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A MODEL FOR CONTACT CENTER ANALYSIS AND SIMULATION

Juan M. Huerta

IBM T. J. Watson Research Center
1101 Kitchawan Road
Yorktown Heights, N.Y., 10598, U.S.A.

ABSTRACT

In this paper we depart from a set of simple assumptions regarding the behavior of a pool of customers associated with an enterprise's contact center. We assume that the pool of customers can access the contact center through an array of communication modalities (e.g., email, chat, web, voice). Based on these assumptions we develop a model that describes the volume of demand likely to be observed in such an environment as a function of time. Under the simple initial assumptions, the model we develop corresponds to a mean-reverting process of the type frequently used in energy options pricing. When independence assumptions are relaxed and correlations between user behavior are included, a jump-diffusion component appears in the model. The resulting model constitutes the potential foundation for key simulation-based analyses of the contact center, like capacity modeling and risk analysis.

1 MOTIVATION

Given their importance in modern enterprise organizations, the analysis and study of *contact centers* (which are modern versions of *call centers* capable of handling customer contact using multiple and heterogeneous channels like chat, web, and email in addition to voice) has become the focus of increased attention. Like many other important operations or processes relevant to large enterprises, questions regarding efficiency, cost, quality, and risk are pivotal in delivering a better picture of the state and value of these systems. Furthermore, insights on these operations can provide guidance in terms of optimization and risk management opportunities. Thus, it is important to have models and methodologies that support the objective and consistent analysis of contact centers.

The work that exist today related to call center analysis focuses mainly on answering idiosyncratic operational issues in telephony environments. Specifically, this work is mostly meant to provide support when dealing with call arrival modeling, staffing level decisions, and quality of service issues (e.g., expected waiting times, average service duration, probability of users dropping out, etc). Examples of these analyses and studies include Brown et al. (2002) and Gans, Koole, and Mandelbaum (2003). Essentially, these approaches see a call center as a telephone-call queuing system.

Due to the convergence of voice and data in enterprise communication channels, the emergence of standards like VoIP and SIP, and the push towards increased utilization of web oriented communication channels (like web pages, chat and email) organizations are moving towards the adoption of technologies like universal queues and modality bridges (e.g., voice-to-text conversion through automatic speech recognition). Consequently, enterprises are shifting their perspectives regarding their contact centers into more holistic ones. Because modern contact centers are about the convergence of various modes of communication, classic telephone-centric call center modeling approaches (e.g., calculating expected waiting times using traditional queuing models) could prove insufficient.

In this work, we provide a model of the contact center based on a different perspective: we look into the set of customers that is associated with a center and develop a model of the set of *tickets* that these customers generate. In this work, a ticket is an issue or circumstance that is prone to generate at least one instance of contact center activity (e.g., a phone call, an email, a web chat). The motivation for this approach is related to the fact that in modern contact centers, agents typically simultaneously address and resolve issues coming from various channels. Compounding the problem is the fact that some of these channels are asynchronous and have substantially longer response times than other modalities (contrast email and voice). Thus, it is valuable to model the issues that are likely to generate such contacts as well as the likelihood of contact generation, rather than modeling the way that these contacts get realized (with the exception of self-service contacts, which by definition avoid agent involvement). In this paper, the terms *call* or *contact* refer to an instance of contact center activity that is addressed by an agent, be it text, web-based, email, or voice-based.

We will model the tickets, which as we said, are the reasons why customers increase their likelihood of placing a call into the contact center. We can describe the probability distribution of call placement using a distribution conditioned on the state of the ticket state variable. Without any loss of generality, in this work, for brevity purposes, we equate the ticket status to call placement (i.e., this relationship is deterministic rather than probabilistic).

