Chapter 2
Literature Survey

This chapter consists of 2 main parts: concerned theories and related thesis, journals and articles. First part describes the theories that used in this thesis. Another part presents the related thesis, journals and articles.

2.1 Concern Theories

2.1.1 Simulation

Simulation is defined as "the process of designing a model of a real system and conducting experiments with this model for the purpose of understanding the behavior of the system and/or evaluating various strategies for the operation of the system" [C Dennis Pegden, Robert E. Shannon, and Randall P. Sadowski, 1995, pp. 3].

Simulation is the next best thing to observing a real system in operation. It allows us to collect pertinent information about the behavior of the system by executing a computerized model. Simulation is a technique for estimating the measures of performance of the model system rather than optimization technique [Hamdy A. Taha, 1997, pp. 673].

According to Jerry Bank, John S. Carson II, and Barry L. Nelson (1996, pp. 4) Simulation can be used for the following purposes:

- Simulation enables the study of, and experimentation with, the internal interactions of a complex system, or of a subsystem within a complex system.

- Information, organizational and environmental changes can be simulated and the effect of these alterations on the model's behavior can be observed.

- The knowledge gained in designing a simulation model may be of great value toward suggesting improvement in the system under investigation.

- By changing simulation inputs and observing the resulting outputs, valuable insight may be obtained into which variable are most important and how variables interact.

- Simulation can be used as a pedagogical device to reinforce analytic solution methodologies.

- Simulation can be used to experiment with new design or policies prior to implementation, so as to prepare for what may happen.

- Simulation can be used to verify analytic solutions.

According to C Dennis Pegden, Robert E. Shannon, and Randall P. Sadowski (2000, pp. 9), the advantages of simulation is described below:

- New policies, operating procedures, decision rules, organizational structures, information flows, etc., can be explored without disrupting ongoing operations.

- New hardware designs, physical layouts, software programs, transportation systems, etc., can be tested before committing resources to their acquisition and/or implementation.

- Hypothesizes about how or why certain phenomena occur can be tested for feasibility.
- Time can be controlled: it can be compressed, expand, etc., allowing us to speed up or slow down a phenomenon for study.

- Insight can be gained about which variables are most important to performance and how these variables interact.

- Bottlenecks in material, information, and product flow can be identifies.

- A simulation study can prove invaluable to understanding how the system really operates as opposed to how everyone thing like operates.

- New situations, about which we have limited knowledge and experience, can be manipulated in order to prepare for theoretical future events. Simulation's great strength lies in its ability to let us explore "what if" question.

However, Pegden, Shannon, and Sadowski also describe the disadvantages of simulation listed as follows:

- Model building requires specialized training. The quality of the analysis depends on the quality of the model and the skill of the modeler. Model building is an art, and the skill of practitioners varies widely.

- Simulation results are sometimes difficult to interpret. Because the model is trying to capture the randomness of the real system, it is often hard to determine whether an observation made during a run is due to a significant relationship in the system or to the randomness built into the model.

- Simulation analysis can be time-consuming and expensive. An adequate analysis may not be feasible given available time and/or resources; a "quick and dirty" estimate that uses analytical methods may be preferable.

Almost any type of system can be simulated, and the broard range of modeling applications almost defines classification. According to C Dennis Pegden, Robert E. Shannon, and Randall P. Sadowski (1995, pp. 6-7), some major simulation applications is described below:

- *Computer Systems*: hardware components, software systems, networks of hardware, database structure and management, information processing, reliability of hardware and software.

- *Manufacturing*: material handling systems, assembly lines, automated production facilities, automated storage facilities, inventory control systems, reliability and maintenance studies, plant layout, machine design.

- *Business*: stock and commodity analyses, pricing policy, marketing strategies, acquisition studies, cash flow analyses, forecasting, transportation alternatives, manpower planning.

- *Government*: military weapons and their use, military tactics, population forecasting, land use, health care delivery, fire protection, police services, criminal justice, roadway design, traffic control, sanitation services.

- *Ecology and Environment*: water pollution and purification, waste control, air pollution, pest control, weather prediction, earthquake and storm analysis, mineral exploration and extraction, solar energy systems, crop production.

- *Society and Behavior*: food/population analysis, educational policies, organizational structure, social system analysis, welfare systems, university administration.

