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COMPUTER-AIDED CAPACITY PLANNING MODEL
FOR
FACILITIES MANAGEMENT

By

Piyarat Nanta

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ABSTRACT

COMPUTER-AIDED CAPACITY PLANNING MODEL
FOR FACILITIES MANAGEMENT

By

Piyarat Nanta

This Computer-Aided Capacity Planning Model for Facilities Management focuses on the simultaneous optimization of the resource utilization ratio and user's waiting time in a shared space environment. The study was conducted in an open campus state university computer lab which is considered a shared space environment. The data collection protocol followed a prescheduled set of observation periods designed to capture a representative sampling of expected usage during one semester. In a perspective, this study employs the same device with two different models of workload characteristics (the IBM compatible section and the Macintosh section). For the Macintosh section, misinterpretation of the data arises from the discordance of the system behavior and the instrumentation along with the design for data collection. By the same token, the problem due to the instrumentation occurs with the *waiting time* data collection for the IBM compatible section. Further investigation to validate this method, should be done by applying it to different kinds of shared resource environments such as hoteling or workplaces that use similar strategies, thus demonstrating whether the methodological results are reproducible in different work environments. Information obtained from the users should be collected in order to compare the results of the resources utilization ratio at each step to verify the strategy being used at the time. Time-lapse video is another unobtrusive tool that can provide a further perspective on patterns of behavior.

To my beloved parents.

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INTRODUCTION

Competitive economics of the late twentieth century have driven the recent acceleration in changing work patterns of business and industry. In order to keep pace, a company's workplace strategies, including the office environment require adaptations to efficiently provide the task requirements of the company's employees. Hence, large and small organizations must reevaluate their strategies related to re-engineering, customer service, quality control, outsourcing, vastly improved communications networks and access to worldwide information systems. These organizations must be concerned that they restructure their business practices in a manner that will lead to success in new and foreseeable business environments, and that maintain flexibility towards new alternatives in the operation of their organization so as to accommodate future requirements.

The new business imperative tends to favor smaller and more flexible organizations; which invariably means fewer, smaller and more flexible employee workspaces (Brill, 1993). To meet these demands, new strategies grouped under the title "alternative officing strategies" have been implemented to create environments that suit the tasks and needs of changing work patterns. In 1995 the IFMA (International Facility Management Association) Foundation and Haworth Inc. conducted research on alternative officing strategies by surveying 4,004 IFMA member organizations (including 352 Canadian members). The study classified the new workplace strategies into two basic categories, on-site premise strategies and off-site premise strategies.

On-site strategies involve modifying, reconfiguring or redesigning the workplace to accommodate changes in processing, staffing or organizational structure. Off-site strategies take advantage of technological advances in communications to offer people more freedom and flexibility to do business from virtually anywhere. The study reported the proportions of alternative officing strategies used among the member organizations surveyed as follows: flexible work schedules (53%), modified office standards (46%), shared space (41%), telecommuting (33%), activity setting (32%), virtual officing (13%), hoteling (7%), and free address (7%)(See Index). The survey showed that many organizations did not adopt a single strategy, but implemented a mixture of strategies specifically tailored to support varied requirements.

Off-site strategies, including telecommuting, virtual officing, and some on-site strategies, such as shared space, hoteling, free address and activity setting, cut facility costs by reducing the amount of office space per employee. The "Alternative Officing Research and Workplace Strategies Study" (IFMA & Haworth Inc., 1995) reported cost reductions of 48% for rent/lease property, 34% of furnishings, and 28% of utilities by using alternative officing strategies.

Even though the 1995 IFMA-Haworth Inc. study observed that on-site strategies are more commonly used today, the trend in usage is steadily shifting towards off-site strategies. In the same year, WIRED magazine reported that 9.2 million Americans would be telecommuters by the end of 1995. Moreover, WIRED's editors anticipate that the number of telecommuters will triple in the next 15 years to encompass 20% of the workforce. Nonetheless, physical space continues to play an important role in alternative workplace strategies. Becker (1995) predicted that a company without a traditional central headquarters would still occupy some physical real estate, and even the virtual corporation of the future would maintain multi-use hubs combining meeting and communication centers. On the other hand, Newhouse (1995) argues that at least half of such a company's personnel would remain at a main office due to widely varied human personalities and job skill types. In general, the provision of office space is a significant expenditure for most organizations. Thus, organizations are under continuous pressure to develop and adopt strategies that provide for its needs while minimizing capital investment. One widely used strategy is the shared space environment, which is increasingly used in both on-site and off-site office space strategies. Stone and Luchetti (1994) introduced a strategy called "behavior setting", which focuses more on "*what people do in certain settings than what people do in certain roles*". In other words, this approach emphasizes providing shared places designated to support particular behaviors. Brand (1995) noted that benefits of this kind of environment include space efficiency, construction cost savings and maximizing space and equipment utilization by increasing the number of multiple users. Thus, the organizations were able to reduce their investment in the increasingly expensive real estate market while shifting their interest into new technology and communication tools.

In order to adjust themselves to today's business climate, many organizations try to implement a new agenda while using out-dated facilities. Such facilities are not designed for the free-flow of communication between employees, new work patterns, changing departmental organizations or customers' requirements. These facilities are generally neither structurally nor mechanically flexible enough to support current upgrades in technology or accommodate future growth. Several problems arise in space management for current use and the prediction of space requirements for future planning. However, the extent to which an organization changes its workplace is largely dependent on its working capital. Other important factors, which influence the implementation of new workplace planning are the resource requirements which depend on policies of the organization. This crucial factor must be considered when making economically efficient decisions. In general, estimation and prediction of physical space planning can be calculated using some type of economic evaluation methodology, such as life-cycle cost, net benefits or net savings. Sanquist (1996) proposes that such databases should include cost per square foot, organization units, ownership, number of employees and types of employees.

Traditionally, in the process of strategic planning and selecting the best alternative for the new workplace, the organization based its decision on a series of on-site workshops involving company executives, consultants, interior designers, architects, and feedback from employees. Similar decision making processes are mentioned in other recent documents published by IFMA & Haworth Inc. (1995), Werts (1996), Froggatt (1997), Health & Thorn-Silverton (1997), Sanquist (1996) and Mosby (1996).

Several methods have been used in order to test and predict resource requirements for shared space strategies. Some organizations, in order to assure that the new alternative will work out as they plan, agree to spend their capital investment on a real life mock-up. Health & Thorn-Silverton (1997) also reported a pilot study using a "*beta-site*" in the main office when implementing alternative workplace strategies such as in the case of Citicorp restructuring. Sanquist (1996) noted that the "*Scenario Concept*" had become another tool, and was widely used for envisioning a future workplace. The scenario process incorporates flexibility in design anticipating potential future needs. This allows facility professionals to test their strategies against different factors in the business environment. According to Herman Miller Research (1997)[1], a large telecommunications corporation in conjunction with Herman Miller Research developed people-to-work ratios (see: Index) for the corporation's shared offices used by its telecommuter employees. However, the report did not discuss how the method was derived though the authors claimed the calculation was based on a simple statistical formula. Furthermore, the report stated that "*the experience base for evaluating this type of data is still in its infancy, and there is no single formula that will fit every organization"*. Thus, these attempts address the fact that organizations have focused their primary interest on space utilization due to expectations of evolving changes in the workplace process.

As discussed earlier, several methods have been used to manage limited resources, such as shared space strategies, yet few forecasting methods for space sharing strategies have been published.

One of the most effective analytical tools that can be applied to this issue is borrowed from management science, a computer simulation model for capacity planning. This method includes trend analysis of differential usage and resource utilization ratios. It is considered an effective method based on accepted statistical techniques. This model can be operated as a computer generated queuing model to calculate the distributions of the waiting time and resource utilization ratio. With the use of trend analysis combined with computer simulation modeling, this technique can potentially ease the task of constructing a complicated queuing model, and greatly reduce analysis time. Another

1 Herman Miller Research Report (1997): http//www.Hermanmiller.com/research/reports/onsite/faq5.html

major advantage of this technique is that analyses can be obtained for almost any specified array of parameters. Given the potentially overwhelming advantages of specialized computer simulations for capacity planning, organizations can hardly afford to ignore development of this tool.

This study will focus on a specialized computer-aided capacity planning model applied to shared space forecasting for facility management. The proposed technique is a combination of both the scenario concept and statistical modeling. This method will then be tested for suitability and accuracy. The shared space setting selected as a study site to test this model, was located in a large educational facility.

In an educational setting which has a large number of occupants such as a university, the shared space approach has been primarily used as a solution to permitting maximum student access to expensive or low usage equipment. These facilities may include computer centers, copy centers. or intramural sports facilities. This strategy provides similar benefits to the university's facility administration system as it would to a business organization. Moreover, it also increases the students' accessibility to some specific resources. However, since the university generally cannot provide enough equipment to meet expanding demand, and space available within most buildings is quite limited, shared resources allow the users to move to a designated place for a specific job which is easier than moving spaces and equipment to people in set locations.

Pre-design programming in this type of setting is critical. Brand (1995) emphasized that "*this approach will not work if people do not have access to the right space at the right time*". In order to make the setting yield the maximum benefit to users and organizations, some important factors have to be taken into consideration during the planning phase. These factors include ratios and distributions of users per unit of equipment and space (resource utilization ratio), accessibility of users to a specified resource (waiting time), trends in the growth of the number of users in that institution, and also patterns of user behavior. Careful analysis of the results of these elements may enable the facility to accommodate an acceptable number of users, which may be expected to increase in the foreseeable future. This process is referred to as "Capacity Planning". Browning (1995) has defined the capacity planning approach as the process of forecasting the current and future system behaviors regarding resource management policies.

In practice, capacity planning usually consists of several steps including data collection, trend analysis, modeling, forecasting and validation of results. The data collection method includes the collection of service time of the users per station or resource unit, accumulation of the waiting queue (inter-arrival time), and behavioral patterns of limited resource users. As suggested by Sisal (1990), the methods for collection of users' behavior patterns should include interviews, focus groups, activity logs and different kinds of observations of physical traces. These techniques are well documented and have been widely used in many organizations. As mentioned above, trend analysis is usually based on subjective interpretations of facility managers or consultants dependening upon experience as the basis for their interpretations. The results in this step, which are trends in the users inter-arrival rate and service time will be used as components to predict the anticipated system behaviors. The outcome of the analysis can be used as an input to the trends forecasting model of resources utilization. Then the validated forecasting results may in turn be put into an original economic assumptions analysis to achieve an integral implementation of policies (Browning, 1995).

Two important factors that cannot be over looked in the decision making process are the waiting time and resources utilization ratio. The distribution of the waiting time indicates the degree of accessibility to a particular resource. At the same time, the resources utilization ratio shows the degree of utilization in relation to total resource capacity. The optimization of these two factors is a function of relative expense of user waiting time to resource cost. The waiting time and resources utilization ratio can be derived from the queuing model constructed from the distributions of the inter-arrival times and the service times.

The pre-design programming phase for shared space in a university deals with planning for a limited resource, a broad scope of activities, implementation policies and various external factors. The direct physical testing of optional policies or the construction of a "beta site" is almost prohibitive because of the considerable amount of capital investment required, in addition to being a time consuming procedure. Therefore, a computer-aided capacity planning model incorporated with other programming methods will be a useful part of the pre-design process. A trend analysis model would help assess potential outcomes of strategic decisions derived from the resource estimation. This cost-effective approach can be replicated in many different environments. The results from this model would illustrate future changes in system behaviors regarding the anticipated policies with minimal risks and costs compared to physical site testing. According to the proposed methodology, this conceptualization of trend analysis and computer-aided capacity planning model is not specific to the environment in this study, but should also be adaptable in the pre-design programming phase of various types of resource-constrained environments.

This study examines an application of computer-aided capacity planning used in space planning facility management. The methodology in this study, which has been widely used in the area of resource management, can also be applied to the sphere of facility management. A statistical methodology comprised of a trend analysis model and computer simulation model for capacity planning is expected to be a valuable device when used in conjunction with other techniques in the decision making process.

The objectives of the study are as follows:

1. To demonstrate that the computer-aided capacity planning model is applicable to space and resource management for facility management.
2. To examine the suitability of the proposed procedure for future space prediction by using the computer-aided capacity planning model.
3. To examine the precision and/or error of the simulation results and use this information as a correction to modify the model for further investigation.
4. To study workload characteristics of the space sharing facility to use as reference for simulation modeling.
5. To create a flexible and logic-based tool to help envision space planning solutions for the facilities manager and end user.

The proposed study is divided into two stages. The first stage investigates the pattern of the users' behavior and trend analysis for capacity planning. In the second stage, the simulation modeling technique will be examined. An accurate waiting time for users and the resource utilization ratio are the expected results to be derived from this model. In addressing these points, the results discussion is divided into three sections. The first section describes the new perspective emerging from the observation of users' behavior and workload characteristics from the field during the observation period. It provides a basis for understanding the influence of different extraneous variables on user behavior over time. This insight is crucial to constructing the simulation model. Second, the accuracy of the results (dependent variables including waiting time and resource utilization ratio) generated by the simulation model are examined by comparison to the raw data collected from observation. The paper concludes with suggestions for further investigation of the computer-aided capacity planning model.

CHAPTER 1

DESCRIPTION OF RESEARCH DESIGN

In testing an application of this computer-aided capacity planning model, it is necessary to understand the principles and characteristics of a queuing system. This chapter discusses the definition of simulation modeling including the functions and relationship of system components, queuing discipline, and the characteristics of the facility in this study.

This research involves the study of the relationship of four variables in a shared space environment. These variables include 1) users' interarrival time, 2) service time of each equipment or computer station being used, 3) users' waiting time, and 4) the resource utilization ratio over the whole cycle of a facility's operation time. The relationship and classification of these variables are illustrated in detail in the next section. This computer section is considered a shared space environment or a system, which is composed of various components. The shared space strategy is chiefly implemented to increase resource utilization by having multiple users per resource unit or station. Resource availability is generally on the basis of "first come, first served" (or *first in first out: FIFO*), though resources can be reserved by scheduling in advance. However, this study focuses on the first in first out queuing discipline, which is the only queuing discipline used in this facility.

Simulation Model and System Component

The simulation model used in the study is a *discrete-event* system simulation. Banks & Carson II (1984) describe this *discrete-event system simulation* as the modeling of the *system* in which the stated variable changes only at a discrete set of points in time. The simulation models are analyzed by numerical methods rather than by analytical methods. Numerical methods employ computational procedures to solve mathematical models rather than using the deductive reasoning of mathematics to solve the model. Banks & Carson II (1984) conclude that *"the output measured from the discrete-event system simulation model) is an artificial history of the system which is generated based on the model assumptions, and observations are collected to be analyzed and to estimate the true system performance measures."*

The system being studied is defined as a group of objects that are joined together in some regular interaction or interdependence with the accomplishment of some purpose. The system component can be defined as an *entity*, an *attribute*, an *activity*, a *state*, and an *event*. An *entity* is an object of interest in the system. An *attribute* is a property of an *entity*. An *activity* represents a time period of a specified length. The *state* of a system is defined to be that collection of variables necessary to describe the system at any time, relative to the objectives of the study. The *event* is defined as an instantaneous occurrence that may change the state of the system.

Figure 1 comprises the definitions and concepts describing system components as defined by Banks & Carson II (1984). They are used as a conceptual framework for constructing the simulation of the queuing system for capacity planning for the computer section examined in this study.

