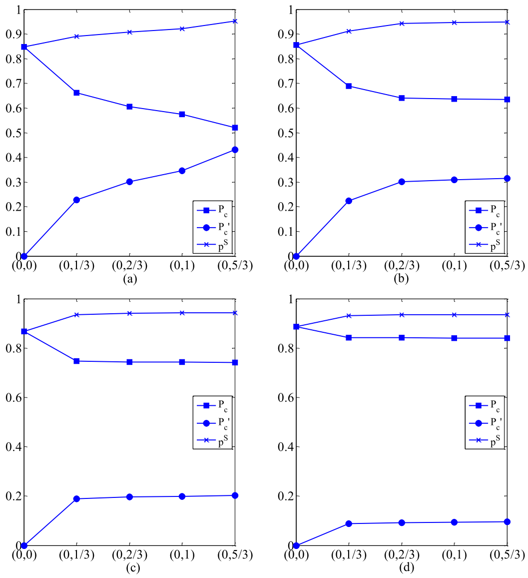

FIGURE 3. Impact of (a, b) on delay information satisfaction and dissatisfaction. (a) $\beta = 0.2$. (b) $\beta = 0.4$. (c) $\beta = 0.6$. (d) $\beta = 0.8$.

coverage probabilities are $\beta = 20\%$, $\beta = 40\%$, $\beta = 60\%$ and $\beta = 80\%$.

Table 2 reveals that the balking probability decreases and the reneging probability increases gradually for a wide range of patience update values (a, b). It is clear that customers who decide to stay for service become more patient when they receive delay information so that fewer customers renege. However, this results in a longer queue, which must lead to more balking customers as a result of longer wait times. Note that the probability of service p^S does vary more and achieve higher values for a wider range of patience update values (a, b) no matter what the coverage probability β is, making the choice of an optimal coverage probability less critical because customers become more patient when they receive delay information.

Second, we show delay information satisfaction and dissatisfaction as functions of a customer's patience reaction in Figures 3(a)-3(d). These changes make it particularly apparent that customers who are less satisfied with the delay information provided have a wider range of patience reactions, but these changes still increase the probability of service p^S. As we can see from Figures 3(a)-3(d), the speed by which delay information satisfaction P_c is decreasing is less than that with which delay information dissatisfaction P'_c is increasing. Therefore, $p^S = P'_c + P_c$ increases until it reaches its unchanged value.

Third, in terms of satisfaction with delay information, having more customers enter service and more patient customers leads to a decrease in the delay information satisfaction probability P_c no matter what the coverage probability β is. P_{c1} increases gradually with a wide range of patience update values. This means that more customers waiting in the queue and entering the service are satisfied with the delay information provided. However, the probability of immediate

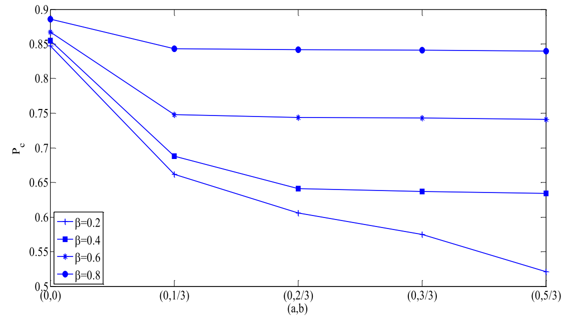

FIGURE 4. Comparison of delay information satisfaction results for different values of β.

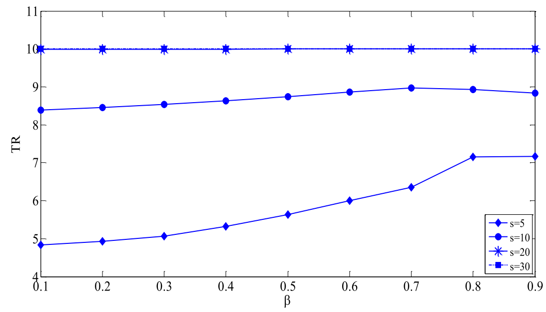

FIGURE 5. Call center revenue without repeat behavior.

service P^I would distinctly decrease because of the increased number of customers in the queue. From another view, shown in Figure 4, the coverage probability β plays a distinct role in decreasing speed of the delay information satisfaction. This is particularly true for small values of β in which delay information satisfaction varies significantly with patience reactions. Therefore, for different ranges of patience update variations, it does matter for a call center manager choosing the correct coverage probability.