- *Biosciences*: sports performance analysis, disease control, biological life cycles, biomedical studies.

Types of simulation models used in this thesis consist of dynamic, discrete, and stochastic simulation models.

According to Averill M. Law and W. David Kelton (2000, pp. 5-6), the types of simulation models mentioned above is describes as follows:

Dynamic Simulation Models

A dynamic simulation model represents a system as it evolves over time, such as a conveyor system in a factory

Discrete Simulation Models

Discrete simulation model describes changes in the status of the system as occurring only at isolated points on time [C Dennis Pegden, Robert E. Shannon, and Randall P. Sadowski, 1995, pp. 6].

Stochastic Simulation Models

Stochastic simulation models concern with the systems that having some random input components. Most queueing and inventory systems are modeled stochastically. Stochastic simulation models produce output that is itself random, and must therefore be treated as only an estimate of the true characteristics of the model.

2.1.2 Discrete-Event System Simulation

The discrete-event systems simulation is the modeling of systems in which the state variable changes only at a discrete set of points in time. The call center system is one of discrete-event systems because its system state is changed only at only at discrete points in time, for example, a system state is defined as the agent status (whether being idle or busy), if there is a new customer that can call to an agent (mean that this agent is available or idle) in a time, that agent will be served that customer at that time, thus the agent status will change from idle to busy.

The major concepts of discrete-event simulation are briefly defined as follows [Jerry Bank, John S. Carson II, and Barry L. Nelson, 1996, pp. 60-61]:

- System: a collection of entities, such as people and machines, that interact together over time to accomplish one or more goals.
- Model: an abstract representation of a system, usually containing structural, logical or mathematical relationships which describe a system in terms of state, entities and their attributes, sets, processes, events, activities, and delays.
- System State: a collection of variables that contain all the information necessary to describe the system at any time
- Entity: any object or component in the system, which requires explicit representation in the model, such as server, customer.
- Attributes: the properties if a given entity such as the priority of a waiting customer.
- List: a collection of associated entities, ordered in some logical fashion such as a customer in a waiting line is ordered by first come, first serve (FIFO).
- Event: an instantaneous occurrence that changes the state of a system such as an arrival of new customer.
- Event notice: a record of an event to occur at the current or some future time, along with any associated data necessary to execute the event; at a minimum, the record includes the event type and the event time.
- Event list: a list of event notices for future events, ordered by time of occurrence, also known as the future event list (FEL)

- Activity: a duration of time of specified length, such as service time or interarrival time, which is known when it begins.
- Delay: a duration of time of unspecified indefinite length, which is not known until it ends, for example, the delay of customer in waiting line may depend on the number and duration of service of other customer.
- Clock: a variable representing simulated time.

2.1.3 Queueing Model

Simulation is often used in the analysis of queueing model. The simple queueing model is shown in figure 2-1.

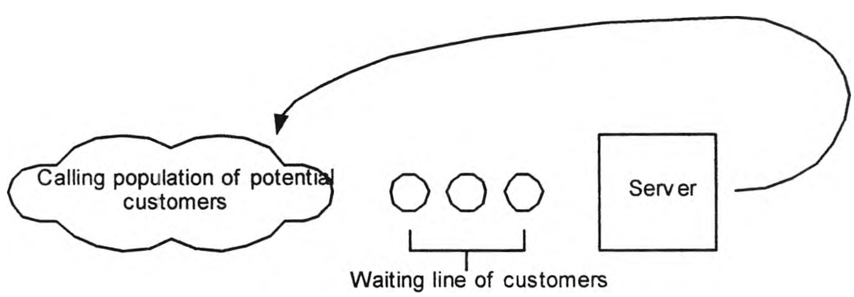

Figure 2-1: Simple queueing model [Jerry Bank, John S. Carson II, and Barry L. Nelson, 1996, pp. 233]

According to Hamdy A. Taha (1997, pp. 607), typical measures of performance of a queueing situation consist of: average customer's waiting time (delays of customers), average queue length (average number of customers who wait for service), and server utilization (percentage of time a server is busy). Queueing theory and simulation analysis are used to predict these measures of performance as a function of the input parameters that consist of: the arrival rate of customers, the service demands of customers, the rate at which a server works, and the number and arrangement of servers [Jerry Bank, John S. Carson II, and Barry L. Nelson, 1996, pp. 234]

Hamdy A. Taha also suggest the elements of queueing system that comprise of:

1. Customers and Servers

   The customer in this case is the people who require some information or want to consult with the bank while the servers are IVR and agents.