System	*A collection of entities (i.e. people and servers) that interact over time to accomplish one or more goals*
Model	*An abstract representation of a system, usually containing logical and/or mathematical relationships which describe a system in terms of state, entities and their attributes, sets, events, activities, and delays*
System state	*A collection of variables that contain all the information necessary to describe the system at anytime*
Entity	*Any object or component in the system which requires explicit representation in the model (i.e., a servers, a users, a machine)*
Attributes	*The properties of a given entity (i.e. the priority of the waiting users, routing of a service)*
Set	*A collection of (permanently or temporary) associated entities, order in some logical fashion (such as all customers in waiting line, ordered by first comes, first served or by priority)*
Event	*An instantaneous occurrence that changes the state of a system (such as arrival of a new user)*
Activity	*A time duration of specified length (i.e. service time or interarrival time), whose length is known at onset (although it may be defined in terms of a statistical distribution)*
Delay	*A time duration of unspecified length, whose length is not known until it ends (i.e. a user's delay in a last in, first out waiting line, which when it begins, depends on future arrivals)*[1]

Figure 1: Source: Banks & Carson II (1994)

In the study of the computer section, the users and the computer stations in the section are the *entities*. The *utilization ratio* of the computer is the *attribute* of the system. The tasks that the users do on the computer station, i.e. checking e-mail, creating a document are the *activities*. The number of occupied computer stations, the number of users waiting in line or being served and the users' *arrival times* are the *System State*.

To describe the *event* in more detail, the term "*endogenous*" refers to dependent *events* and activities occurring within a system, while the term "*exogenous*" refers to independent *events* and *activities* in environment that effect the system. Again, in this study the arrival of users is an *exogenous event* while the time completion of the task on the computer station (service time) is an *endogenous event*.

[1] **Modified from Banks & Carson II (1984).**

System Capacity

In the computer lab, the number of the computer stations limits the capacity of the system. However, there are no limits on the number of the users allowed to wait in the queue. Hence, an arriving user who finds the system fully occupied must either wait in line or return to the *calling population.* In the queuing system of this study, the *calling population* refers to as a population of potential users that may be defined as finite or infinite.

Queuing System and Simulation Model Implementation

This section gives an overview of basic principles of the queuing model that apply to this research. The terminology used in the queuing model and simulation model are identified in conjunction with the computer lab (system). The latter sections of this chapter discuss the characteristics, meaning and relationship of the variables in the queuing model which are used as a component of the simulation model.

Queuing Models and Simulation of Queuing Systems

In this work, the system being investigated is referred to as a queuing system. The key elements of a queuing system are composed of customers and servers. The *customers* refer to any entity that arrives at the facility and require service. The *server* refers to any person or machine providing the requested service. Thus, in the computer section, the users are the customers and the computer stations are servers. (See Figure 2)

System	Customers	Servers
Computer Section	Users	Computer Stations

Figure 2: The queuing system of the Union Building computer section.

Banks & Carson II (1984) state that a queuing system is described by its *calling population*, the nature of the arrival and the services, the system capacity and the queuing model in discipline. In this study the *calling population* is treated as an infinite population (approximately 40,000-student population). Users may be considered to be from an *infinite calling population*, since the number of the customers being served or waiting in the queue for service at any given time is always a negligible proportion of a potential calling population. Thus, the *arrival process* of the *infinite population* is unaffected by the number of users who have left the *calling population* and join the queuing system. As a result, when the *arrival rate* over time from the infinite population is homogeneous and usually assumed to be constant, the *waiting time* depends on the number of users being served and waiting in the queue (SEE Figure 3).

A queuing model can be solved mathematically or analyzed through simulation modeling. The queuing model is considered a powerful tool for designing, analyzing and evaluating the system performance. Moreover, a computer driven simulation reduces the complications and time consumed while enhancing flexibility in the computation process. The computer generated queuing model allows the computation of many different scenarios within a short time.

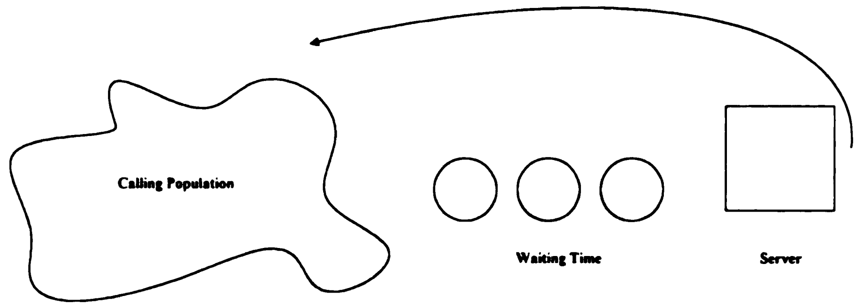

Figure 3: Simple Queuing Model (Source: Banks & Carson II, 1984)

Queuing Notation

In 1953, Kendall proposed a widely adopted notational system for parallel server systems. These letters represent the following variables for system characteristics:

A represent the interarrival time distribution.
B represents the service time distribution.
[Common symbol for A and B include M (exponential), **D** (Constant or deterministic), **E**$_k$ (Erlang of order k), and **G** (arbitrary or general).]
c represents the number of parallel servers.
N represents the system capacity.
K represents the size of the population.[2]

The queuing model used in this study is based on the same format which can be composed as M/M/x/∞/∞ model. The M/M/x/∞/∞ model describes a system that has x servers, unlimited queuing capacity, and an infinite population of potential arrivals, and the interarrival time and service time are exponentially distributed. When N and K are infinite, they may be dropped from the notation. Hence these M/M/x/∞/∞ is shortened to M/M/x.

---

[2] **Banks & Carson II (1984).**

Additional Banks & Carson II (1984) notation applied to this study are described in figure 4. These notations are based on the parallel server systems that use the *FIFO* queuing discipline.

A	Interarrival-time distribution
A_n	Interarrival-time between user ***n-1*** and ***n***
λ	Arrival rate
S_n	Service time of the *n*th arriving customer
ρ	Server or resource utilization
W_n	Total time spent in the system by the *n*th arriving customer
${}_nW^Q$	Total time spent in the waiting line by customer ***n***
	Note: $(W_n = W_{Qn} + S_n)$

Figure 4: Modified from Banks & Carson II (1984).

Even though this study focuses on the computer simulation, the principal and the component of the computer section system are similar to the basic queuing model system mentioned earlier. The variables in the study include interarrival time, service time, waiting time, and resource utilization ratio. These variables influence the pattern of the users' behavior, users' satisfaction, and the *system* performance. The users' interarrival time (*exogenous event*) and service time (*endogenous event*) are assumed to be independent variables. The interarrival time and service time influence waiting time (user satisfaction in terms of line length and delay of the waiting queue) and the resource utilization ratio (percentage of time the computer station being used). Hence these two dependent variables can be derived by using the users' interarrival time and the service time collected from the observations as input variables for the computer generated queuing model. The waiting time and resource utilization ratio generated by the simulation model are the output measures of the system. The characteristics of these variables and system limitations are described in the following section.

Queue Behavior and Discipline

Queuing behavior refers to users' actions while in a queue waiting to enter the system. In the case of the computer section in the university, the incoming users may wait in the queue for the service to begin, "*balk*"(leave when they see the line is too long), or "*renege*"(leave after being in the line when they see the line is moving too slowly). Normally when multiple queues are available in a congested system, the users form a new line and then "*jockey*" (move from one line to another when they think they have chosen a slow line) (Banks &Carson II, 1984). The latter behavior does not occur in this computer section system.

Queue discipline refers to the logical ordering of users in the queue and determines which users will be chosen for the service when the server becomes free. The common queue discipline used in this computer section is called *first in, first out* (*FIFO*). This *FIFO* implies that the utilization of service commences in the same order as arrival, but the users may leave the system in a different order because of irregular individual service times (Banks &Carson II, 1984).

The Arrival Process and Interarrival Time (A)

The *interarrival time* is the elapsed time between the arrival of consecutive users. The distribution of *interarrival times* determines the frequency and sequence of the users' entry. The interarrival time, which is an *exogenous event*, affects *waiting time* and the *resource utilization ratio*. In the arrival process, users may arrive individually or in batches. Batch arrivals may be regular or random. For instance, the computer lab users arrive in random size batches. *Arrival* of the computer lab users occurs at random times described by a *Poisson arrival process*[3]. Banks & Carson II (1984) define the *Poisson arrival process* as in the following:

> *"If A_n represents the interarrival time between customer n-1 and customer n (A_1 is the actual arrival time of the first customer), then for a Poisson 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 Poisson distribution with mean λt customers."*

The *Poisson arrival process* has proven accurate in predicting arrival for many service facilities including restaurants and drive-in banks, and other facilities that provide service by the same process (See: Also Chapter 3: description of the computer section's arrival time and distribution).

Service Mechanism and Service Time (S)

Service time is the length of time that each user spends on the *service station*. The *service time* of successive arrivals are denoted by S_1, S_2, S_3, etc. They may be of constant or random duration. The *service times* of the users in the computer section are of random duration since there is no rule regarding time limitations in this particular facility. In this case, the service process is commonly characterized as a sequence of independent and identically distributed random variables. In addition, *service time* in this facility influences the length of *waiting times*. Considering this public computer lab as the facility the university provided for all students, the service time also depends on time of

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[3] **Banks & Carson II (1984), Ross (1993).**

the day, day of the week and time of the semester. (See: Also Chapter 3: description of the computer section's service time and distribution)

Resource Utilization (ρ)

Server or *resource utilization* is defined as the proportion of time that a *server* (or *service station*) is busy. Observed resource utilization, denoted by ρ, is defined over a specified time interval ($\boldsymbol{0,T}$). Resource utilization ratio is the percentage of time that the service station is being used. Resource utilization ratio is the factor that indicates the utilization of the facility and resources. The administrator of the facility tends to increase the resource utilization concerning the return of investment and maximum performance of a system.

Waiting Time (W)

Waiting time is the length of time that each user spends waiting in the queue. *Waiting time* is the factor that indicates the user's satisfaction in terms of line length and delay spent in the waiting queue. Not surprisingly, waiting time and dissatisfaction are directly proportional.

Relationship of Resource Utilization (ρ) and Waiting Time (W)

In order to achieve optimum facility operation performance, there are trade-offs between resource utilization and user's waiting time that the facility managers must consider. The relationship of resource utilization and waiting time (the interest of the users) are often in conflict. For instance, the shorter the waiting time, the greater the user's satisfaction. In order to reduce the waiting time, the number of servers have to be increased which results in reduction of the resource utilization ratio. Different scenarios of the relationship between resource utilization and waiting time are illustrated in figure 5.

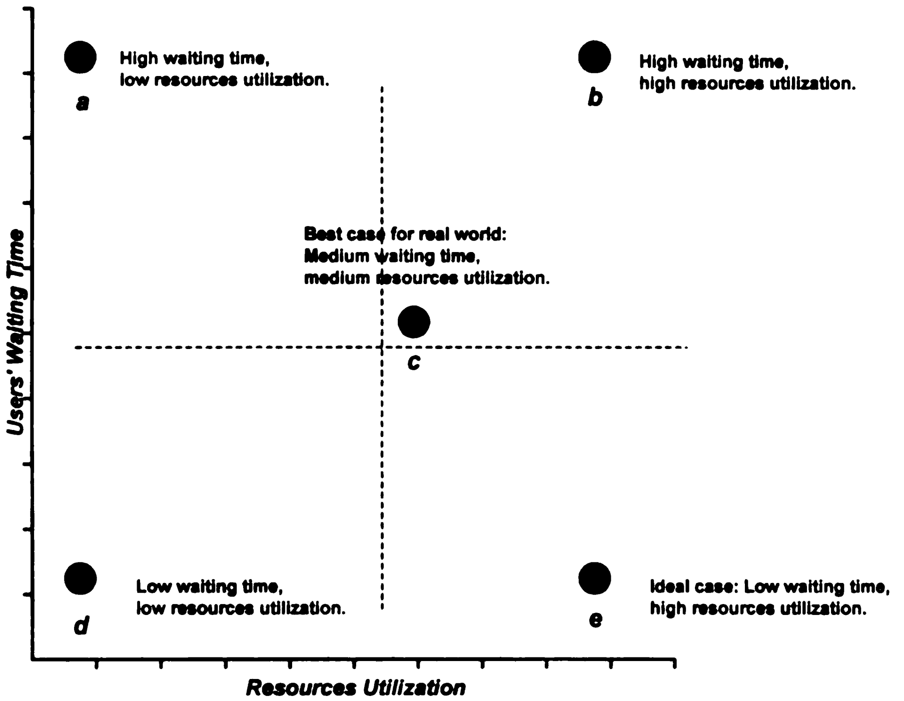


Figure 5: The Relationship between the Users' Waiting Time (w) And the Resources Utilization Ratio (ρ).

Point a) Poor management: high waiting time, low resources utilization.

Point b) Low users satisfaction: high waiting time, high resources utilization.

Point c) Best case in real world: medium waiting time, medium resources utilization.

Point d) Poor resources allocation estimation: low waiting time, low resources utilization.

Point e) Ideal case: low waiting time, high resources utilization.

From the diagram of the relationship between the user's waiting time and the resource utilization ratio, "point C" is the best case scenario for the system operation for space sharing facility without implementing any scheduling system. The user's waiting time and resource utilization depends on the service time and interarrival time. For instance, "point e" seems to be the most preferable case for any facility, it is less likely to happen in the space sharing facility that open to the public without pre-designated space.

In summary, queuing models have been found to be very useful in analysis of facilities where congestion for scarce resources may occur. The administrator of the facility can use the queuing model, based on data collected from the field, to generate one or more artificial histories of the system, such as for this computer lab. This simulation-generated data in turn can be used to estimate desired performance measures.

The users' interarrival time and service time are independent variables that influence the latter two variables, users' waiting time and resource utilization ratio. Operation cycle and time factor influences workload characteristics which are examined and used as guidelines for construction of the simulation model due to the unique characteristics of the facility being investigated.

The computer-aided capacity planning model is expected to be a useful space-planning tool in forecasting use of the shared space environment, consistency and reliability of the results before use in predictions of what-if scenarios have to be verified. This rationale leads to the main purpose of this research, which is to test the validity of this method by comparing the computer generated results to the field observations. The tested factors *include waiting time* and *resource utilization ratio* which are computer generated by using the input parameter (*interarrival time* and *service time*). Then they are compared to the raw (existing) *waiting time* and *resource utilization ratio* from the same observation session. Their independent variables are used as an input to the simulation model.