We derive our initial contact center model making the assumption that the customers switch ticket status randomly following an independent and identically distributed random variable. After relaxing some of our initial assumptions of independence, our final model reflects the occurrence of more complex events in the system, like sudden jumps or spikes in service demand due to underlying correlations in issue generation. Our model also allows the factoring-in of parameters like automation rate which is needed when self-help mechanisms are in place. Thus, our modeling approach is flexible as well as extensible.

Using our model, it is possible to compute expectations of ticket pool size at the end of an operation cycle, and thus produce measurements of expected reward/loss, risk, and other metrics that can aid in performance projection and planning, problem prediction (e.g., degradation in the level of service, etc.), and problem avoidance. Furthermore, these projections that use the proposed model, can be carried out in an on-line fashion, i.e., during the course of an actual operation, and can help measure actual risk conditioned on the current observed state of the system. In this way, our model provides a consistent, parsimonious, and efficient measurement of risk and sensitivity of the ROI (return on the investment) of the operation to changes in the underlying variables and assumptions. It can also facilitate the direct comparison of multiple operations or configurations in a consistent way, and thus can provide support to operation diagnostics, operation planning, performance prediction, as well as business side activities like proposal pricing and support (in operation outsourcing bidding), and effective risk management. These are key activities in the ever more competitive area of contact center outsourcing, consolidation, operation, servicing, consulting, and management.

2 THEORETICAL MODEL

We now derive a model for a contact center departing from a set of basic assumptions. Our goal is to find an equation that describes the behavior of tickets, or issues, associated with a set of customers of an enterprise.

2.1 Terminology and Definitions

Assume an environment $\mathscr{M} = \{A^s, A^d, Q\}$ comprising a finite number of participants. Assume two types of participants: supply agents A^s, and customers (or demand agents) A^d. A supply agent *provides* a service in the environment $\mathscr{M}$, for example answers calls and emails, etc. While a demand agent, or a customer, places the *requests* for services in the form of telephone calls and emails, for example. More specifically, let A^s represent the number of supply agents and let A^d the number of customers in $\mathscr{M}$.

Let customers, or demand agents, have associated with them internal states. For simplicity we consider the case of only two discrete states: OK and NOT-OK. Let the probability of a customer placing a service request given that her internal state is OK during a unit of time be equal to zero and conversely, equal to one when the state is NOT-OK as long as no other ticket has been placed by the customer. A more complex model might describe probabilistically these relations as well as allowing for multiple tickets being generated by a single customer. Finally we assume that the state of a customer is described by a Random Variable and that these RV's are independent and identically distributed across all customers.

Let Q represent the non-priority queue where the tickets that the customers acquire are centralized. Let Q be of infinite length so that no tickets are lost. We denote Q as the *ticket pool*. This queue does not necessarily have a physical equivalent in a contact center environment, but rather, is the logical repository of existing issues. By creating a model for its expected size at any given time, we can derive knowledge regarding other measurements which carry physical meaning, like the expected number of issues active at a time, or the time elapsed in the pool for each issue.

Depending on its internal status at time t a demand agent (a customer) can be in either one of two states: requesting $A_t^{d,r}$ for customers in NOT-OK status, or non-requesting $A_t^{d,\bar{r}}$ state for customers in OK status, so that the sum $A^d = A_t^{d,\bar{r}} + A_t^{d,\bar{r}}$ of demand agents in requesting state and the demand agents in non-requesting state is always equal to A^d.

Let us assume at this point that the discrete process that a non-requesting demand agent follows when switching to a status state (and thus a requesting state and owning a ticket) is independent of extraneous factors and has probability p. Intuitively, at every discrete step a collection of trials (i.e., Bernoulli trials) that the set of non requesting agents will follow when they collectively randomly switch from OK to NOT-OK is a binomial process.

Let us assume we analyze a period of time T. Let us discretize this period into N units of length Δ_t each, such that $T = N\Delta_t$. Thus the variable t has integer values from 1 to N (time steps). At this point we are not making any assumption on the smallness of the time step, we are just discretizing the analysis period.