2. Interarrival time and Service time

   The arrival process for infinite-population models is typically described in terms of interarrival times of successive customers. Normally, both interarrival time and service time are used in terms of probabilistic rather than deterministic.

The most important model for random arrivals is the Poison arrival process. According to Jerry Bank, John S. Carson II, and Barry L. Nelson (1996, pp. 236-237), "if A_n represents the interarrival time between customer n-1 and n (A_1 is the actual arrival time of the first customer), then for a Poison arrival process, A_n is exponentially distributed with mean $1/\lambda$ time units. The arrival rate is λ customers per time unit. The number of arrivals in a time interval of length t, say $N_{(t)}$, has the Poison distribution with mean λt."

The service times of successive arrivals are denoted by S_1, S_2, S_3, ... In case of random duration, $\{S_1, S_2, S_3, \ldots\}$ is typically characterized as a sequence of independent and identically distributed random variables.

3. Queue Behavior and Queue Discipline

   Queue behavior refers to customer actions while in a queue waiting for service to begin. Customers may jockey from one queue to another because they hope that it can reduce their waiting (move from one line to another if they think they have chosen a slow line). They may also balk from a queue altogether because they see the line is too long, or may renege from a queue because they have been waiting too long.

   Queue discipline represents the order in which customers are selected form a queue. The most widely used discipline for queueing model is first come, first served (FCFS). FCFS is the type of queue discipline in this thesis.

4. Finite Source and Infinite Source

   Finite source limits the customers arriving for service while infinite source has a large population of potential customers. The potential customer of a bank is a type of the infinite population. Thus, the source from which customers are generated in this thesis is infinite.

A simplest queueing system is single-server queueing system. This queueing system consists of one server, such as one agent. However, there are several types of single-server queueing systems. M/M/1, a single-server system that has unlimited queue capacity and an infinite population of potential arrivals while the interarrival times and service times are exponentially distributed, is used as example in this case. According to Jerry Bank, John S. Carson II, and Barry L. Nelson (1996, pp. 258-261), if the value of arrival rate is higher than that of service rate, then the M/M/1 queue has a steady-state probability distribution with steady-state characteristics as given in figure 2-2.

$$\rho = \frac{\lambda}{\mu}$$
$$L = \frac{\lambda}{\mu - \lambda} = \frac{\rho}{1-\rho}$$
$$w = \frac{1}{\mu - \lambda} = \frac{1}{\mu(1-\rho)}$$
$$w_Q = \frac{\lambda}{\mu(\mu - \lambda)} = \frac{\rho}{\mu(1-\rho)}$$
$$L_Q = \frac{\lambda^2}{\mu(\mu - \lambda)} = \frac{\rho^2}{1-\rho}$$
$$P_0 = 1 - \rho$$
$$P_n = \left(1 - \frac{\lambda}{\mu}\right)\left(\frac{\lambda}{\mu}\right)^n = (1-\rho)\rho^n$$

Figure 2-2: Steady-state parameters of the M/M/1 queue [Jerry Bank, John S. Carson II, and Barry L. Nelson, 1996, pp. 261]

Where:

P_n = Steady-state probability of having n customers in system
λ = Arrival rate
μ = Service rate of one server
ρ = Server utilization
L = The number of customers in system
L_Q = The number of customers in queue
w = Long-run average time spent in system per customer
w_Q = Long-run average time spent in queue per customer

2.1.4 Probability and Statistic

As mentioned above, typically, the interarrival time and service time are represented in term of probabilistic. Thus, the theories about probability, such as Poison and exponential distribution, as well as statistic techniques, such as student *t* test are concerned.

2.1.4.1 Poison Distribution

Poison distribution, named after S. D. Poisson (1837), describes many random processes quite well and is mathematically quite simple. According to Erwin Kreyszig (1993, pp. 1180), the Poison probability function is given by

$$f(x) = \frac{\mu^x}{x!} e^{-\mu} \qquad (x = 0, 1, \ldots)$$

Where mean $\mu > 0$. One of the important properties of the Poison distribution is that the mean and varience are both equal to μ.