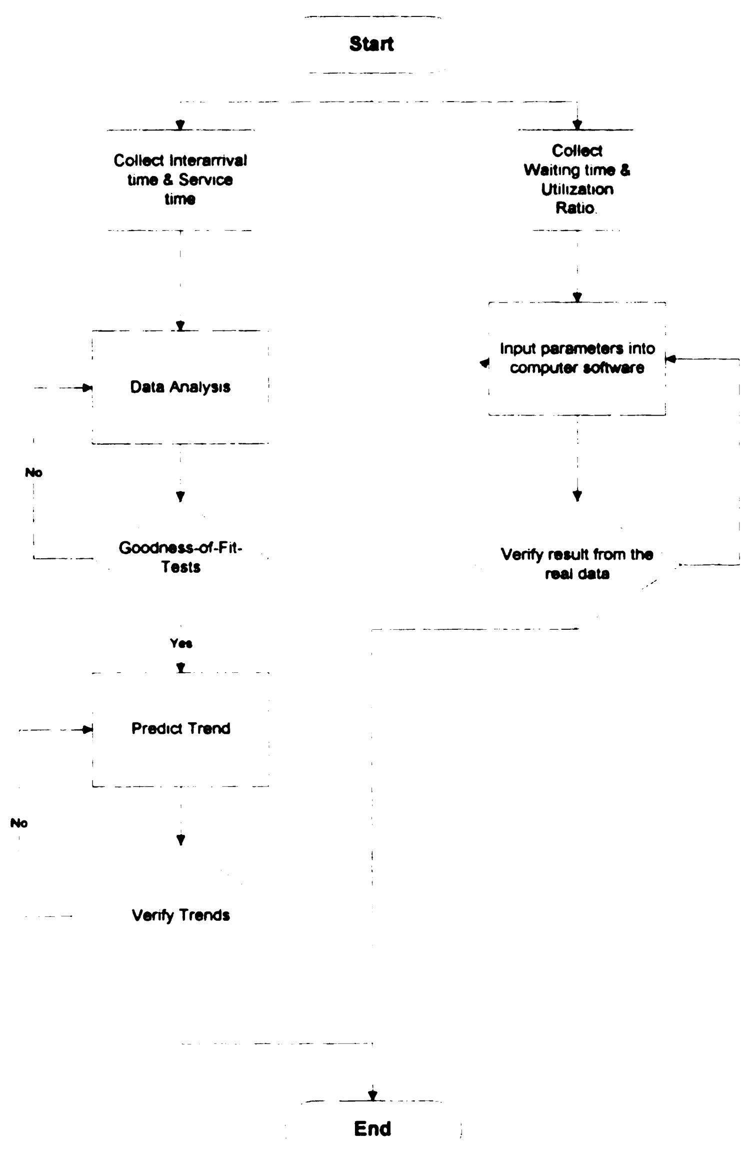
The selected facility for this investigation is a university students Union Building "public" computer lab in Michigan State University. The section provides computer stations for students and is accessible to all students on campus. The workload characteristics of the users cycle over the course of each semester. The workload characteristics include the distribution of service time, interarrival time, and the proportion of the different type of users who use the computer station (i.e. number of IBM compatible users versus number of Macintosh users). These factors influence the operation of any facility. The extensive understanding of workload characteristics leads to a better facility planning and implementation of a policy that support the majority of users' demands.

The computer section possesses a simple characteristic of a shared space environment. The operation of this computer section is based on the *FIFO* and neither has any reservation system, nor the restriction of time used on the computer station. It is suitable for the primary study of the workload characteristic and the variable produced by these factors (*waiting time* and *resource utilization ratio*) and compared with the simulation's results.

The proposed study is divided into two stages. The first stage investigates the pattern of the users' behavior and workload characteristic for capacity planning. The process includes data collection of users' interarrival time, service time. Then the data will be analyzed and calculated the statistical distribution for each parameter to be used as input for the simulation model.

In the second stage, the simulation modeling technique will be examined. A customized computer simulation model (in JAVA) for capacity planning is used as a tool to generate scenarios based on parameters and the model derived from the first stage. Results of the computer generated waiting time for users and the resource utilization ratio are compared to the raw data collected from the field.

Figure 6 illustrates an application of the computer-aided capacity planning model based on the principal of queuing system modeling discussed in this chapter.



CHAPTER 2

DATA COLLECTION

This chapter discusses the data collection process, including the design of observation periods and sampling methods. The environment of the study site, workload characteristics and operation cycle are investigated to determine the factors and constraints influencing the system being studied. The devices used in data collection including customized Visual basic software, observers' tasks and JAVA simulation program are presented for further understanding of the data collecting process.

Environment of the Data Collection

The data are derived from the real life events of the every day activities over eight weeks of field observation. The setting of this computer section is an open environment. In order to obtain a precise information and evaluation of the variables being investigated, any action that might introduce an artifact into the data was avoided.

Study Location

The studied site is a computer lab in the student Union Building of Michigan State University (MSU), East Lansing, Michigan. This section is a computer facility open to all MSU students seven days a week. This computer facility provides a total of 82 computer stations, pooled dot-matrix printers, and a laser printing service. There are two different kinds of computers. These include 32 IBM compatible computers and 50

Macintosh computers. The rationale for selecting this computer section for the study of space sharing was based on the service mechanism of this particular computer section. Similar to the typical shared space system, this computer lab is considered an unassigned workspace. The "service" provided in this computer lab is based on a *FIFO* (first in, first out) queuing discipline. This is a result of a policy that aims at increasing multiple users per resource (computer station) and yields the maximum convenience (accessibility) for users.

Workload Characteristics (Types and characteristics and behavior of users)

The majority of the users of this public computer section are Michigan State University students. However, the policy of this computer section allows some guest users to utilize the computer service for tasks not requiring a student ID; such as for word processing or database programs. The tasks that users perform in this computer section are as follows:

- Class registration
- Checking e-mail
- Using the internet
- Homework and report preparation
- Others

CLASS REGISTRATION

Students may register for courses for the current semester at the beginning of semesters, and at the end of the semesters for upcoming semesters. During this period, the computer section is very crowded and is expected to have a short interarrival time and short service time.

CHECKING E-MAIL

Checking e-mail results in irregular service times on each computer station. The service time when users only check their e-mail is shorter than when they reply to mail. This task induces a high turn over rate of the users of this computer facility. In the beginning of the semester, the new users such as freshman students need to set up their e-mail accounts, which increases a total service time of the facility.

USING THE INTERNET

This task time may vary depending on the preference of each user. Normally when users come to use the Internet, they may check their e-mail and play computer games to pass their time. (See: the result from the observation.)

HOMEWORK AND REPORT

Students use the computer stations to do home work and reports throughout the semester. However, when collecting data for the study, it is expected that the number of users will increase before the semester break (i.e. before the midterm examination) and before final examinations at the end of the semester. These behaviors result in the fluctuation of interarrival time and service time of that period mentioned above. In addition, sometimes when the students have to do a group report, multiple students may be working in groups on one or two computer stations

OTHERS

This public computer section at the Student Union Building also provides some typing tutorial software and other software with similar functions. The utilization of these programs leads to the longer service time on the computer station as well. In addition, there are some software games such as solitaire and jig saw puzzle on some computer stations. However, it is not possible from current observations to record or determine how the utilization of these programs contributes to the distribution of service time in the computer section.

The Operation Cycle

Understanding the operation cycle is critical to the data collection process and simulation of the performance of the facility. The whole data collection process should cover the facility's operation cycle, which contains the critical value of the users' interarrival time and waiting time. This information (maximum and minimum users' interarrival and waiting times) is essential to a thorough evaluation of the performance of the system.

In this computer facility, the operation cycle corresponds to the semester year and university calendar. The operation cycle begins before the university is opened because the computer section has to allow some time for the students to enroll and set up their e-mail accounts. However, the university accepts new students in fall, spring, and summer semester, which leads to a fluctuation in the number of users in the computer section at the beginning of each semester. Normally, fall semester represents the major arrival time for incoming students, resulting in a greater user interarrival time distribution in the computer section than at any other time of the year. The computer section has different working hours during the semester break and summer semester in accordance with the smaller number of students on campus at this period of time.

Devices

This section describes the method and devices used in the collection of the variables critical to this study. The data collecting process focuses mainly on the recording of users' interarrival time and service time throughout one semester. The data regarding users' waiting time is collected in order to verify the result generated by the computer simulation model. The data collection plan and schedule are described in the next section.

This study focuses on recording and evaluating of the numerical data (interarrival time and service time), which then is interpreted into the characteristic of the distribution of each variable throughout the whole study period. The customized software and devices including the observers in the data collection process are described below.

Customized Visual Basic programs

Two customized Visual Basic programs software were written specifically for this data collection process. Each program was used to collect the interarrival time, and service time of each station. These programs are designed to count time, number of users, and then file the report in the form of a data log. These two customized data collecting programs are for the documentation of: 1) interarrival time and service time, 2) waiting time in the queue. (See: Figure 7-**Figure**)

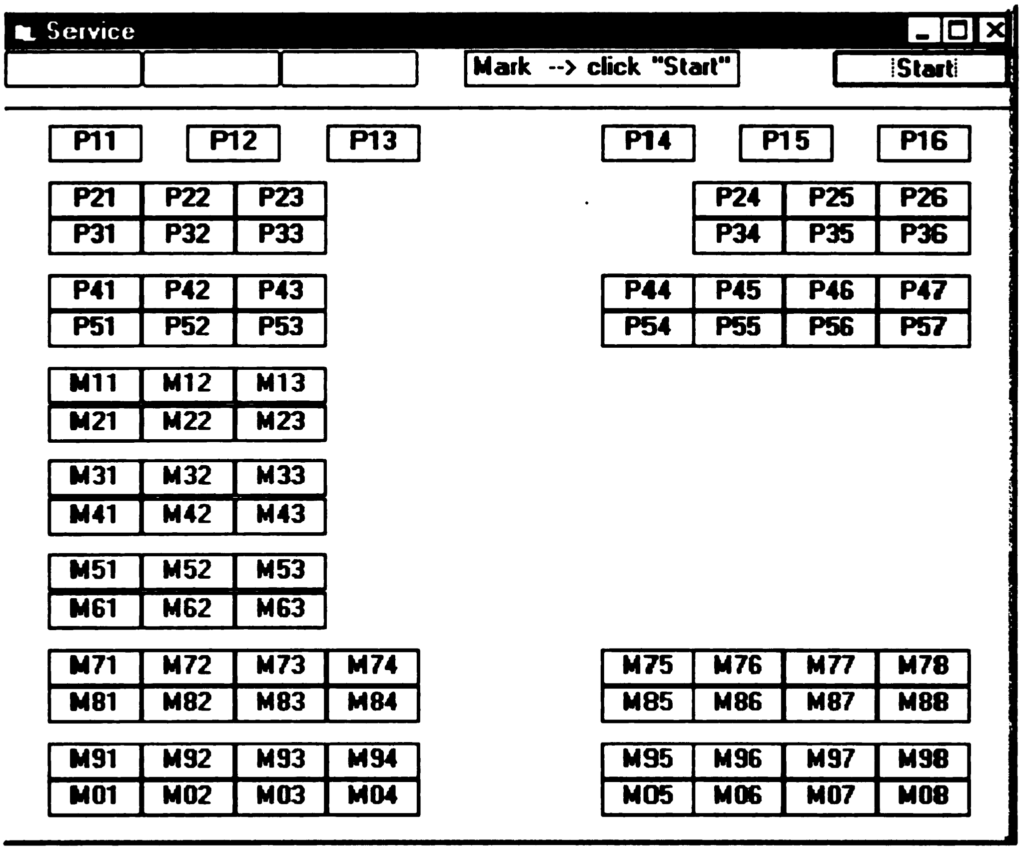


Figure 7: GUI of Interarrival time and service time recording program on Visual Basic

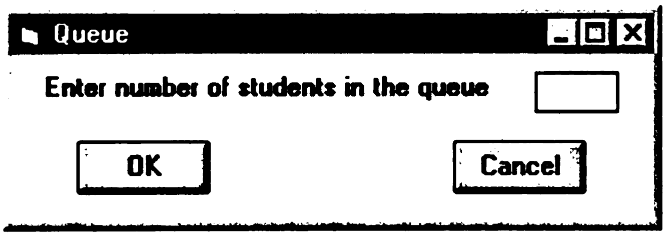


Figure 8: GUI of Queuing recording program on Visual Basic

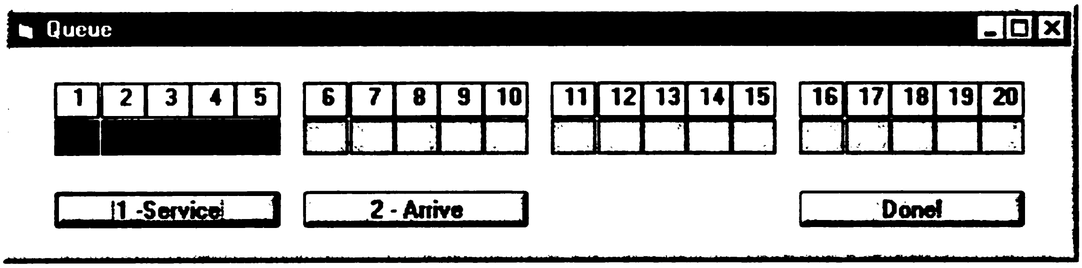


Figure 9: GUI of queuing recording program on Visual Basic

Data were collected by three observers using these programs. One observer was responsible for recording the data including user's interarrival time and service time aided by the other two observers who were responsible for monitoring arrival times and also observing the users' behavior in the computer section.

Customized JAVA program for simulation

The customized JAVA program for simulation of the distribution of waiting time and utilization ratio is used to simulate the pattern of the users' behavior based on the given parameters (mean interarrival time and mean service time) derived from the previous statistical analysis of the data collected. The simulation model in JAVA generates the users' waiting time and resource utilization ratio within the time period specified. The results of the waiting time and the utilization ratio were then compared to the sampling data collected from the field.

Similar simulation software is commonly used for predicting the outcomes on service lines in manufacturing systems. However, this software is quite expensive, thus this study used the customized JAVA program, which is able to perform the same functions, and can be viewed on the Internet with a standard web browser.

This customized JAVA program contains the following basic features:

1) *Input boxes* for:

- Mean of users' interarrival time (seconds)
- Mean of service time (seconds)
- Simulation time (second)
- Unit of service stations or computer stations

(See: Figure 10-Figure 12 below.)

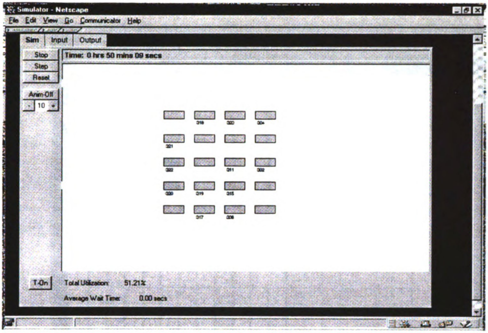


Figure 10: GUI of simulation Results

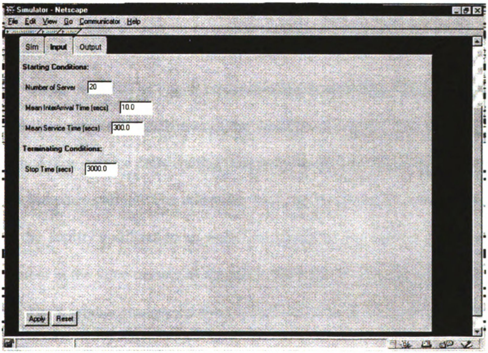


Figure 11: Input Measures Menu

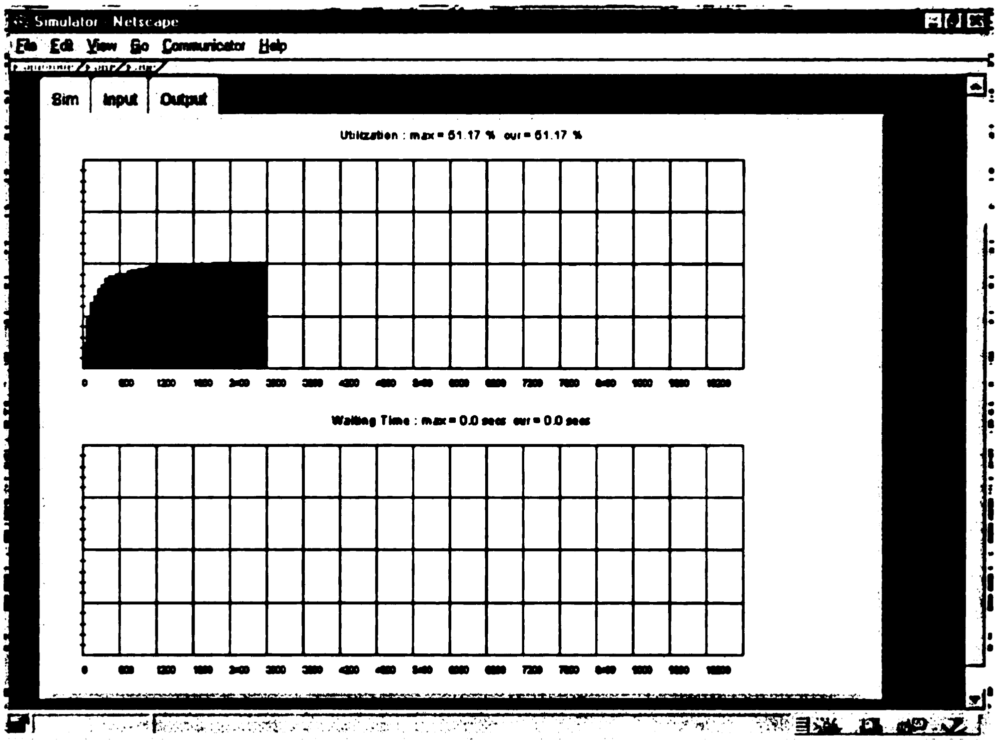


Figure 12: Graphic display of Users' waiting time and Resource Utilization Ratio

2) *Output report.* The output report displays several forms including the time log, and real time graphical distribution of the variables of interest. The time log includes user's arrival time, service time, waiting time in the queue line log and trace of the utilization of the computer stations. The utilization ratio can be displayed in real time as a percentage of the facility's utilization as well. The length of the waiting queue is displayed as a symbol in the same manner as the real event when a user enters the facility. The color of the user's symbol changes corresponding to the time the user spends waiting in the queue line.