2.2 Status Switch and Binomial Law

Let us assume that the set of non requesting demand agents collectively execute the status switch experiment at the beginning of every time period. Let us assume that the probability that a specific demand agent will switch its status from non-requesting to requesting agent in the period of time Δ_t is $p_{\Delta_t} = p\ \Delta_t$, where p denotes the switch probability per unit of time, i.e., the rate, and p_{Δ_t} is the analysis-window-duration adjusted probability.

Thus, at time i, the number of non-requesting demand agents that switch to requesting status follows a binomial distribution (i.e., a series of Bernoulli trials), in which the number of independent trials is equal to the number of non-requesting customers at that time, $A_t^{d,\bar{r}}$.

The probability that at period t, and during an analysis window equal to one unit of time (i.e., $p_{\Delta_t} = p$),exactly k_t customers switch their status from non-requesting to requesting is provided by the binomial law:

$$\begin{aligned} b(k_t; A_t^{d,\bar{r}}, p) &= \binom{A_t^{d,\bar{r}}}{k_t} p^{k_t}(1-p)^{A_t^{d,\bar{r}}-k_t} \\ &= \frac{A_t^{d,\bar{r}}!}{(A_t^{d,\bar{r}}-k_t)!k_t!} p^{k_t}(1-p)^{A_t^{d,\bar{r}}-k_t} \end{aligned}$$

where k_t is the number of new tickets placed in Q at the beginning of the t period by demand agents switching status, and b denotes the binomial law which is the probability of getting k successes in n independent tries with individual Bernoulli trial success probability p (Stark and Woods 1986).

We can think of $k_t(p_{\Delta_t}, A_t^{d,\bar{r}})$ as a binomial Random Variable with parameters p_{Δ_t} and $A_t^{d,\bar{r}}$. To stress out the fact that p should be normalized we will use the following notation

$$p(\Delta_t) = p_{\Delta_t} = p\ \Delta_t.$$

Finally, let us assume that the number of supply agents is constant for every t and that the amount of work provided by these agents is r per agent per unit of time, thus during the course of Δ_t, the number of tickets resolved is $r\Delta_t$. This deterministic agent productivity characterization can be later replaced by a more adequate stochastic characterization.

2.3 Pool of Open Tickets

We now derive a stochastic characterization of the size of the pool of open tickets.

Assume that at time t the pool Q has S_t open tickets. At time $t+1$ the number of tickets in Q will be affected by the deterministic closing rate r and by k_t the number of tickets opened at time t (i.e., between $t-1$ and t).

$$\begin{aligned} S_{t+1} &= S_t + k_t(p(\Delta_t), A_t^{d,\bar{r}}) - r\Delta_t \\ &= S_t + \Delta_{S_t} \end{aligned}$$

where

$$\Delta_{S_t} = k_t(p(\Delta_t), A_t^{d,\bar{r}}) - r\Delta_t.$$

Now by making $\Delta_t \to dt$, Δ_{S_t} becomes dS_t

$$dS_t = k_t(p(dt), A_t^{d,\bar{r}}) - rdt.$$

2.4 Asymptotical Brownian Motion: A Stochastic Differential Equation

The R.V. k_t follows a binomial law, and for a large N k_t will converge to a Gaussian R.V. $k_t \sim N(\hat{\mu}_t, \sigma^2)$. Then,

$$dS_t = \hat{\mu}_t - rdt + \sigma dW_t.$$

In the equation above, dW_t is Normal and denotes the Brownian motion process as $dW_t = \varepsilon_t\ \sqrt{dt}$ and $\varepsilon_t \sim N(0, \sigma^2)$, where

$$\begin{aligned} \hat{\mu}_t &= A_t^{d,\bar{r}} p(\Delta_t) \\ &= A_t^{d,\bar{r}} p dt. \end{aligned}$$