C. COMPARISION OF MODELS WITH REPEAT BEHAVIOR

If the probability of repeat behavior c_i is equal to 0 and the equilibrium arrival rate is its original value, the model represents the traditional research setting without repeat customers. As the traditional scenario does not consider repeat behavior, λ_e remains unchanged. Here, based on the experiments of these three scenarios, without repeat behavior, with heavy repeat behavior, with light repeat behavior, we will draw certain conclusions that contrast with the traditional studies and explore the effect of repeat behavior on call center revenue. We consider these models with the parameters $\lambda_{new} = 10$ and $(a, b) = (0,1/3)$.

The performance rules for customer behavior without repeat behavior were introduced in the previous section; therefore, we only introduce the results of call center revenue for each staffing level $s \in \{5, 10, 20, 30\}$ in Figure 5. Obviously, the more the staff there are at the call center, the higher its efficiency is. In Figure 5, we see the call center revenue as a function of the coverage probability without repeat

TABLE 3. Impact of heavy repeat behavior on performance measures.

β	s=5				$s=10$			
	p^S	λ_e	TR	ρ	p^S	λ_e	TR	ρ
0.1	0.392	12.63	4.95	2.526	0.663	14.34	9.51	1.434
0.2	0.38	13.11	4.98	2.622	0.662	14.56	9.62	1.456
0.3	0.367	13.68	5.02	2.736	0.657	14.86	9.77	1.486
0.4	0.379	14.38	5.44	2.876	0.653	15.29	9.99	1.529
0.5	0.427	15.21	6.49	3.042	0.657	15.93	10.46	1.593
0.6	0.562	16.33	9.18	3.266	0.697	16.85	11.73	1.685
0.7	0.604	17.26	10.43	3.452	0.84	18.26	15.4	1.826
0.8	0.714	18.42	13.15	3.684	0.821	19.27	15.82	1.927
0.9	0.655	18.88	12.37	3.776	0.786	20.19	15.87	2.019
β	s=20				$s=30$			
	p^S	λ_e	TR	ρ	p^S	λ_e	TR	ρ
0.1	0.903	19.1	17.25	0.955	0.982	23.32	22.91	0.777
0.2	0.908	19.2	17.43	0.96	0.984	23.36	22.97	0.779
0.3	0.912	19.31	17.61	0.9655	0.985	23.42	23.08	0.781
0.4	0.918	19.41	17.82	0.9705	0.988	23.49	23.21	0.783
0.5	0.939	19.47	18.28	0.9735	0.988	23.64	23.35	0.788
0.6	0.934	19.92	18.61	0.996	0.988	23.8	23.5	0.793
0.7	0.926	20.44	18.94	1.022	0.987	23.97	23.65	0.799
0.8	0.916	21.13	19.34	1.0565	0.986	24.18	23.85	0.806
0.9	0.898	21.94	19.7	1.097	0.984	24.41	24.03	0.814

customers. As β is increased, call center revenue always increases due to the increased probability of a customer entering service. However, the role of coverage probability β mainly depends on the system size in this regime. When the system's congestion is low, the probability of entering service p^S is nearly maximized, which means that the staffing effect improves the call center's performance, thereby reducing the role of the system to the choice of the coverage probability β. In particular, the probability of entering service p^S is 1 when the staffing level s is 20 and the variation with β disappears. That is the reason that the lines with $s = 20$ and with $s = 30$ coincide at the optimal value of p^S.

We choose both models' parameters so that satisfied customers are simply classified into heavy and light with respect to repetition. The heavy user segment has $c_1 = 0.6$, $c_2 = 0.2$, $c_3 = 0.3$, and $c_4 = 0.1$. At the same time, the light user segment has $c_1 = 0.3$, $c_2 = 0.1$, $c_3 = 0.2$, and $c_4 = 0$, for each staffing level $s \in \{5, 10, 20, 30\}$, which is consistent with the repeat characteristics that were analyzed in Section III.B. To maintain consistency with a no-repeat model, we also set $\lambda_{new} = 10$, with the system operating in an efficiency-driven regime.