Observers

Observers are trained to use the data collection programs mentioned above. In each data collecting session, one of the observers is administering and recording the data using the data collecting program (customized Visual Basic program) on one of the computer section's IBM compatible stations. At the same time, one or two of the other observers are monitoring the arrivals, length of service time and departures of the computer section users and inform the observer who is responsible for recording the data.

Data Collection Schedule

The data collection periods were separated into subcategories based on the academic calendar, which is described as follow:

a) Beginning of the semester (four weeks)

b) Midterm examination (four weeks)

c) After midterm examination (four weeks)

d) Final week (four weeks)

Data collected from period "a. to b." was analyzed and used in constructing the trend analysis of the users' interarrival time and service time. Then this trend was projected and customized to predict the future trend (period "c. to d.") based on the data in period "c." In the same period of time ("a. to d.") the waiting time and the resource utilization were collected in order to verify the result from the computer simulation model. The data collected in period "c. to d." were used in verifying the result from the trend analysis. (See Figure 1: Study Plan Flow Chart).

Period of Observation

We assumed that the distribution of interarrival times and the service time of the users might vary from day to day and even from hour to hour. As the operation cycle of the university's facility depends on the semester and class schedule as well as the students' activities during the weekdays and weekend. From the 16-week duration of observation, data collection schedules were designed to cover a representative cross section of the data. However, the data collected from every observation session were examined the different and of their distribution in order to test the assumption we formed before the beginning of this investigation. The result of this test is presented in the next chapter.

Data collection for statistical analysis

As described in the plan for data collection, this process utilized customized Visual basic programs and observers to collect the users' interarrival time and service time from the beginning of the semester until the week after the midterm examination. The collecting time was distributed into 14 groups, which are described as following:

-Beginning of the semester (First quarter of the observation session)

-Midterm examination (Second quarter of the observation session)

In each week the collecting time will be distributed into:

-Weekdays

-Weekend

During weekdays, the time will be distributed into:

-Before 10:00 a.m.

-10:00 a.m. - 2:00 p.m.

-2:00 p.m. - 6:00 p.m.

-After 6:00 p.m.

During weekend, the time will be distributed into:

-12:00 a.m. - 2:00 p.m.

-2:00 p.m. - 6:00 p.m.

-After 6:00 p.m.

These 14 groups cover the duration of the first 8 weeks of spring semester, which consists of approximately 182 periods. To obtain the data, 3 periods for each grouping were randomly selected for 2-hour observation sessions. This schedule produces 42 total observation sessions. The plan for data collection was designed to investigate the variability of the distribution of the interarrival time and waiting time corresponding to the computer lab hours. (See: Table 1-Table 2)

Sampling Method

The sampling method used to collect the users' interarrival time and service time is designed to cover the cross section of the entire 8 weeks of spring semester. From the total 182 observation sessions derived by the criteria stated above, we decided to examine thirty percent of the total time period which produces 42 observation sessions.

The criteria used to select the observation sessions were based on the *stratified random sampling* method in which the data population is divided into a number of mutually exclusive subpopulations (or subgroups). Each *stratum* that we assumed to have a homogenous data distribution is selected to be observed by a simple random sampling method. The selection was done by randomly drawing the number assigned for each period in the duration of the study from each grouping (or *stratum*). The planning strata sample size of this study is based on the allocation of the total sample size of the total sample size to the individual *strata.(Tables 1 & 2).*

Beginning of the semester (The First Quarter of the Semester)	Week days	Before 10:00 a.m.
		10:00 a.m. - 2:00 p.m.
		2:00 p.m. - 6:00 p.m.
		After 6:00 p.m.
	Weekend	10:00 a.m. - 2:00 p.m.
		2:00 p.m. - 6:00 p.m.
		After 6:00 p.m.
Midterm examination (The Second Quarter of the Semester)	Week days	Before 10:00 a.m.
		10:00 a.m. - 2:00 p.m.
		2:00 p.m. - 6:00 p.m.
		After 6:00 p.m.
	Weekend	10:00 a.m. - 2:00 p.m.
		2:00 p.m. - 6:00 p.m.
		After 6:00 p.m.

Table 1: Data Collection Periods

Week day : The First Quarter		Weekend : The First Quarter	
January	13 14 15 16 17	January	18 19
	20 21 22 23 24		25 26
	27 28 29 30 31		1 2
	total = 15 days		total = 6 days

Week day : The Second Quarter		Weekend : The Second Quarter	
February	3 4 5 6 7	February	8 9
	10 11 12 13 14		15 16
	17 18 19 20 21		22 23
	24 25 26 27 28		1 2
	total = 20 days		total = 8 days

Week day : The Third Quarter		Weekend : The Third Quarter	
March	10 11 12 13 14	March	8 9
	17 18 19 20 21		15 16
	24 25 26 27 28		22 23
	total = 15 days		total = 6 days

Week day : The Forth Quarter		Week : The Forth Quarter	
April	31 1 2 3 4	April	29 30
	7 8 9 10 11		5 6
	14 15 16 17 18		12 13
	21 22 23 24 25		19 20
	total = 20 days		total = 8 days

Total of 98 days observation.

Table 2: Periods in Springs Semester based on MSU academic calendar. (Not including Spring Break.)

CHAPTER 3

DATA ANALYSIS: METHODOLOGY

This chapter describes the data analysis and methodology used in order to obtain the parameters of interarrival distribution and waiting time used to construct the simulation model. Then the parameters from each group of the data, including users' interarrival time and service time are used as inputs for the simulation model to generate the waiting time and resource utilization ratio. Finally, the simulation results are compared to the raw data (real waiting time and resources utilization ratio) from the sample and examined as to the accuracy of the model. This chapter is divided into two sections including; 1) Data analysis for constructing the simulation model and 2) the comparison of the results generated by the simulation model and the data collected from the field.

Data analysis for constructing the simulation model

Data from each of the 42 observation sessions was analyzed to determine the appropriate distributions as described in the following:

a) Collect data of *interarrival time* of users, and *service time* of users per computer from a selected public computer section.

b) Group the data and identify the distribution by constructing a histogram. Then make the distribution assumptions of the data on the basis of the histogram shape.

c) Estimate the distribution of parameters.

d) According to Poisson distribution the distribution of interarrival time and service time are assumed to be exponentially distributed.

e) Test the hypotheses with a Goodness-of-Fit test (Kolmogorov-Smirnov test) to verify whether the interarrival time and service time are exponentially distributed.

f) If the distribution of interarrival time and service time are exponential, use the *average* of each group of data as the estimator.

g) Use the estimator from each data group to construct the computer simulation model Discrete-Event System Simulation.

h) Compare the results of waiting time and resource utilization ratio generated by the simulation model with data collected by observation.

Estimation of the Data Distribution (interarrival time and service time) Based on Principal of Poisson Process

The estimation of the data distribution is very important in determining the input parameters used in the simulation model. According to Banks & Carson II (1984), "*the arrival time and service time may be described as a counting function **N (t)** define for all **t ≥ 0**. This counting function will represent the number of event that occurred in **[0,t]**. Time zero is the point at which the observation began, whether or not an arrival occurred at that instant. For each interval **[0,t]**, the value N **(t)** is an observation of a random variable where only possible values that can be assumed by N **(t)** are the integers 0,1,2...*"

The counting process, {*N (t)*, ***t ≥ 0***} is said to be a Poisson process with rate λ if the following assumptions are fulfilled:

1) Arrivals occur one at a time.

2) $\{N(t), t \geq 0\}$ has stationary increments: The distribution of the number of arrivals between t and $t + s$ depends only on length of the interval s, and not on the starting point t. Thus, arrivals are completely at random without rush or slack periods.
3) $\{N(t), t \geq 0\}$ has independent increments: The number of arrivals during nonoverlapping time intervals are considered independent random variables. Thus, a large or small number of arrivals in one time interval had no effect on the number of arrivals in subsequent time intervals. Future arrivals occur completely at random, independent of the number of arrivals in past time intervals. [1]

If arrivals are in accordance with a Poisson process, then the process meets the three assumptions above. In the Poisson process, it is proved that all the interarrival times (A_1, A_2,...), are exponentially distributed and independent with mean $1/\lambda$. As an alternative definition of a Poisson process, it can be shown that if interarrival times are distributed exponentially and independently, then the number of arrivals by time t, say $N(t)$ is a Poisson process.[2]

According to the property of Poisson process, if the distribution of interarrival process in this computer facility meets the three assumptions as mentioned above, the distribution of the interarrival time is assumed to be exponentially distributed. Similarly, the distribution of the service time in this computer facility can be performed with the same process.

Hence the distribution of the interarrival time and service time are assumed to be exponentially distributed, which is required to test the hypothesis (distribution assumption) before using the estimator of the data as the input to the simulation model.

[1] **Banks & Carson II, 1984.**

[2] **Ross, 1981.**

Kolmogorov-Smirnov Test for Goodness of Fit for Exponential Distribution

The Kolmogorov-Smirnov (K-S) test is a test of uniformity and used in verification of a new generator. The test measures the degree of agreement between the distribution of a sample of generated random numbers and the theoretical uniform distribution. It is also based on the null hypothesis of no significant difference between the sample distribution and the theoretical distribution.

The K-S test is particularly useful when the sample sizes are small. If the size of the data set from each observation session is varied, it is appropriate to use the Kolmogorov-Smirnov test in this study. In order to use the K-S test to examine the distribution of interarrival process, the null hypothesis and its alternate are formed as follows:

H_0 : *the interarrival times are exponentially distributed*
H_1 : *the interarrival time are not exponentially distributed.*

According to Banks & Carson II (1984), when the data are collected over the interval 0 to T, it is proved that if the underlying distribution of inter arrival time (T_1, T_2,...) is exponential, the arrival times are uniformly distributed on the interval (0,T). The arrival times (T_1, T_1+T_2, $T_1+T_2+T_3$,....,$T_1+.....+T_n$) are obtained by adding interarrival times. The arrival times are then normalized to a (0,1) interval so that the Kolmogorov-Smirnov test can be applied.

The K-S test utilizes a statistic that is based on the differences between the cumulative sample function and the cumulative probability function for the population. The K-S Test does not depend on the specific form of the cumulative probability function of the population. The K-S test procedure can be applied to the hypothesis testing of the service time distribution, thus it can be used to test whether the cumulative probability function has a specific form. Since the estimator for exponential distribution is an average, the averages of interarrival time and service time are valid to use as the input estimators in the model. After the interarrival time and service time distribution are proven to be exponential, the estimators (mean of interarrival time and mean of service time) from each group of data are used to generate the waiting time and resources utilization ratio of that session.

Data Interpretation

Users' interarrival time and service time of each data collecting session are converted into numerical data by the same customized Visual Basic program that was used in the data collecting process. Data from each observation session are composed of two sub group: 1) data for the 50 Macintosh Computer Stations and 2) data for the 32 PC (IBM Compatible) computer stations. The users' *interarrival time* and *service time* of each sub groups are recorded and analyzed independently.

The following section discusses briefly the conceptualization of each variable and the method used to derive their estimators.

INTERARRIVAL TIME

Interarrival Time is the elapsed time between two consecutive user arrivals. The unit of *interarrival time* is in "seconds." The estimator used to represent each data set is the average (μ). Though in the analysis of *interarrival time*, λ ($1/\mu$) is used as an estimator for the distribution of *interarrival rate*. Since *interarrival rate* is equal to 1/interarrival time, μ is an appropriate estimator used for the distribution of *interarrival time* when assuming that it is exponentially distributed. In collecting the data of the *arrival process*, we are able to identify whether the users come to use the PC (IBM compatible) stations or Mac stations. The procedures used to estimate the average *interarrival time* of the users of each type of the computer station are as follows:

N = Total number of users arrival

n_{PC} = number of PC (IBM compatible) users

n_{MAC} = number of Macintosh users

Avg. interarrival time (Avg. (N)} = Avg. interarrival time of each data set (PC+MAC)

Average Interarrival time of IBM Compatible Section= $Avg.(N) \times \frac{N}{nPC}$ **(Seconds)**

Average interarrival time of MAC stations = $Avg.(N) \times \frac{N}{nMAC}$ (Seconds)

SERVICE TIME

Service time is a length of time that each user spends at the *service station*. The unit used in measuring *service time* is in "seconds." In addition, the distribution of *service time* does not depend on the *arrival* of users to the facility. In opposition to the data collection of the *interarrival time*, we are able to identify the *service time* that each user spends on the station and type of computer station that is being used. In this situation, we do not have to estimate the *average* usage of the PC station and MAC station by using the total *service time*. The calculation for *average* of service time of each data group is shown as the followings:

n_{PC} = number of PC (IBM compatible) users

n_{MAC} = number of MAC users

$$\textbf{Average Service time of PC stations} = \frac{TotalPCserviceTime}{nPC} \textbf{ (Second)}$$

$$\textbf{Average Service time of MAC stations} = \frac{TotalMACserviceTime}{nMAC} \textbf{ (Second)}$$

RESOURCE UTILIZATION RATIO

Resource utilization ratio is the percentage of time that the service station is being used. The *resource utilization ratio* indicates the percentage of the resource used at the discreet point of time. The total *resource utilization ratio* can be the calculated in two different ways. The first method is to calculate the *resource utilization ratio* for every time interval (second, minute, and etc.), and then use the average of the summation of total utilization ratio as the estimator for that observation period. The second method is to calculate the *resource utilization ratio* whenever there is a change in number of users (users' arrival or leaving), then use the *average* of the summation of total *resource utilization ratio* of that period as the estimator of that observation period.

N = numbers of the station being used
N_S = numbers of station available

$$\textbf{Resource utilization} = \frac{N}{nS} \times 100 \qquad \textbf{(Percent)}$$

WAITING TIME

Waiting time is a length of time that each user spends waiting in the queue. The unit of *waiting time* used in this study is "seconds." It can be derived directly from the time that each user spends waiting in the queue line. The estimator for *waiting time* used in comparison to the result generated by the simulation model and raw data is the *average* (μ) of the *waiting time* for each observation period.

Cluster Analysis

A total of 42 data collecting sessions for the period of data collection in Spring semester are separated into two major periods: approximately one month from the beginning of the semester (period a) and another month before the midterm examination. Within each period, the data collections are separated into weekdays and weekend assuming that the *interarrival time* and *service time* may have different characteristics (distributions). And we the weekday data collection are separated into four periods, weekend into three periods corresponding to the computer section hours and in order to cover the cross sectional of the data distributed within the facility.