while the standard deviation is

$$\sigma = \sqrt{A_t^{d,\bar{r}} \hat{p}(1-\hat{p})}.$$

$\hat{p}$ is a convenience notation referring to the normalization of p for a short period dt. We can relate the size of the customer set, the size of the ticket pool and the number of non-requesting agents using $A_t^{d,\bar{r}} = A_t^d - S_t$. Then,

$$\begin{aligned} dS_t &= \hat{\mu}_t - rdt + \sigma dW_t \\ &= ((A_t^d - S_t)p - r)dt + \sqrt{A_t^{d,\bar{r}} \hat{p}(1-\hat{p})} dW_t. \end{aligned}$$

$$dS_t = (-S_t p + (A_t^d p - r))dt + \sqrt{A_t^{d,\bar{r}} \hat{p}(1-\hat{p})} dW_t.$$

$$dS_t = p((A_t^d - \frac{r}{p}) - S_t)dt + \sqrt{A_t^{d,\bar{r}} \hat{p}(1-\hat{p})} dW_t.$$

2.5 Mean-reverting Brownian Process

The above equation corresponds to a standard mean reverting process.

$$dS_t = \eta(m - S_t)dt + \sigma dW_t \quad (1)$$

where η is the speed of convergence (given by p), m is the mean to where the process reverts to (given by $m = (A_t^d - \frac{r}{p})$). And σ is defined above. This type of mean reverting processes (also known as Ornstein-Uhlenbeck processes)are frequently used as the bases for models to price real options and energy options (e.g., Lari-Lavassani, Sadeghi, and Ware 2000, Deng 2000).

2.6 The Role of Self-help and Automation Rate

We said that r denotes the ticket closure rate which we associated directly with the pool of supply agents. More specifically, r has two components: the work provided by supply agents and the closure rate provided by self-help mechanisms (web pages, FAQ's, IVR etc.). Due to its potential impact, self-help plays a very important role in contact centers (e.g., Suhm and Peterson 2002). While making $r = r_{agent} + r_{self\_help}$, does not change the equations obtained so far, in reality the agent pool and the self help mechanisms have stochastic behavior with distributions and moments that can substantially affect the outcome of the analysis. We will continue assuming a single deterministic r but advise the reader to keep in mind that this is a simplification.

2.7 Relaxing the Customer Independence Assumption

We have assumed that the internal state of the customers that drive the event placement probability is a set of random variables independent across customers. This is an unrealistic assumption, as in typical situations a good number of issues that trigger contact activity in the contact center are caused by events that affect groups of users simultaneously (e.g., product recalls, local environmental phenomena, regional service failure, etc.).

Thus, a more realistic model should include the effect of substantial jumps (up, or down) in the creation of tickets. As we said, such jumps can be associated to sudden events occurring through time and whose nature will depend on events that affect clusters of customers. We model these peaks in demand as a Poisson process and are additive to the demand that is generated due to the independence assumption of the customer status and that we described previously.

In this way, our model becomes a jump-diffusion process, which is a combination of a generalized Wiener process and a Poisson process and is frequently used in Energy Options pricing (Deng 2000). The general form of the equation is

$$dS_t = a(S_t,t)dt + b(S_t,t)dz + (\Phi - 1)S_t dq.$$

In our case,

$$dS_t = \eta(m - S_t)dt + \sigma dW_t + (\Phi - 1)S_t dq.$$

We now make a few modifications in our equation,

$$dS_t = \eta(m - S_t)dt + \sigma dW_t + \hat{\Phi} S_t dq, \quad (2)$$

which more closely resembles the formulation in Cartea and Figueroa (2005) and where dq is the Poisson arrival term with parameter λ_J defined by:

$$dq = \begin{cases} 0 & \text{with probability } 1 - \lambda_J dt; \\ 1 & \text{with probability } \lambda_J dt. \end{cases}$$

and $\hat{\Phi}$ follows a log-normal process, i.e., $\hat{\Phi} \equiv \ln J \sim N(\mu_J, \sigma_J^2)$

The above equation is the final model we assume for our pool of tickets. Depending on the nature of the business that the contact center M is servicing, one can eventually factor seasonality of the demand placed by the customers into the model (Cartea and Figueroa 2005).