First, we consider a model with heavy repetition. The results are shown in Table 3. After incorporating repeat behavior, the equilibrium arrival rate increases markedly. For the sake of concision, we only note that the model has different performance than a no-repeat model. The probability of entering service is a curve which changes with increased coverage probability β, this is common to the models with and without repeats. In terms of the system load, a higher staffing level improves the performance measures and compresses the advanced space of repeat behavior, thereby reducing the load on the system.

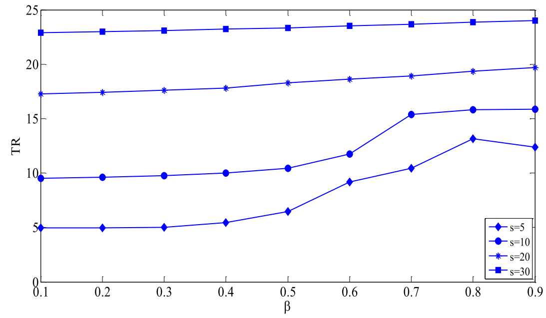

FIGURE 6. Call center revenue with heavy repeat behavior.

TABLE 4. Impact of light repeat behavior on performance measures.

β	s=5				$s=10$			
	p^S	λ_e	TR	ρ	p^S	λ_e	TR	ρ
0.1	0.445	11.03	4.91	2.206	0.75	12.11	9.07	1.211
0.2	0.449	11.24	5.05	2.248	0.754	12.19	9.19	1.219
0.3	0.466	11.49	5.35	2.298	0.758	12.29	9.32	1.229
0.4	0.496	11.77	5.84	2.354	0.763	12.41	9.46	1.241
0.5	0.534	12.09	6.45	2.418	0.768	12.57	9.66	1.257
0.6	0.574	12.42	7.14	2.484	0.785	12.79	10.04	1.279
0.7	0.613	12.76	7.83	2.552	0.851	13.14	11.18	1.314
0.8	0.714	13.21	9.43	2.642	0.834	13.39	11.16	1.339
0.9	0.656	13.38	8.77	2.676	0.806	13.63	10.99	1.363
β	$s=20$				$s=30$			
	p^S	λ_e	TR	ρ	p^S	λ_e	TR	ρ
0.1	0.983	14.04	13.81	0.702	1	14.29	14.29	0.476
0.2	0.985	14.06	13.85	0.703	1	14.29	14.29	0.476
0.3	0.986	14.08	13.88	0.704	1	14.29	14.29	0.476
0.4	0.988	14.1	13.92	0.705	1	14.29	14.29	0.476
0.5	0.989	14.12	13.96	0.706	1	14.29	14.29	0.476
0.6	0.989	14.15	14	0.708	1	14.29	14.29	0.476
0.7	0.99	14.17	14.03	0.709	1	14.29	14.29	0.476
0.8	0.989	14.2	14.05	0.71	1	14.29	14.29	0.476
0.9	0.989	14.23	14.08	0.712	1	14.29	14.29	0.476

In Figure 6, it can be seen that the increasing equilibrium arrival rate λ_e and the curve representing the probability of service p^S both result in changes in call center revenue. However, the role of the coverage probability β also depends on the system size. As it does in the model without repeat behavior, the staffing effect improves the system's performance, thereby reducing the role of the system to the choice of the coverage probability β.

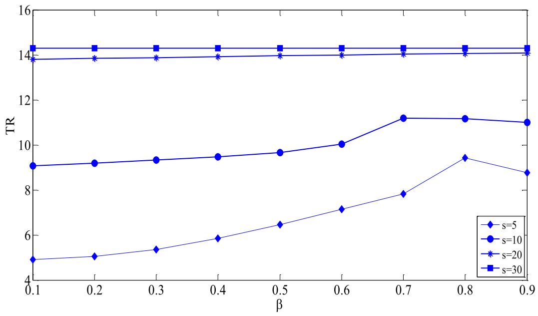

FIGURE 7. Call center revenue with light repeat behavior.

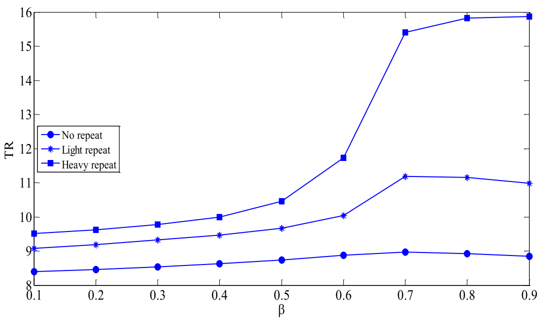

FIGURE 8. Comparison between the models with different repeat levels.