Though, the data collections are dissected into several different subgroups based on the assumption that they may have different attributes, the cluster analysis is used to test the dispersion of the data throughout the data collection process. The scatter plot using the coordination of *interarrival time* and *service time* of each data collecting session verifies whether or not the data set possesses a different distribution and is divided into groups as per our prior assumptions. Two different scatter plots for the MAC computer stations and IBM Compatible computer stations are created for this cluster analysis.

Comparison of the Results

This section gives the general idea of the method and principles in comparison of the simulation results to the data collected from the field observation. The overview of the simulation events generated by the computer described in the following section will give a better picture of how it works. Characteristics of the system being studied and criteria in using the simulation results as the estimator to verify this model are also described.

Data collection for verification of the computer simulation results

The *waiting time* and the *resource utilization ratio* was collected from the beginning of the semester to the week before midterm examination periods. Data were then compared to the simulation result at that specific time to test the simulation model.

The Computer Simulation for Queuing Model

The model used in predicting the *waiting time* and *resource utilization ratio* in this study is the M/M/1 queuing model, which is a discrete event simulation. As mentioned in a prior chapter, this basic queuing model generates the output measures for a discrete point in time, which permits the evaluator to test the capacity of the resource available in different scenarios. These input measures influence the utilization of the facility including number of *stations* available, *interarrival time* and *service time*. As opposed to a more complicated model, it is not able to generate continuous output measures throughout the operation cycle (semester year). However, the results from discrete-event simulation can be put together "manually" and used in predicting the capacity of the facility throughout the operation cycle as well.

In order to simulate usage of this computer lab at the MSU Union Building, the simulation is separated into two models including the IBM compatible stations and the MAC stations. Upon arrival, users of different types of computers wait in a different queue. Normally, there is only a *waiting queue* for PC stations, which have a smaller number of resources available. When MAC users arrive, they will go directly to the available MAC stations without spending time in a *waiting queue*. The two types of computer stations have different user interfaces. It is common that the users will use, and wait in the queue line if it is not available, for the type that they are familiar with. Though, the MAC stations and PC stations are in the same computer section, they are located in different sections and groupings, which allows the user to determine the availability of the type of stations that they prefer to use. The observations reveal that some of the MAC users tend to stay longer, over two hours (observation session), and sometimes use more than one computer station at a time (the station that they use and the adjacent one). According to the different characteristics of the users and the computers themselves, it is appropriate to evaluate the two types of computers in a different model for clarity of the output measures extraction.

The M/M/1 queuing model principal is described as follows:

ENTER- *Arrival Time* (t)

- Random next user *arrival* ($t+_{\Delta}t$)
- Put event **"ENTER** ($t+_{\Delta}t$)**"** into Event Queue
- Check if there is any computer station available
    - If available, enter the computer station and use
    - If not available, wait in the *Waiting Queue*

USE- Service Time (s)

- Random service time ($t+_{\Delta}S$)
- Put event **"EXIT** ($t+_{\Delta}S$)**"** into Event Queue

EXIT

- First user in the *Waiting Queue* enters the computer station
- Exit

The simulation model is programmed to be operated continuously following the event from the discipline described above within the time given by the evaluator. However, in the beginning of the computer simulation process, the number of users in the system starts from zero as when the facility opens in the morning. In contrast, the number of users in a normal computer operation hour that we want to test does not begin with zero since there are some users already in the lab. To obtain the precise waiting time and resource utilization ratio of those periods, we have to run the simulation more than the two hours (simulation time) to let the program pass the transient state, and then the waiting time and resource utilization ratio climbs up to the steady state.

From Monday through Friday, the computer section is considered a *non-terminating* system since it is operated 24 hours continuously. The *non-terminating* system differs from the terminating system in that the *non-terminating* system study is focused on the characteristics or the behaviors in the steady state or the long-run properties. The steady state of this system refers to the typical running operation whereas the transient stage refers to the running operation that starts from the empty or idle stage. During the *transient* stage, "*within a replication, there will be a higher than the typical probability of the system being uncontested for time close to 0*" (Banks & Carson II, 1984). As a result, the estimators derived from the simulation will be biased low, and this bias can lead to misleading results.

Considering the characteristics of a *non-terminating* system, it is important not to be influenced by the initial condition of a model at time 0 in the study. Hence, when simulating the system, we have to monitor the variables produced by the model. When the value of the variable stops rising and remains in the steady range, this value will be a valid estimator for the analysis. From the experience in simulating the model in this study, the typical transient stage requires approximately two-simulation hours. The value of waiting time and resource utilization ratio obtained after the first two-simulation hours are considered reliable as a replicate of a system behavior and in turn used as the output measures for the analysis.

Output Analysis (Paired t test)

The examination of output analysis for each type of output is determined by the result from the steady state to obtain a reliable output report. The test used in comparison of the simulation results and the historical inputs is a "paired *t* test" based on the *Central Limit Theorem*. In the paired *t* test, the historical out put is paired with the model output since each was produced by the same input data set.

The Central Limit Theorem is defined as follows: "*The distribution function of arithmetic of a large number of independent, identically distributed random variables is approximately equal to standard normal distribution function (approximately adjusted)....*" (Larson, 1969). This theorem is applied when analyzing the simulation output. Harrel et al. (1996) describes that "*a performance response produced from a single replication of a stochastic... (or process composed of randomly occurring events)... simulation can be considered a single sample from the distribution of all possible responses. Each independent model replication made thereafter produces another sample from the response distribution.*"

Banks & Carson II (1984) and Harrel et al. suggest the formula for computation of ***t*** statistic by

t_0 = Sample mean different

μ_d = True mean different

S_d = Deviation from mean

K = number of input data sets

$$\boxed{t_0 = \frac{\bar{d} - \mu_d}{S_s / \sqrt{K}}}$$

Similarly, in this study we do not know the probability distribution which represents all the possible outcomes. However, we know that the collection of the ***K*** sets of input data are separated in time, it is reasonable to assume that the K differences (between the historical outputs and model output) are statistically independent. Thus, the pairs of differences of the historical outputs and model outputs constitute a random sample and are approximately normally distributed with some mean μ_d and variance σ^2_d. With this information, we can use a standard normal probability density function to define confidence intervals for the point estimate of μ_d.

Then the t test of the null hypothesis of no mean difference are used as follow:

$H_0 : \mu_d = 0$

Versus the alternative of significant difference:

$H_1 : \mu_d \neq 0$

The test of no mean difference is done by computing the t_0 statistic using the paired t test mention earlier, and comparing the value obtained with the critical value $t_{\alpha/2,K-1}$ from the Table of Percentage Points of the Students t Distribution with υ Degrees of Freedom. (See: Appendix D). The criteria for the test is if $|t_0| \leq t_{\alpha/2,K-1}$, do not reject H_0 of no mean difference and conclude that test provides no evidence of model inadequacy. If $|t_0| > t_{\alpha/2,K-1}$, reject the reject H_0 of no mean difference and conclude that the model is inadequate (Banks & Carson II, 1984).

CHAPTER 4

RESULTS & DISCUSSION

This study focuses on testing the applicability and suitability of the Computer-Aided Capacity Planning Model for Facilities Management. The suitability of the data collection procedure including the methods of data collection and observation session, especially the data collection schedule and planning, are examined and discussed in detail. This chapter concludes by comparing the simulation results to the data derived from the field observation to validate the model. The accuracy of the waiting time and resource utilization ratio which are the main purpose of the simulation including the results from the IBM compatible section and Macintosh section are presented and compared.

Field Observation and Workload Characteristic

In the data collection planning process, the *workload characteristic* is taken into consideration when grouping data into *strata* for observation. As mentioned in the early chapters, we assume that the independent variables influence the capacity planning of the computer section including interarrival time and service time and should depend on the cycle of operation (university schedule). On the other hand, the variation of workload characteristics is a result from the users' activities; which cycle over the semester.

These activities include class registration, coursework, checking e-mail, using the Internet, etc. The major activities assumed to have most influence on the interarrival time and service time are class registration and coursework during midterm and final exams. Class registration may contribute to interarrival rate (or high arrival rate: large numbers of users arrive continuously) and the service time is assumed to be in the intermediate to long duration. Coursework during examination periods may contribute to a low interarrival time (high arrival rate) and very high service time.

Similarly, we assume that weekday interarrival and service times differ from the weekends. Weekdays may have low interarrival time (high arrival rate) because of the high number of the students on campus who would come and use the computers in this Union building computer lab. On the contrary, weekends are assumed to have high interarrival time (low arrival rate) and high service time because fewer students remain on campus and they may come and use Internet, check e-mail or even do their homework. However, the weekend users do not have much time constraints on use as compared to weekday users since there are less or none users waiting outside in the queue line.

The Union Building computer lab is composed of two different kinds of computer stations. Observations revealed different workload characteristics of the IBM compatible users and the Macintosh users. IBM compatible users tend to have a longer period of service time, and normally spend some time waiting in the queue during peak weekday hours before entering the section. This is the result of the smaller number of computer stations available (32 computer stations), and one or two stations usually out of service, further reducing available the number of available workstations. Because of the relative scarcity of IBM compatible machines, users tend to be more possessive towards a station once occupied. When the queue grows long, users waiting at the end tend to abandon their place when the waiting time exceeds ten minutes. This may reduce user satisfaction toward operation of this computer lab.

Unlike IBM compatible users, Macintosh users tend to move around, select and change computer stations until they are satisfied. Some users occupy multiple stations. The same group of users may use a computer longer than a couple hours at one time. These users may leave their belongings at the station that they use and leave the section and then return to resume using that computer. This occurrence may happen more than one or two times per session for the Macintosh users. The Macintosh section is less crowded than the IBM compatible section. The users do not have to form the queue in order to enter the section. When the Macintosh users arrive and find the waiting line for IBM compatible computer stations, they will go directly into the Macintosh section to avoid waiting in the line. These assumptions for variations in interarrival time and service time are tested by using cluster analysis.

Cluster Analysis

Cluster analysis is used to determine the grouping of data. We performed separate tests for the IBM compatible section and the Macintosh computer section since their operation and users are independent. The cluster analysis used the coordination of the plotted average of interarrival time and service times from the same observation. These are used to test the assumption of the variation of the workload characteristics correlated with the stratified random sampling method. (See: Appendix A: IBM compatible computer section and Macintosh computer section's Interarrival Time and Service Time). In these scatter plots, the interarrival time and the service time of each data set represent its unique characteristic. If the assumptions that the data have 14 different characteristics as we expected prior to the data collection is true, then the data sets from each stratum should be clustered in the same group and vice versa.

PC Section (IBM Compatible)

The PC section is composed of 32 IBM compatible computer stations. Normally, at least one to two computers are out of service, reducing the true count to 30-31 computer stations available for the users. Figure 13 illustrates the scatter plot of the IBM compatible section using the coordinate of interarrival time and service time of each observation period. We can see that the *average interarrival time* for the IBM compatible section clusters around 300 seconds (5 minutes), and *service times* vary from 900 seconds (15 minutes) to5000 (approximately 1 hour 33minutes). The only outlier data set is "1251739" which is from Saturday, January the 25 at 17:39 hours. This data set is also an outlier data in the cluster analysis for Macintosh section.

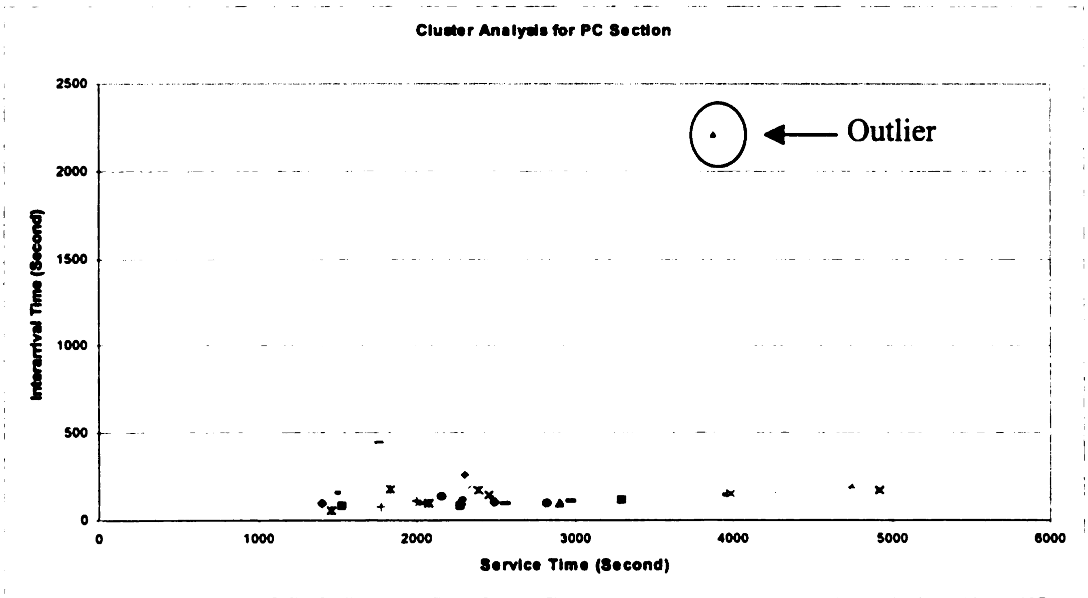


Figure 13: Cluster Analysis for PC Section (Full Scale)

Figure 14 shows the close up grouping of the clustering data in the range of 0 to 300 seconds (5 minutes) of interarrival time. We can see that the greater number of data sets (Cluster **A**) cluster around interarrival time of 60 to 180 seconds (1to 3 minutes) and the service time around 1200 to 3000 seconds (20 minutes to 50 minutes). In Cluster **B**, the data sets group around interarrival time of 120 to 180 seconds (2 to 3 minutes) and service time around 3600 to 5000 seconds (60 to approximately 80 minutes).

From the grouping of the data set in the scatter plot shown in Figure 14, it is obvious that period of time in the day does not influence the interarrival time and service time of the users of the IBM compatible computer section as we assumed before collecting the data. 78.69% of the data collected are cumulated in cluster **A,** which contains the data set from weekdays in different time periods of the day.

Most of the data sets (13.04%) in cluster **B** are comprised of the data from the weekend which have high interarrival time (low interarrival rate: small number of users enter the section) and high service time. A few fragments of the data sets from cluster **B** are from the weekday in the week of midterm examination. The high service time and low interarrival time in this analysis is consistent with to the assumption we proposed before collecting the data.

For the outliers, the data sets are from the first period quarter of the semester in the afternoon period. The proportion of the data is only 8.27%, which is insignificant when comparing the grouping of the entire data set. In the close up figure (Figure 14), there are two outliers including two data sets from weekend. These data are from the verge of the first and second quarter of the semester. We are not surprised to see the data sets from the weekend of the third and forth week of the semester that have high interarrival time (range of 250 to 260 seconds) and medium service time (2300 to 3000 seconds).