3 EXPECTATION, SENSITIVITY, AND PAYOFFS

3.1 Expected Pool Size at Time T and Payoff

Given the model shown in Equation 2, we are now now interested in being able to compute $F(T)$ which is the expected pool size at the end of the period T,

$$F(T) = E_t[S_T]. \quad (3)$$

A more interesting metric, however, relates a cost (or reward) function associated with the number of tickets in the pool. The most straightforward assumption is that the cost or reward attained at time T is directly related to the size of the pool at that time. Then the expected cost-reward after the period T is simply,

$$C_T = E[f(S_T)], \quad (4)$$

where $f(S_t)$ represents the cost-benefit function of the pool size and C_T is the expected cost at time T. We define the *expected payoff* of the contact center as $-C_T$, i.e., the negative of the expected cost.

Other more realistic payoffs would consist of trigger functions that become active if the number of tickets go above (or below) certain thresholds. While making more difficult to compute payoff, these non-linear kind of functions are more realistic.

3.2 Sensitivity to Changes in Parameters and Risk Interpretation

Besides of the contact center expected payoff after time T, we are interested in assessing the sensitivity of this payoff to the model parameters. These metrics reflect the risk of operating a contact center. This situation is analogous to option pricing risk assessment using what collectively is know as *the Greeks* (Crouhy, Galai, and Mark 2001), because they have names taken from the Greek alphabet, which are the family of partial derivatives of C with respect to the parameters of the model (in options pricing C denotes the expected payoff of the instrument). In table 3.2 we show the basic list of Greeks frequently used in financial options modeling as well as the additional partial derivatives that we introduce for our contact center model (last 3 rows in the table).

Table 1: Partial derivatives for risk and sensitivity analysis.

Name (Options Pricing)	Expression
Delta, or price risk	$\delta = \frac{\partial C}{\partial S}$
Gamma, or convexity risk	$\gamma = \frac{\partial^2 C}{\partial S^2}$
Vega, or volatility risk	$\nu = \frac{\partial C}{\partial \sigma}$
Theta, or time decay risk	$\theta = \frac{\partial C}{\partial T}$
Rho, or discount rate risk	$\bar{\rho} = \frac{\partial C}{\partial r}$
Automation risk	$\bar{\rho_A} = \frac{\partial C}{\partial r_{self\_help}}$
Magnitude of Jump Risk	$\bar{\rho_M} = \frac{\partial C}{\partial \mu_J}$
Frequency of Jump Risk	$\bar{\rho_F} = \frac{\partial C}{\partial \lambda_J}$

The most relevant partial derivatives for a contact center are described below:

- Automation or Resolution risk: For contact centers experimenting with self-help technologies (e.g., IVR, language technologies) it is important to measure how sensitive the expected payoff is to automation or resolution rate. The Automation rate r_{self_help} reflects many underlying variables like complexity of the domain, robustness of the application (or training of the agent, if it's an agent oriented environment), and quality of the User Interface (Suhm and Peterson 2002). An environment with low predictability or high variance of the automation rate and high sensitivity to it, would reflect a risky environment to deploy these technologies. Another useful interpretation would be the change in payoff given a change in the automation, providing some guidance on the potential value of investing on technology and improving and robustifying the applications that provide automation.