Second, we consider a model with light repeat use in Table 4. The model with light repeat use shows similar trends in the probability of service, equilibrium arrival rate and system load. The difference is that the performance measures do not improve as a result of light use when $s = 30$. We note that the staffing level has an important effect on the choice of optimal β.

According to Figure 7, both models have almost the same trend with respect to call center revenue, which shows that the service level is underestimated in the no-repeat model. All in all, the repeat parameters play an important role in determining the call center's revenue when customer satisfaction is taken into account.

To summarize, Figure 8 shows the different call center revenues for different repeat levels when $s = 10$. As expected, the call center revenue with heavy repeat behavior is always greater than that with no and light repeat behavior because of the repeated revenue. These results verify the underestimation of revenue in traditional research. Clearly, the coverage probability β plays an important role in determining the optimal revenue. Repeat behavior has the effect of increasing the call center's revenue, thereby improving its sensitivity to the optimal coverage probability. This makes the choice of optimal β critical when considering the heavy-repeat case.

D. HOW THE OPTIMAL ANNOUNCEMENT COVERAGE VARIES WITH SYSTEM SIZE

To incorporate delay information satisfaction and repeat behavior into the model, we analyze the optimal announcement coverage for optimal revenue generation as a function

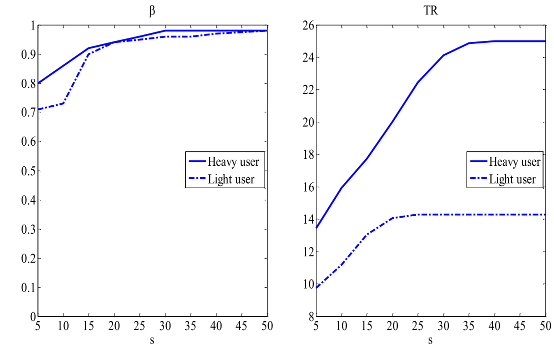

FIGURE 9. Relative optimal β and revenue with different staffing levels.

of the system size in Figure 9. The parameters are $\lambda_{new} = 10$ and $(a, b) = (0, 1/3)$, and the repeat coefficients for heavy use remain $c_1 = 0.6$, $c_2 = 0.2$, $c_3 = 0.3$, and $c_4 = 0.1$, and the light user segment has $c_1 = 0.3$, $c_2 = 0.1$, $c_3 = 0.2$, and $c_4 = 0$ for each staffing level $s \in \{5, 10, 20, 30\}$.

The results with repeat behavior are different from Jouini's results [20], and we note that the optimal announcement coverage gradually increases with the system size. It does matter that a manager chooses a value for β after considering delay information satisfaction and repeat behavior to a greater extent. The performance measure of delay information satisfaction P_{c1} improves with higher values of β, in contrast to Jouini's results, which ignored the customers who were satisfied with the delay information provided. This is one reason that the system needs to provide a higher reliability β when congestion is high. In addition, incorporating repeat behavior allows one to distinguish balking behavior from reneging behavior and other satisfaction behaviors. For larger systems operating in a quality- or efficiency-driven regime, customer satisfaction is still important because of repeat behavior.

V. CONCLUSIONS

In the paper, we formulated and analyzed a call center with anticipated delays to customers, setting delay information satisfaction and customer abandonment metrics. That satisfaction with delay information can be different from the case of Jouini's research as well as repeated behavior impact on call center revenue is another key distinguishing feature of this model.

The numerical analysis illustrates how to balance different behavior satisfaction that has to be made in choosing the announced delay coverage, and demonstrates the role that repeated behavior has on choosing for call center optimal revenue. These results show that managers should provide relatively higher announcement percentile in the presence of different customer satisfaction.

In future work, first, it will be useful to investigate customer behavior with a field data set of call centers. Such work allows a direct comparison between practice and theory approximation. Second, in terms of the systems for different markets, our implementation may encounter problems with regard to customer satisfaction, and further refinements of the method would need to be investigated.

Possible extensions of current analysis are to considering staffing issue while incorporating customer satisfaction. In additional control of announcement coverage, combined with the role of staffing, it is interesting to provide manages with a means of improving system performance and revenue.

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