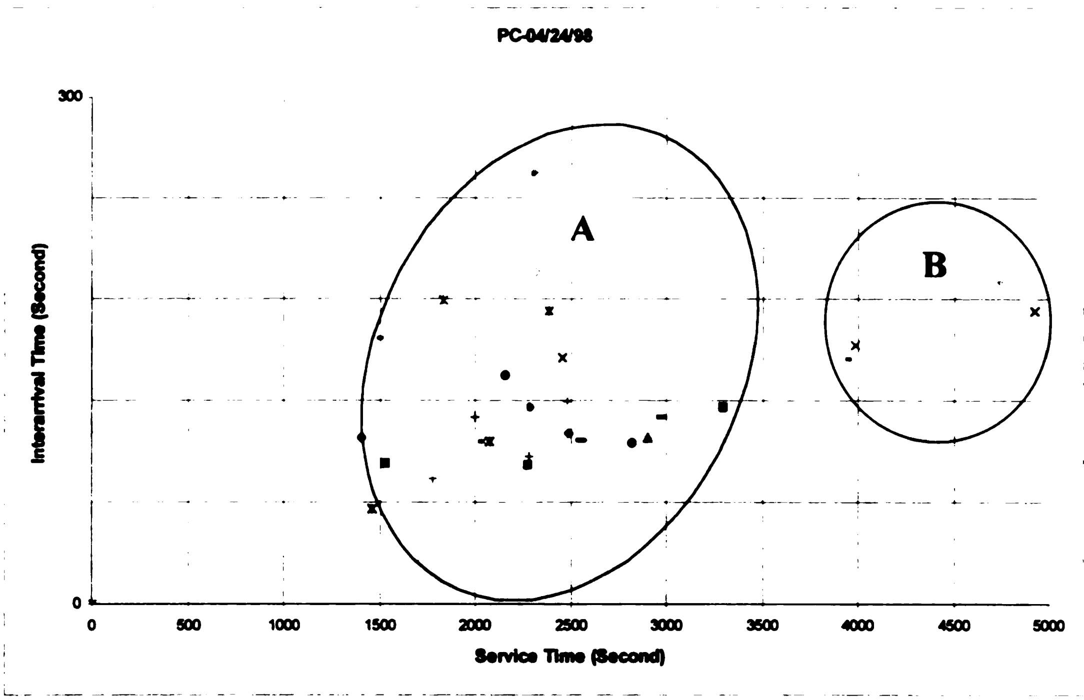


Figure 14: Cluster Analysis for PC Section (Close up)

Macintosh Section

50 Macintosh computer stations are provided in the Macintosh section of the Union Building computer section. Similar to IBM compatible section, 3 to 4 the Macintosh computers are normally out of service at the time leaving only 46 to 47 computer stations remaining available for the users.

From the full-scale cluster analysis (Figure 15) for Macintosh section, we found the same outlier data set which also appeared on the IBM compatible section. This data set was from Saturday, January the 25th which was the beginning of the semester. Regardless the outlier, the major group of data cluster around the service time of 600 to

3800 seconds (10 to 63.34 minutes) and the interarrival time around 60 to 270 seconds (1 to 4.5 minutes)

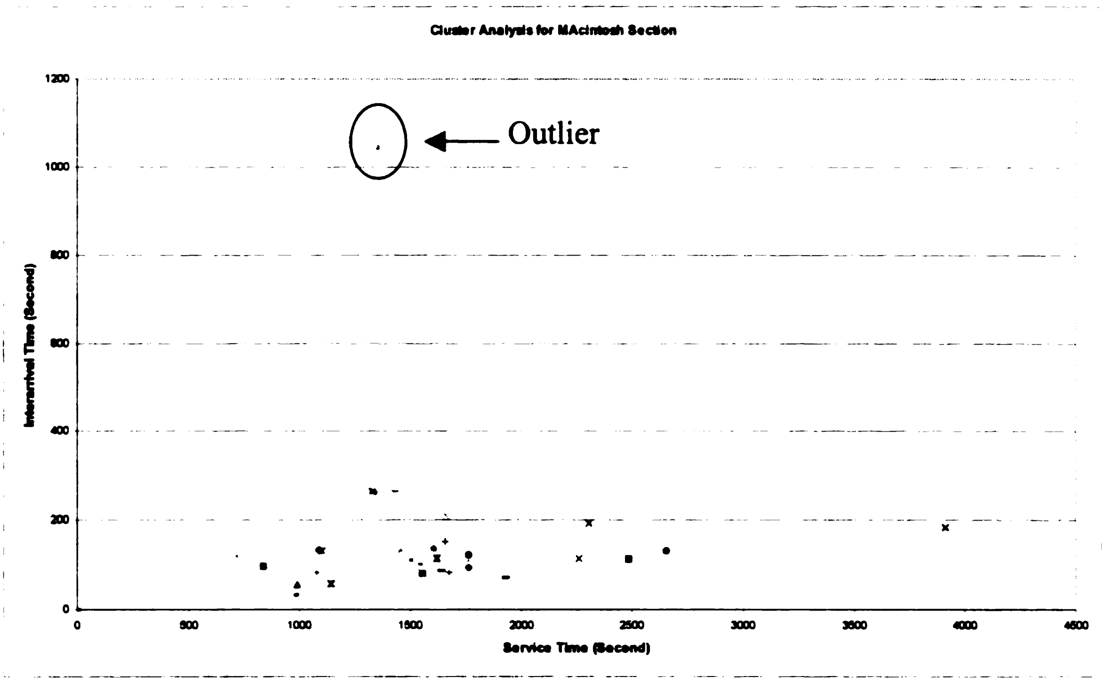


Figure 15: Cluster Analysis for Macintosh Section

A characteristic that complicates collection of Macintosh users' data is that users tend to change computer stations quite often. This results from a fair amount of the computers in the Macintosh section being out of service. Moreover, there are some users who occupy more than one computer over a few hours, and may leave the station unattended from time to time and eventually return to that computer again. These particular characteristics contribute to the low overall service time of the Macintosh section. Obviously, it is a pitfall from using the software which is not designed to trace subjects continuously moving from station to station. The program counts discrete service time from the time user begins using the computer until he finishes using that station.

From the observation, fewer users enter the Macintosh section than the IBM compatible section, and occasionally more than one user uses a single computer station at one time. With a greater number of the computer stations provided in the Macintosh section and a lower average service time, there is not a waiting line for the Macintosh users at all.

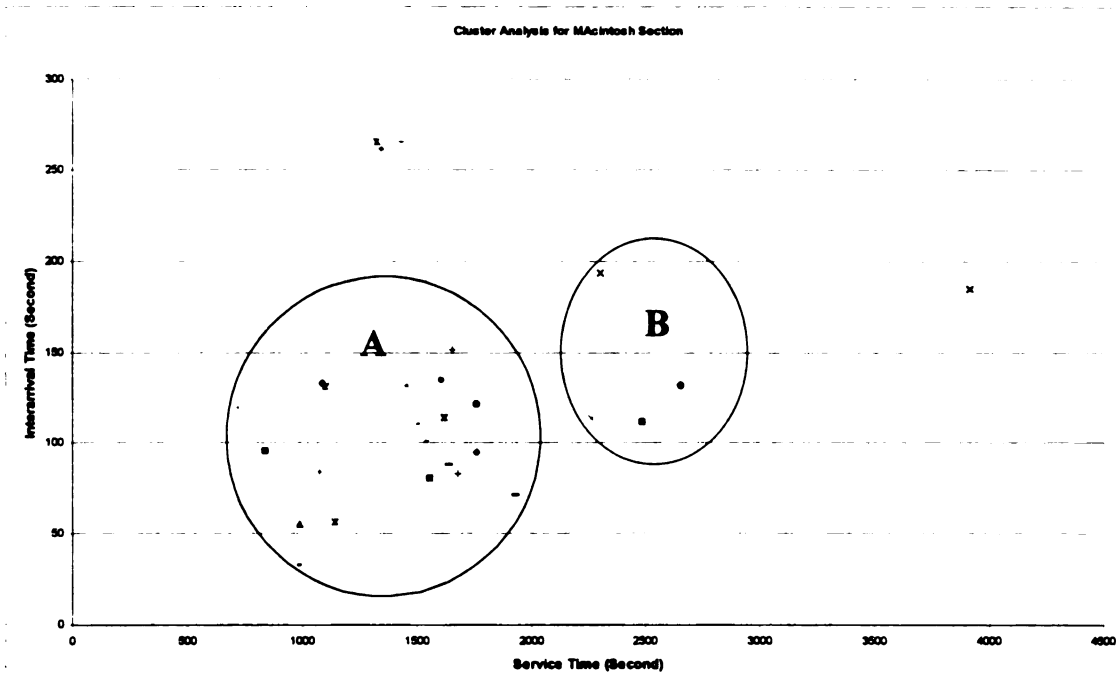


Figure 16: Cluster Analysis for Macintosh Section (Closed up)

When taking a close look at the grouping of the data set, we find that the data set divided into two clusters (see Figure 16). 84.78% of the over all data sets have the service time in the range of 1200 to 1800 seconds (20 to 30 minutes) and the interarrival time in the range of 80 to 300 seconds (1.34 to 5 minutes). Within this cluster, the data groups heavily around service time of 1500 to 1800 seconds (25 to 60 minutes) and the interarrival time around 80 to 150 seconds (1.34 to 2.5 minutes).

In the smaller cluster, 14.21% of the total data sets group around the service time of 2200 to 2800 seconds (36.67 to 46.67 minutes) and the interarrival time of 90 to 200 seconds (3 to 3.34 minutes). These data sets are from both weekdays and weekends in the different periods of time. The data set in the range of high service time usually derived from a week closer to the examination period and the period of time in the day does not produce a significant contribution to the high service time.

When analyzing the proportion of the stratum of data collection within each cluster, we found that different quarters of the semester and weekday and weekend period contribute to the different workload characteristics of the computer lab users. However, the different quarters of the semester do not have significant influence on the distribution of the workload characteristic as much as the difference on the weekday and weekend. The outlier data does not have any characteristics in common with one another. There is no trend in the distribution of the outliers. In conclusion, the strata designed for data collection planning are not correlated with the characteristic (interarrival time and service time) of the data sets.

For a further examination of the distribution of the data from each stratum, we calculate the percentage of the distribution of the data set from different strata within each cluster to identify for a stronger conclusion (support of the conclusion). The following tables and pie charts show the calculation of the distribution of the data-collecting stratum per cluster and per overall data set. The tables and pie charts show that the data from different strata scatter in both clusters and the outliers which means that the characteristics of the data set within each stratum are not associated with the planning of data collection as we assumed.

	Frequencies (Times)		First Quarter (Times)	Second Quarter (Times)	Total Frequencies (Times)
Weekdays	32	**Period 1**	3	4	7
		Period 2	4	5	9
		Period 3	4	4	8
		Period 4	3	4	7
Weekends	11	**Period 1**	2	1	3
		Period 2	4	2	6
		Period 3	2	1	3
Total	**43**	**Total**	**22**	**21**	**43**

Table 3: Frequency of the Data Collection (Stratum)

		Cluster 1 (Major sets of data)	Cluster 2	Others (Outliers)
IBM Compatible	Proportion	78.69%	13.04%	8.27%
	Service time	1200-3000 s.	3600-5000 s.	N/A
	Interarrival Time	60-80 s.	120-180 s.	N/A
Macintosh	Proportion	84.78%	14.21%	1.01%
	Service Time	1200-1800 s.	2200-2800 s.	N/A
	Interarrival Time	80-300 s.	90-200 s.	N/A

Table 4: Proportion of the Data Set in Each Cluster of the IBM Compatible and Macintosh Section

N=43	PC			Total	MAC			Total
	Cluster A	Cluster B	Outliers		Cluster A	Cluster B	Outliers	
Weekday	93.75%	6.25%	0.00%	100.00%	75.00%	12.50%	12.50%	100.00%
Weekend	54.55%	27.27%	18.18%	100.00%	54.55%	9.09%	36.36%	100.00%
Quarter 1	77.27%	13.64%	9.09%	100.00%	63.64%	13.64%	22.73%	100.00%
Quarter 2	90.48%	9.52%	0.00%	100.00%	76.19%	9.52%	14.29%	100.00%
Period-1 Weekday	100.00%	0.00%	0.00%	100.00%	100.00%	0.00%	0.00%	100.00%
Period-2 Weekday	100.00%	0.00%	0.00%	100.00%	77.78%	22.22%	0.00%	100.00%
Period-3 Weekday	100.00%	0.00%	0.00%	100.00%	100.00%	0.00%	0.00%	100.00%
Period-4 Weekday	71.43%	28.57%	0.00%	100.00%	14.29%	28.57%	57.14%	100.00%
Period-1 Weekend	100.00%	0.00%	0.00%	100.00%	0.00%	0.00%	100.00%	100.00%
Period-2 Weekend	50.00%	33.33%	16.67%	100.00%	100.00%	0.00%	0.00%	100.00%
Period-3 Weekend	0.00%	50.00%	50.00%	100.00%	0.00%	50.00%	50.00%	100.00%

Table 5: Distribution of Stratum Within Different Cluster

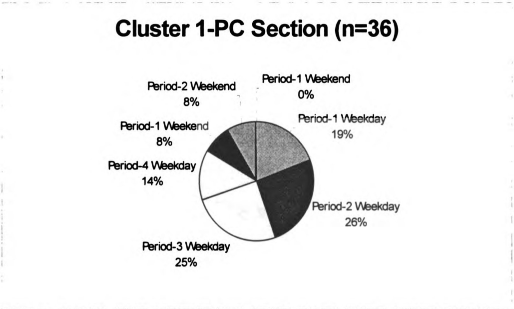


Figure 18: Distribution of Different Periods of Day in the Week within Cluster 1 of PC Section

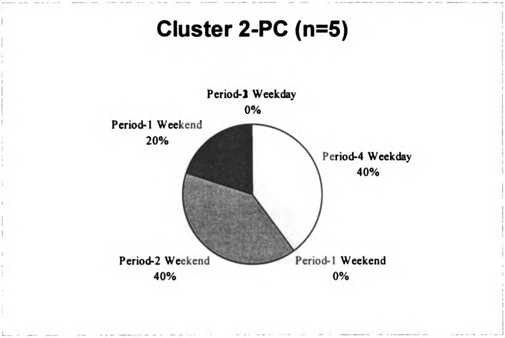


Figure 19: Distribution of Different Periods of Day in the Week within Cluster 2 of PC Section

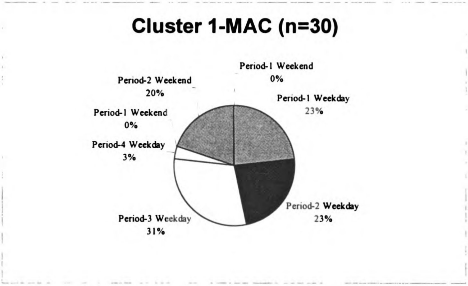


Figure 20: Distribution of Different Periods of Day in the Week within Cluster 1 of Macintosh Section

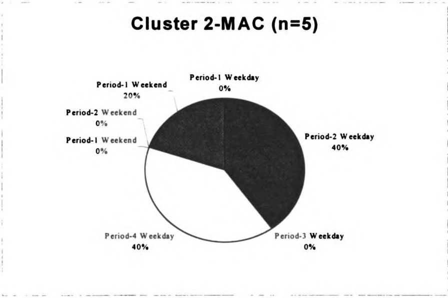


Figure 21: Distribution of Different Periods of Day in the Week within Cluster 2 of Macintosh Section

To this end, we can conclude that the *stratum* that we have planned prior to the data collection is too fine, and the period of observation of each session may be too short. The data sets from different time of the day do not have significant differences in their characteristics. The cluster analysis reveals that the variation of data groupings depends on the cycle of operation (users' time line and work due to the university schedule) and the different users' pattern of behavior on weekday and weekend.

Though the service times of the Macintosh Section users should be viewed with caution, due to their attributes in computer use and the instrument designed for data collection, the service times derived from the same group of users are reliable. On the contrary, the data collected from the IBM compatible stations is quite reliable due to the rigid characteristics and constraints upon the relatively small number of computers in this section. The service time and interarrival time derived from this group of users are more reliable than that of the Macintosh users.