2.1.4.2 Exponential Distribution

According to Jerry Bank, John S. Carson II, and Barry L. Nelson (1996, pp. 203-204), the exponential distribution has been used to model interarrival times when arrivals are completely random and to model service times, which are highly variable. The exponential probability function is given by

$$f(x) = \begin{cases} \lambda e^{-\lambda x}, x \geq 0 \\ 0, \quad \text{elsewhere} \end{cases}$$

Where λ (a rate: arrivals per hour or service per minute) > 0. Its mean and variance is equal to $1/\lambda$ and $1/\lambda^2$, respectively.

2.1.4.3 Kolmogorov – Smirnov Goodness of Fit Test

According to H. V. Elson, revised S. E. Meikle (1996, pp.9), this technique only employ with continuous distribution, but can be used for small samples. According to Jerry Bank, John S. Carson II, and Barry L. Nelson (1996, pp. 299-300), its procedure is shown below:

1. Rank the data from smallest to largest. Let $R_{(i)}$, denote the ith smallest observation, so that

$$R_{(1)} \leq R_{(2)} \leq \ldots \leq R_{(N)}$$

2. Compute

$$D^+ = \max_{1 \leq i \leq N} \left\{ \frac{i}{N} - R_{(i)} \right\}$$

$$D^- = \max_{1 \leq i \leq N} \left\{ R_{(i)} - \frac{i-1}{N} \right\}$$

3. Compute $D = \max(D^+, D^-)$
4. Determine the critical value, D_α, from Table A.1 for specified significance level α and the given sample size N.

If the sample statistic D is greater than the critical value, D_α, the null hypothesis is rejected.

2.1.4.4 Kolmogorov-Smirov Two-Sample Test

For building the call center model, it is necessary to gather the multiple set of data from populations that are separated by time. Thus, it is importance to know whether the distribution of interarrival time and service time is the same (homogeneous) across the hours of the day and days of the week and month. There are many tests for homogeneity, but in this thesis, we consider a distribution-free test for homogeneity: the Kolmogorov-Smirov two-sample test [Stewart V. Hoover and Ronald F. Perry 1989, pp.221-222]. Given samples from two populations, $G_{(x)}$ and $H_{(x)}$ the Kolmogorov-Smirov two-sample test can be used to test the hypothesis:

$$H_0: G_{(x)} = H_{(x)}$$
$$H_1: G_{(x)} \neq H_{(x)}$$

To perform the test, the two sets of data are used to construct the two-sample cumulative-distribution functions $G_{(x)}$ and $H_{(x)}$. The test statistic is the maximum of the absolute value of the difference between the empirical cumulative distribution $H_{(x)}$ and $G_{(x)}$. That is, the test statistic D is:

$$D = \sup_{all\,x} \left| G(x) - H(x) \right|$$

In this test, we have to measure the difference between $G_{(x)}$ and $H_{(x)}$ whenever either function changes. The critical values of D have been derived by F.J. Massey. For large n_1 and n_2 (n_1, n_2 > 15) the critical values of D for α = .05 and .01 are:

$$D_{.05} = 1.36\sqrt{{(n_1 + n_2)}/{n_1 n_2}}$$

and

$$D_{.01} = 1.63\sqrt{{(n_1 + n_2)}/{n_1 n_2}}$$

2.1.4.5 Kruskal - Wallis Hypothesis Test

To merge the sets of observations, it is necessary to recognize whether these data sets are homogeneous. According to Averill M. Law and W. David Kelton (2000, pp.394-395), Kruskal – Wallis statistic is used to test for homogeneity. It is nonparametric test since no assumptions are made about the distributions of the data.