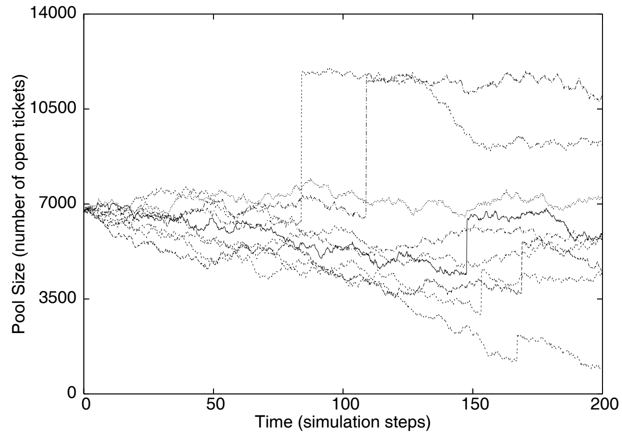

Figure 1: Sample paths.

- Magnitude and Frequency of Jump Risk: This indicator can reveal information on how sensitive our contact center is to bursty call arrival behavior. It could be that a certain contact center provides good expected payoff as long as the call volume is relatively constant and not many *peaks* of calls occur and becomes unstable when the frequency increases.
- Time decay risk: Relates the sensitivity of the payoff as the closure of the term T approaches.

4 SIMULATION BASED ANALYSIS

4.1 Expected Final Pool Size and Expected Payoff

We now illustrate the application of the model to contact center simulation based analysis. We assume an environment with a starting pool containing 6750 open tickets. We are interested in carrying out an analysis spanning 200 units of time (e.g., days).

Figure 1 shows a set of nine sample paths of a Monte Carlo simulation of the Eulerized version of equation 2 with the following parameters: 1000 analysis steps (spanning 200 units of time), the initial ticket pool is 6750 open tickets, tickets are consumed at a rate of 0.4 tickets per time step ($\eta\ dt = 0.4$), the standard deviation for the Brownian process is 100, while the log-Jump process follows a normal distribution with mean 0.75 and variance 0.2. The parameter lambda for the Poisson jump process is 0.0003.

We now compute the distribution of the value of S_T running a total of 100,000 sample path simulations. Figure 3 shows a histogram of the distribution of the ending values. Averaging the results yields an average of 8917 ending tickets while the peak shows at around 4000 tickets.

To compute C_T, the expected cost of operating the contact center, we assume a negative payoff function shown in Figure 2. This simple function means that S_T is larger than the initial number of tickets in the pool S_0, the cost

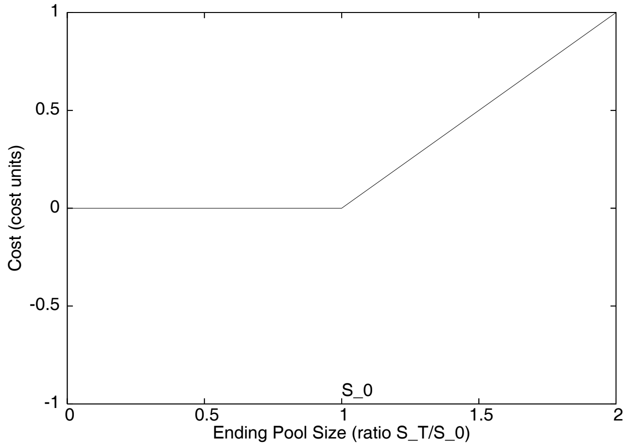

Figure 2: Cost function.

(or negative payoff) is directly proportional to $S_T - S_0$ and is zero otherwise. This function resembles the payoff of a long position of an European call option. We can simply combine Figures 3 and 2 to obtain this value. This type of cost function is valuable for analysis of final contact center state after a fixed period of time T. Another interesting insight, is that it is very easy to evaluate this cost using only the histogram distribution of the values of S_T.

A different kind of cost function triggers a reward/cost only if the path of S_t crosses a certain level (up, down, or either). Let us assume that the function triggers a cost of 10000 if S_t goes above 10000 tickets at anytime and zero otherwise. From Figure1, we can compute this final value by observing that twice the paths crossed the threshold out of nine times, thus the computation of this cost is results in 2222. This cost function is equivalent to a long position in knock-in barrier option. This kind of analysis is valuable when assessing the risk assumed in the contact center operation of going above operation points that can result in failures in Service Level Agreement delivery.