In conclusion, the design for data collection can be improved for the further investigation by reducing the *stratum* of data collection period and focus on the different workload characteristics of: 1) weekday versus weekend and 2) cycle of the semester. The observation session in the facility that has 24-hour operation like this must have an intensive preliminary study to cover the users that use the resource for longer than 2 hours to obtain a precise service time distribution. Instead of spending a small fraction of the observation session to investigate the different users' patterns of behavior in the different times of the day, we should focus more on the longer observation session based on the *stratum* suggested above. Moreover, the instrument used in recording data must be able to trace the users who move around and change computers or occupy more than one computer at a time.

Trend Analysis

Trend analysis is normally used to describe and predicting the underlying process of the operation of the system of interest. In the 8-week duration of an intensive study of the computer section, cyclical components of a time series are suitable to use in predicting change or variation for the future trend due to its ability to capture the factor' s influence on the pattern or cycle of the operation. In this study we hope to use the cyclical component analysis to evaluate the short-term outlook of the pattern of the users in the Union Building computer section and forecast the pattern of the users' behavior in the next 8 weeks in the third and forth quarters of the semester.

When proposing the study for Computer-Aided Capacity Planning for Facilities Management, we also planned to use the same set of data in predicting the cyclical component of the variable in this study as well. In the beginning of data collection for sample of interarrival time and service time of the computer section, we assumed that the data collected for the simulation should be pertinent to the trend analysis for the cyclical component as well. Thus we spent 42 sessions of observation which produced 84 hours of observation time. However, when the service times and interarrival times were plotted, they did not lend themselves to fitting the periodic function. The plotting lines have erratic movement of an irregular component and did not allow us to predict the alternating pattern of expansion or contraction of the cycle. (See Figures 19-21 below).

Figure 19-21 illustrate the result of the interarrival time and service time over the observation period of 8 weeks plotted versus time. Evidently, they cannot be used to predict trends of the interested variables. However, we can see the fluctuation of the (high) interarrival time in the beginning of the semester in the period after class registration was over. (Please note that the higher interarrival time the longer the next user arrival after the prior one). For the rest of the semester the interarrival time in this time series plot does not lend itself to fit any assumptions we had prior to the data collection.

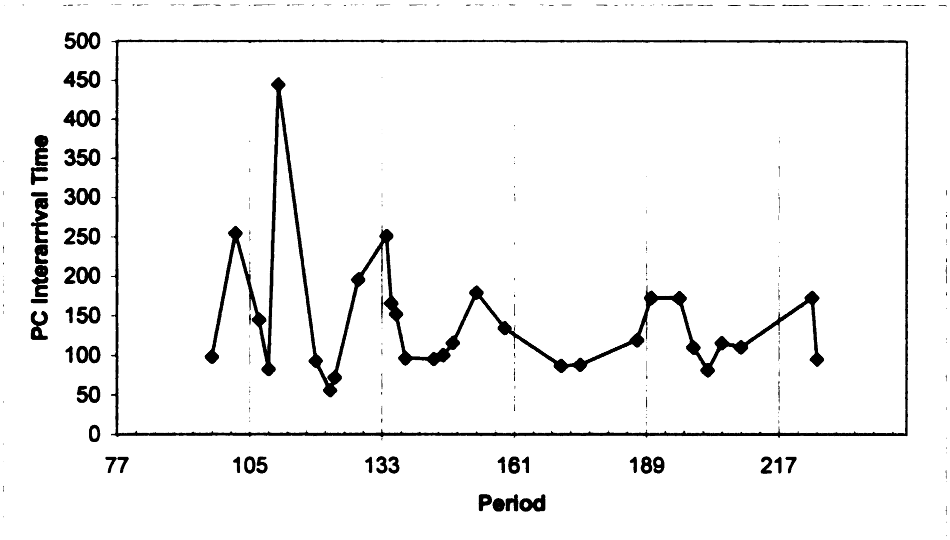


Figure 22: Time Series Plot of PC Interarrival Time

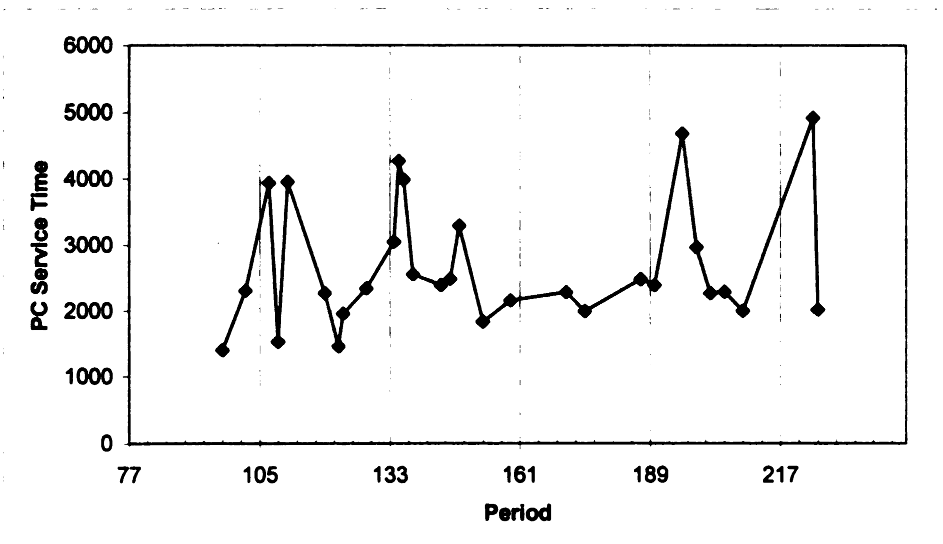


Figure 23: Time Series Plot of PC Service Time

In summary, data collection using a stratified sample mixed with simple random sampling techniques is not appropriate to apply to the cyclical component trend analysis in this experiment as designed. The reading of the data for trend analysis should be made at equally time intervals, and it should be fine enough to be able to smooth the fluctuation in a time series. To obtain a reliable and readable result for trend analysis, we should collect the data for a longer period of time which would cover at least a whole cycle of operation of the facility.

Simulation results

In this section, simulation results and the field data are compared and analyzed to complete the test of the Computer-Aided Capacity Planning Model for Facilities Management in this study. However, the main purpose of this research is to test the assumptions of applicability and suitability of this model when implemented in a real setting used a shared space strategy. The advantages and pitfalls of the procedure and the instruments designed for collecting the data in this study are determined when the simulation results are correlated with the raw data.

The variables of interest in verification of simulation results are overall waiting time and the resource utilization ratio. As described in the early chapters, the waiting times are collected by using the customized Visual Basic program (Figure 8: GUI of Queuing recording program on Visual Basic.) to collect the queue line and the length of waiting time of the users in the line. These waiting times are from the IBM compatible section alone since, from the observation, the users of the Macintosh section do not have to wait in a queue line at all.

The comparison of resource utilization ratio for both IBM compatible section and the Macintosh section.

Raw data for resource utilization ratio from each observation session is calculated individually by using the formula described in chapter 4. Then the raw utilization ratio from each session (historical outputs) is compared to the results from the simulation (model outputs). In the following section, we will examine the simulation results (or the model output) by the category variable of interest.

The tables showing the comparison of the historical outputs and the model outputs of both resource utilization ratio (IBM Compatible section & Macintosh section) and the waiting time (IBM Compatible section) are in the Appendix B. (See Table 7.)

Resource Utilization: Model Outputs

On the two systems studied, IBM compatible and Macintosh sections, each system is independent and has different workload characteristics. The model designed for this study tends to match with the characteristics of the IBM compatible section rather than the Macintosh section.

The following charts show the difference of the historical outputs (resource utilization ratio) and the model outputs from each observation session. From the chart, we can see that the model outputs of resource utilization for the IBM compatible section is more precise than those of the Macintosh section. The results of the paired t test of no mean difference support the assumptions that we have based on the experience from the field observation.

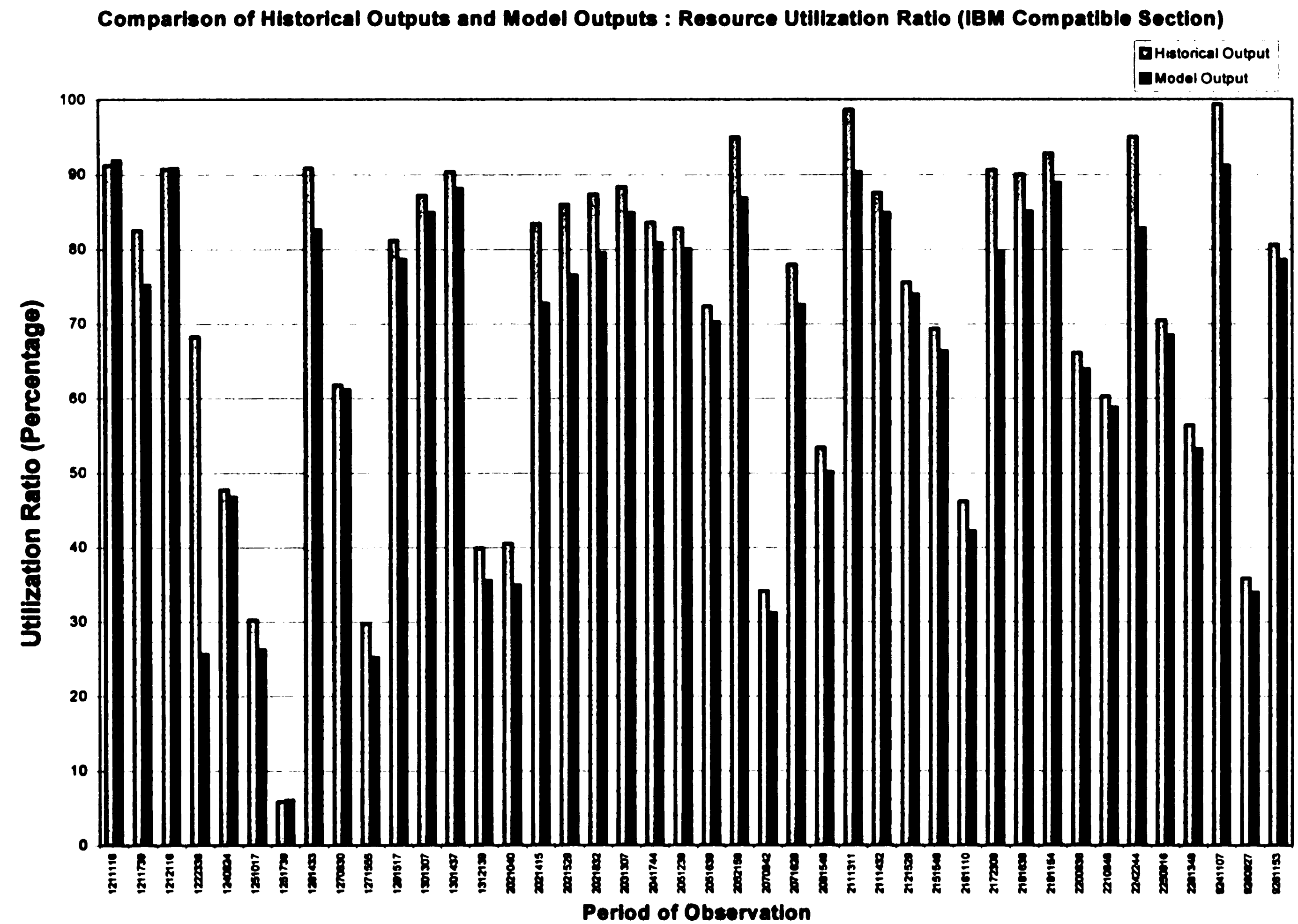


Figure 24: Comparison of Historical Outputs and Model Outputs: Resource Utilization Ratio (IBM Compatible Section)

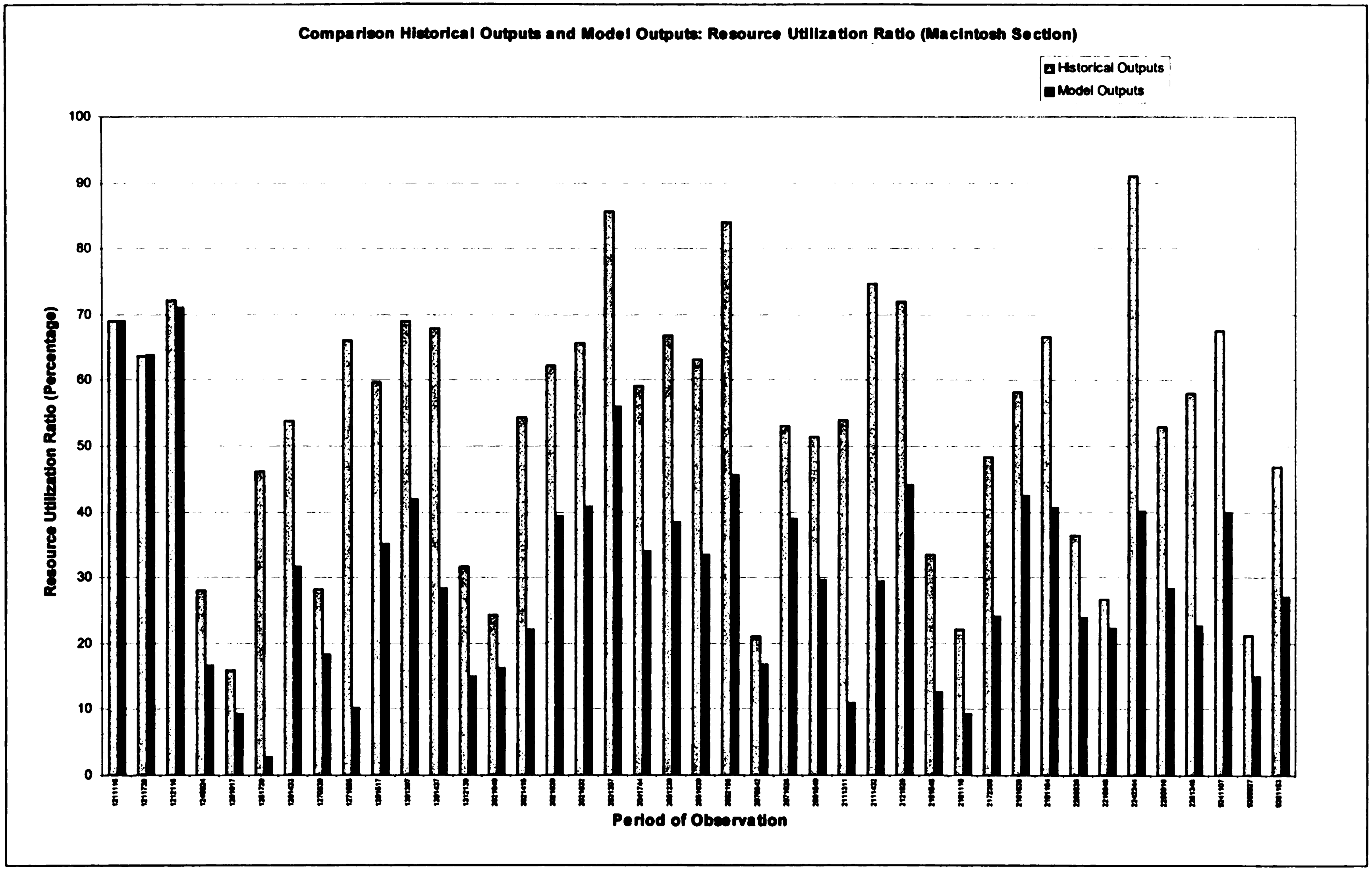


Figure 25: Comparison of Historical Outputs and Model Outputs: Resource Utilization (Macintosh Section)

The results of the ***t*** test at 99 percent Confidence Interval of null hypothesis of no mean difference for both IBM Compatible and Macintosh's utilization ratio are shown below.

t_0 = Sample mean difference

μ_d = True mean difference

S_d = Deviation from mean

K = number of input data sets

$H_0 : \mu_d = 0$
$H_1 : \mu_d \neq 0$

THE IBM COMPATIBLE SECTION: RESOURCE UTILIZATION RATIO

At 99 percent Confidence Interval: $t_{.0.05,\,40} = 2.70$

$\bar{d} = 1.040688$

μ_d = True mean difference (assume = 0)

$S_d = 2.496101$

$K = 41$

$$t_0 = \frac{\bar{d} - \mu_d}{S_s / \sqrt{K}} \qquad = \frac{1.40688}{2.496101 \;/\sqrt{41}}$$

$t_0 = 2.669625$

Since $| t_0| = 2.669625 < t_{\alpha/2,K-1} = 2.70$, the null hypothesis of H_0 of no mean difference can not be rejected and conclude that no inconsistency is detected between system response and model prediction in terms of mean production level. This means that the model for predicting IBM Compatible section resource utilization works reliably.