Suppose that we have k independent samples of possibly different sizes, and that the samples themselves are independent. Denote the ith sample of size n_i by $X_{i1}, X_{i2}, \ldots, X_{in_i}$ for $i = 1, 2, \ldots, k$; and let n denote the total number of observations

$$n = \sum_{i=1}^{k} n_i$$

The null hypothesis is set as:

H_0: All the population distribution functions are identical

While, the alternative hypothesis is set as:

H_1: At least one of the populations tends to yield larger observations than at least one of the other populations

To establish the Kruskal – Wallis statistic, assign rank 1 to the smallest of the n observations, rank 2 to the second smallest, and so on to the largest of the n observations, which receives rank n. Let $R(X_{ij})$ represents the rank assigned to X_{ij}, and let R_i be the sum of the ranks assigned to the ith sample, that is,

$$R_i = \sum_{j=1}^{n_i} R(X_{ij}) \qquad \text{for } i = 1,2,\ldots,k$$

Then the Kruskal – Wallis statistic T is defined as:

$$T = \frac{12}{n(n+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(n+1)$$

The null hypothesis will be rejected if $T > \chi^2_{k-1,1-\alpha}$ where $\chi^2_{k-1,1-\alpha}$ is the upper $1 - \alpha$ critical value for a chi-square distribution with k-1 degrees of freedom.

2.1.4.6 Sample Size

An important question for input modeling is how many observations are needed in a sample. Typically, if we use the large sample size, the sampling accuracy will increase. Before determine the sample size, we have to determine the two interrelated factors: level of confidence and confidence interval. For large populations, Louis M. Rea and Richard A. Parker (1997, pp. 117-118) suggested the method to calculate the number of sample size as follows:

$$n = \left(\frac{Z_\alpha (.5)}{C_p} \right)^2$$

Table 2-1 illustrated the minimum sample sizes for variables expressed as proportions.

Confidence Interval (Margin of Error, percent)	Sample Size	
	95% Confidence	99% Confidence
±1	9,604	16,590
±2	2,401	4,148
±3	1,068	1,844
±4	601	1,037
±5	385	664
±6	267	461
±7	196	339
±8	151	260
±9	119	205
±10	97	166

Table 2-1: Minimum sample sizes for variables expressed as proportions [Louis M. Rea and Richard A. Parker, 1997, pp. 119]

In case of small sample size, Louis M. Rea and Richard A. Parker (1997, pp. 118-119) also suggested the method to calculate the number of sample size shown below:

$$n = \frac{Z_\alpha^2(.25)N}{Z_\alpha^2(.25)+(N-1)C_p^2}$$

Table 2-2 shows the minimum sample sizes for selected small populations.

Population Size (N)	Sample Size					
	95% Level of Confidence			99% Level of Confidence		
	±3	±5	±10	±3	±5	±10
500	250[a]	218	81	250[a]	250[a]	125
1,000	500[a]	278	88	500[a]	399	143
1,500	624	306	91	750[a]	460	150
2,000	696	323	92	959	498	425
3,000	788	341	94	1,142	544	158
5,000	880	357	95	1,347	586	161
10,000	965	370	96	1,556	622	164
20,000	1,014	377	96	1,687	642	165
50,000	1,045	382	96	1,777	655	166
100,000	1,058	383	96	1,809	659	166

Table 2-2: Minimum sample sizes for selected small populations [Louis M. Rea and Richard A. Parker, 1997, pp. 119]

Note: [a]Population sizes for which the assumption of normality does not apply; in such case, the appropriate sample size is 50 percent of the population size.

2.1.5 Simulation Package and Language

The simulation package and language that used for developing the system model for this thesis is Arena and SIMAN, respectively. The details of them is shown below:

2.1.5.1 Arena

Arena is a general-purpose simulation package that used to develop the simulation model in this thesis. Systems Modeling Corporation (Sewickley, Pennsylvania) markets this package. Modules or modeling constructs, are organized into several templates such as Basic Process, Advanced Process, and Advanced Transfer.

Basic Process template contains modules that are used in many models such as modules for modeling entity arrival, departure, and service). The Advance Process template has the modules that used to perform very specific logical functions such as choosing a queue when several are available. Lastly, the Advanced Transfer template contains modules that used to describe the transfer entities from one part of the system to another.

A model is constructed by dragging and dropping modules into the model windows. After that, we connect the modules and indicate the flow of entities through the simulated system. And then, we detail these modules by using the Arena's dialog boxes or its built-in spreadsheet.

Arena has two-dimensional animation and allows displaying the dynamic graphics. The users can use 12 standard theoretical probability distributions including empirical distributions. And, it has a built-in capability for modeling nonstationary Poison process, which is a model for entity arrivals with a time-varying rate.