4.2 Sensitivity Analysis

To perform sensitivity analysis we need to compute the partial derivatives described in Table 3.2. To avoid simulating at multiple parameter values the method of path-wise derivative estimation (or infinitesimal perturbation analysis) should be considered (Broadie and Glasserman 1996). We now assume that we are interested in computing the sensitivity of the payoff to changes in S_0 when the payoff C_T follows the equation below, (i.e., an Asian option)

$$C_T = [\bar{S} - K]^+, \bar{S} = \frac{1}{m}\sum_{i=1}^{m} S_{t_i}, 0 < t_1 < \ldots < t_m < T.$$

Following an infinitesimal perturbation approach not only yields an unbiased estimator, but it requires very small computational cost in addition to the path simulation.

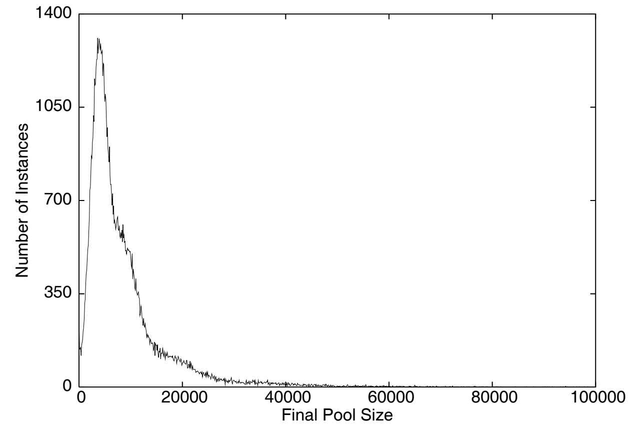

Figure 3: Histogram of S_T

5 DISCUSSION AND FUTURE WORK

In this work we have departed from a set of basic assumptions regarding a contact center environment and arrived at a model that reflects the size of the tickets, or issues, that generate traffic in such environment. This model can be used as a tool to obtain analysis of expected values, expected payoffs, sensitivity and risks. The simulation and analysis methods used on this model are similar to those used in option pricing in general, and electricity options in particular. Thus there is the opportunity to leverage the large amount of work developed in option pricing.

There are two future directions to take the proposed model. The first is about revisiting the underlying assumptions especially those related to independence in issue generation, resolution rate (going from deterministic to stochastic characterizations), seasonality, as well as developing a more accurate description of the contact generation given the status of the user. Additionally, the assumption that only one ticket is held per user can be generalized into a probabilistic model that allows for more than one concurrent ticket per customer; also a set of variable size of demand agents (i.e., customers) could be assumed, which is the reality in enterprises: customer sets grow and shrink.

The second direction takes the model that the current assumptions have taken us to, and focuses on pursuing more computationally efficient and powerful analysis techniques. One example is of course, the application of modeling techniques like binomial trees. But other areas might explore the question of parameter estimation and inference. Bayesian Network frameworks can be used to model and reflect the conditional dependencies across data in the environment.

While the above are just some ideas of where the take the current work, the significance and contribution of this work lies in developing a model that provides the ability of modeling disparate, heterogeneous, and asynchronous modes of accessing a contact center in a consistent, objective, parsimonious, and relatively well justified model. We have also elaborated on and illustrated how this model can be applied in simulation and risk-focused analyses.

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AUTHOR BIOGRAPHY

JUAN MANUEL HUERTA is a Research Staff Member at IBM T.J. Watson Research Center in Yorktown Heights New York. He holds a Ph.D. from Carnegie Mellon University, a M.S. from Boston University, and a B.S. from ITESM. His interest include Speech Recognition; Natural Language understanding, processing, and analytics; as well as the development of models and frameworks for contact center analysis.