Arena can make the output reports of a simulated system and obtain point estimates and confidence interval for performance measures of interest. This simulation package can built a number of plots, such as histograms, bar chart, time plots, and correlation plots.

Moreover, because the Microsoft Visual Basic for Applications (VBA) is available in Arena, thus, the users can read or write the data from other application such as Microsoft Excel and create the familiar interface for entering model parameter as well as customized report.

2.1.5.2 SIMAN

SIMAN is a general-purpose simulation language for modeling discrete, continuous, and/or combined system [C Dennis Pegden, Robert E. Shannon, and Randall P. Sadowski, 1995, pp. 24-25].

SIMAN is designed conform to the logical modeling framework (developed by Zeigler) that comprise of model component and experiment component. The model describes the physical elements such as machines, workers, information, etc., while the experiment specifies the experimental conditions under which the model is to run such as resource availability, type f statistic gathers, length or run, etc.

Some features of SIMAN is listed below

- A set of special-purpose constructs to simplify and enhance the modeling of manufacturing system.
- Compatibility of minicomputer and microcomputer versions to permit movement between computer systems without modification.
- Interactive graphics capability for building models, defining experiments, and displaying model outputs.
- A run controller for interactive monitoring and control of simulation execution.
- The Cinema system, which generates a real-time, high-resolution, color graphics animation of the modeled system.
- Arena System extends SIMAN/Cinema to support hierarchical modeling.

2.2 Related Thesis, Journals, and Articles

2.2.1 Kunawut Atthasis

The aim of this research is to develop traffic queue prediction models at traffic detector for signalized junctions. The CU Traffic Simulation Model is used as a basic tool. First, vehicles are generated onto a simple network in which traffic detectors were incorporated. Results of the simulation were traffic volume pass over detectors entering signalized junction and volume and time occupancies detected at detectors. Next, the queued-length model is developed based on traffic parameters: volume and time occupancy. Finally, a suitable position of traffic detectors is recommended. The queue length models were developed into two parts: based on traffic volume and time occupancy. If traffic volume parameter were used, a suitable position of detector from stop-line for a uniform arrival model is approximately 50 percent of road link. If the traffic arrival is random, the suitable position is approximately 90 percent. With regard to time occupancy, the suitable position of traffic detector from the stop-line is approximately 40 percent and 90 percent for uniform and random arrival, respectively. From this research, it can be concluded that traffic queue at signalized junctions can be predicted by traffic volume or time occupancy. If the traffic volume was used the traffic stream model, namely Greenshield, was applied. Time occupancy could directly be used for prediction of queue length, by using simple linear regression.

2.2.2 Thongchai Jintanawongse

Develops a computer simulation as a model to analyze traffic condition at isolated signalized intersection at different types of intersection. Employs the FORTRAN IV language to construct a program studying important traffic behaviors such as vehicle arrival, roadway representation, lane changing process, car-following, stopping, and departure as being observed at Ratchadapisake and Lard-phrao intersection as well as some information from government agencies. All these behaviors are calculated and the results are queue length, delay, and average velocity. The outputs from the simulation show some difference from the ones from field observation as the data input derived from many sources

2.2.3 Dararat Saelee

This research is to present the process-oriented simulation for studying computer system behavior. This can help computer designers to evaluate and analyze processor performance. Because behaviors of computer systems are difficult to specify as mathematical models, developing simulation models using process-oriented simulation approach is convenient and useful for observing program behavior on novel computer architectures. In this research a process- oriented simulator was built to simulate quasi-parallel systems in which many processes existed and evolved independently. A processor model similar to the architecture of Intel microprocessor 8086 was developed for simulation. Benchmark programs were used to test the model. It was found that instructions with simple addressing modes were often used. Many architectural features were also studied to see their effects to the overall performance. This included the instruction queue and cache memory. It was found that processor performance was improved significantly with these features

2.2.4 Systems Modeling Corporation, "Call Center, Simulation, and Call$im

For call center managers and directors, their business problems are far easier to describe than to solve.

- "I've got my staffing budget for the next fiscal year, but I don't know how many people I need to make service levels, what shifts to hire for, or what skills to train my workers on."
- "Service levels look pretty good right now, but our peak season is coming up. What I don't know is how badly our speed of answer and abandonment rates will suffer if our call forecasts turn out to be too low."
- "Our service levels are in bad shape. We are considering either extending our hours of operation or hiring an outsourcer to help share the call-handling load. I wish I knew where to get the most bang for the buck."
- "My telecomm guy has a new set of routing scripts to make use of some of our advanced phone switch capabilities. I wonder how this is going to impact our average speed of answer and our staff utilization."
- "Marketing has come up with a new program giving our 'preferred customers' a special priority when they call us with questions. What I'm worried about is how this new program will effect the waiting times that the rest of our customers experience."
- "We've been asked to provide telephone service and support for another business unit. They're asking us how much staff we need to hire or cross-train in order to handle this increased load. If we cross-trained our existing staff, I wonder what we would need to do to maintain service levels."

Call center managers have traditionally attacked these types of problems with "gut feel" estimates, back-of-the-envelope calculations, elaborate spreadsheets, and analytical queuing formulas such as Erlang C. Each of these approaches, however, has significant limitations when applied to call centers systems, due to the variability of call arrivals, call routes, and call handling times (as well as the interaction between calls, trunk lines, agent priorities, agents skill sets).

<u>Simulation is the only analysis methods that can effectively and accurately models a call center</u> (or a network of call centers) and studies its performance. The simulation method is based on creating a computerized "copy" of the actual or proposed call center system and running this system on the computer for a period of time representing a day, a week, a month, or longer. In particular, simulation explicitly models the interaction between calls, routes, and agents, as well as the randomness of individual call arrivals and call handle times.

2.2.5 Vijay Mehrotra, Onward Inc.; David Profozich, Systems Modeling Corporation; and Vivek Bapat, Systems Modeling Corporation

When you design and build a new call center, you are making a major capital investment. When you make any significant change to the way your call centers are configured, you are making a serious decision about the way you do business. In either case, you are putting a lot on the line. From a business perspective, you want to understand the impact of these types of decisions before you make your key decisions, before you take your business risks.

Traditional methods such as back-of-the-envelope calculations and Erlang models are somewhat useful. However, these tools are of very limited value, in large part because they are unable to account for skills-based routing, simultaneous queuing, call transfer and other routine features of today's call center.

Regardless of the complexity of your call center, simulation gives you answers to the types of questions you want to ask about your business before you make a significant design or redesign decision. As a responsible manager of a top-notch call center, you own it to your organization and your clients to sincerely consider the use of simulation in managing your call center

2.2.6 Bill Hall, Call Center Services and Dr. Jon Anton, Purdue University

In the past few years, simulation tools have begun to emerge in the call center industry. There are two important reasons for this, 1) call centers are extremely complex, and much too important to run by intuition or "gut feel," 2) simulation tools are being designed specifically for call centers making them more intuitive and much easier to learn and use.

Let's take a minute to really understand computer simulation. Simulation is a way to create models of real-world processes, in this case study, the call center. A call center model is a logical description of how the many processes of the call center interact and work together.

To develop a call center model, you begin by inputting facts such as call arrival patterns, the different types of calls, how the calls are routed, the agents (with skills and schedules), the trunk groups, and many more.

Once the model is built it can "simulate" the actual behavior of the call center over a particular planning period. The outputs are the typical call center metrics that you see every day, for example, the number of calls, average handle time per call, agent utilization, number of abandoned calls, service level, and many more.

Simulation works very well in a call center environment because it is able to generate calls the way they actually arrive at the call center (randomly and in bunches). Secondly, most simulation tools allow you to document the process graphically and animate it. The result is a model that is easy to understand and accurately "acts like" the call center, as you know it. Once the model is established it can be used time and again to support and verify important management decisions.

Even if you are meeting your goals, simulation can offer new ways of addressing the problem, leading to more cost-effective ways of processing calls. Because many call centers are in a continual state of change, simulation lets you test the effect of these changes before actually implementing them.

Let's explore in more detail how to use simulation to improve your call center operation. Simulation can be used in two ways as follows:

- First it can verify where you are. We'll call this the assessment phase. The key question becomes "how efficient and effective is my operation today?"
- Secondly, simulation can be used to address "what if" questions and develop scenarios of how the call center may operate in the future. It provides a means to analyze and measure the impact of changes as a result new technology, a changing business strategy, increased workload, and more.