THE MACINTOSH SECTION: RESOURCE UTILIZATION RATIO

At 99 percent Confidence Interval: $t_{.0.005,\,40} = 2.70$

$\bar{d} = 22.79002$

μ_d = True mean difference (assume = 0)

$S_d = 26.82225$

$K = 41$

$$t_0 = \frac{\bar{d} - \mu_d}{S_s / \sqrt{K}} \qquad = \frac{22.79002}{26.82225 \; / \sqrt{41}}$$

$t_0 = 5.440533$

Since $| t_0| = 5.440533 > t_{\alpha/2,K-1} = 2.70$, then we reject H_0 of no mean difference and conclude test is that the model is inadequate. Unlike the IBM model, the model for predicting the Macintosh section's resource utilization ratio does not work reliably.

As explained in the cluster analysis section, the IBM compatible users have more static work patterns which permit the observers to collect a reliable users' service time on the computer station. On the contrary, the Macintosh users tend to move around and have irregular work patterns that do not conform with the devices designed for collecting the service time. Therefore the Macintosh users' service time derived from observation has a tendency to be lower than their actual service time. This factor contributes to the mean difference between the historical output (derived from the observation) and the model output.

Another input variable studied is the interarrival time. The interarrival time collected for both types of computers are reliable since the observers are able to monitor and record all of the user arrivals of both sections with the provided data collecting device.

With a reliable interarrival time and the unreliable service time of the Macintosh section, we found that the model is not able to predict the valid utilization ratio for this system. The historical outputs of each input data set that derived from the observation are calculated based on the following method:

Ui = Utilization ratio at interval i

Δt_i = length of time interval i

T = Total observation time

$$\textit{Avg. Utilization Ratio Historical Outputs} = \frac{\sum_{i=1}^{n}(U_i \times \Delta t_i)}{T}$$

The interval i is determined by a change in the system when a user enters the system and begins using a computer and/or user finishes using the computer. The total observation time (T) is the summation of the length of time interval at each constant utilization ratio of the system.

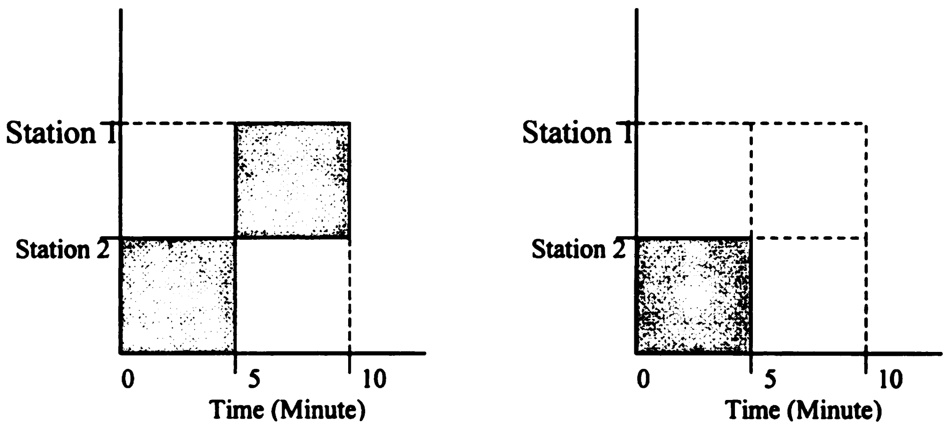
The model output of the Macintosh utilization ratio based on the given input number of interarrival time and the service time of the same observation period of those specific historical outputs (raw data of interarrival time and service time) used in comparison.

Since the Macintosh users have the irregular work patterns such as: 1) an individual occupied more than one computer, 2) an individual occupies the computer but he may leave the lab and return to that computer again, 3) an individual moves from the station to station, and 4) an individual occupies the computer longer than the observation period. These factors contribute a higher resource utilization ratio of the actual system than the model output using the same input data (service time and interarrival time).

The work patterns described above have induced a service time and resource utilization ratio to be shorter than the actual value.

The effect of this work pattern can be seen on the different case in a simple system of two computers and two different pattern of users' behavior. First example, the user enters the system and uses the first computer for 5 minutes, and then moves to the second computer and spends another 5 minutes on another station. When using the data collecting device designed for this research, the program will record that there are two of 5 minute-time interval during which the computers are occupied. Thus, the average of service time for this system is equal to 5 minutes. In comparison, the same user enter the system of two computer and uses only one computer for 10 minutes and leaves the system when he finishes. Therefore the average service time of the system is equal to 10 minutes even though a total service time of the first case and the second case are the same.

The similar problem affects the inaccuracy of the estimation of utilization ratio model outputs. When we observed the waiting time from the system when the user moved from one station to another station such as the example in the first case, the average service time is shorter than the actual service time (total time user spends in the system). Since the model output (result) is based on the given (unreliable) service time and interarrival time, the result generated by the model should be different (shorter) than the system utilization historical outputs. Figure 28 illustrates the different utilization ratio of the actual system utilization ratio derived from the observation and the utilization ratio model outputs.



The actual system utilization **The model outputs of system utilization**

Figure 26: The comparison of Actual Service time and the Service time used as inputs for the model

The gray areas in each figure indicates utilization ratio of the system at each interval. These two systems have the same value of the average service time (5 minutes). The average utilization ratio of the actual system is two times higher than the model output because users move from one station to another. In the simulation model, we are able to input the historical service time, but not the pattern of computer swapping. Therefore the model randomly generates a user who uses the system with an average service time of 5 minutes and then leaves the system when the user finishes using the first station that he occupies.

To correct this deficiency, the data-collecting device should be able to trace the user pattern of behavior and allow the researcher to identify the total service time of each user instead of the fraction of the service time. Then we should be able to obtain the correct service time and the resource utilization ratio to use as the historical outputs and the valid input for the simulation model.

Waiting Time: Model Outputs

In the verification of waiting time, we are able to perform the paired *t* test only for the historical output and the model outputs of the IBM Compatible section. For the Macintosh section which has more computer stations available and less users arrival, there is no waiting line for the Macintosh users at all.

In this study, we collect the waiting time of the users in the queue line in order to represent the waiting time historical output to compare with the model outputs. However, we do not focus in the study on the distribution of the waiting time historical outputs. Thus, we have set up the criteria for leaving probability for the simulation model based on the experience from the field observation. The criteria are as follow:

1. A user is not considered waiting if he enters a computer station within 30 seconds after he arrives.
2. A user may leave immediately if there are at least 10 users ahead of him in the queue. The probability of leaving is 80%
3. A user in the queue may leave if there are at least 5 users ahead of him in the waiting line and he has waited for at least 15 minutes. The probability of leaving depends on his position in the waiting line, but will not exceed 75%.

The following chart and paired ***t*** test results show the mean difference of waiting time historical outputs and model outputs. The table of the mean difference of waiting time historical outputs and model outputs are shown in the Appendix. (See: Appendix B).

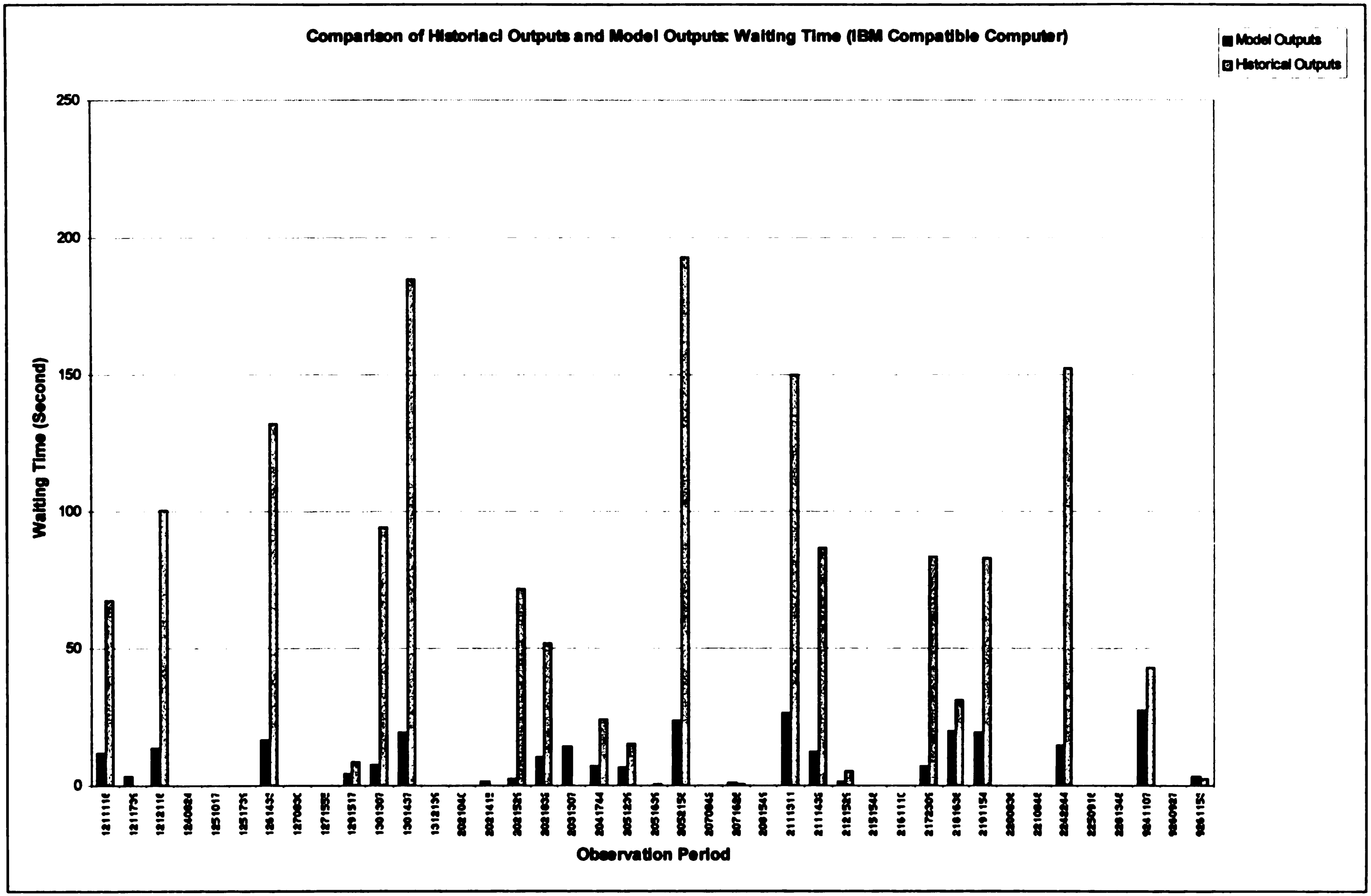


Figure 27: Comparison of Historical Outputs and Model Outputs: Waiting Time (IBM Compatible Section)

The waiting time model outputs derived from using the interarrival time and service time inputs correlate with the leave criteria that we have set up. The paired *t* test for mean difference of waiting time historical outputs and model out puts are as follow:

THE IBM COMPATIBLE SECTION: WAITING TIME

At 99 percent Confidence Interval: $t_{0.05,40} = 2.70$

$\bar{d} = -31.92939$

μ_d = True mean difference (assume = 0)

$S_d = 50.78866$

$K = 41$

$$t_0 = \frac{\bar{d} - \mu_d}{S_s / \sqrt{K}} \qquad = \frac{-31.92939}{50.78866 \ / \sqrt{41}}$$

$t_0 = -4.025462$

Since $|t_0| = 4.025462 > t_{\alpha/2,K-1} = 2.70$, then we reject H_0 of no mean difference and conclude that the model is inadequate. This paired *t*-test shows that the model and leaving criteria used for the IBM compatible section's waiting time does not work.

The inadequacy of the waiting time model outputs may derive from several factors. First, it may be due to insufficient study of the waiting queue. Sometimes a group of users will wait in a queue line to use one computer, when it comes to their turn, the whole group of users will leave a waiting line at the same time to the available computer station. In this case, the record of the average waiting time from the observation is higher than the actual waiting time that the users wait in the queue line. Secondly, we do not know the actual distribution of users criteria, therefore the leaving criteria used in the simulation model are merely the assumptions. The probability of the leaving used in the simulation model may be higher or lower than the actual distribution of the leaving pattern of the users in the waiting line.

Waiting time is the factor that has the most effect on the users' satisfaction. To achieve reliable waiting time model outputs, we have to perform an extensive study of the waiting queue and behavior of the users in the line. The results from the study of the distribution of leave behavior can be used as a valid leave criteria for the simulation model. Another aspect from the user viewpoint is that the criteria to estimate users' satisfaction should be the average waiting time of the users in the waiting line. Even though it is common to use the overall waiting time (average waiting time of all users in the system) to evaluate a system capacity and users satisfaction. The average waiting time of the users in the waiting line may represent the fluctuation of the waiting time and the users who may be effected by the congestion of the system.

Application

Collecting data for the Computer-Aided Capacity Planning Model reveals different aspects of the problem of modeling the Union building computer lab study site. Data collection also allows the evaluator to understand experience of the user within the facility instead of looking at the facility operation from an ivory tower. However, the goal of each facility is varied and depends on the policy of the organization. In the university computer lab, the administrative staff may desire to focus on maximizing the resource utilization ratio rather than minimizing the users' waiting time. On the contrary, the policy of the business organization, which the users' satisfaction means maximizing profits, the facility manager may have to maintain a balance of resource utilization and users' waiting time.

Data collected for constructing the Capacity Planning Model can be used to determine system operation in terms of the relationship between resource utilization ratio and users' waiting time. When plotting the actual resource utilization ratio against the users' waiting time, the distribution of the data sets from the observation may give a clear picture of the true characteristic of the system. A scatter plot chart using the coordination of the actual resource utilization ratio and the users' waiting time of each data set from the IBM Compatible section are used to evaluate the overall state of the resource utilization ratio and the users' waiting time of this section.

Figure 28 shows the relationship of the resource utilization ratio and overall users' waiting time of the data sets. The area of the scatter plot is divided into quarters based on the theoretical model (see figure 5). The following table shows the distribution of the data sets in each quarter.

Resource utilization ratio versus overall average users' waiting time	
Quarters	**Percentage**
High waiting time, high resource utilization ratio	12.19%
High waiting time, low resource utilization ratio	0.0%
Low waiting time, low resource utilization ratio	19.51%
Low waiting time, high resource utilization ratio	68.29%

Table 5: Distribution of the data sets in the scatter plot using coordination of the actual system's resource utilization ratio and overall users' waiting time.

Figure 28: Scatter Plot of IBM Compatible Section's Resource Utilization Ratio and Average of Overall Users' Waiting Time

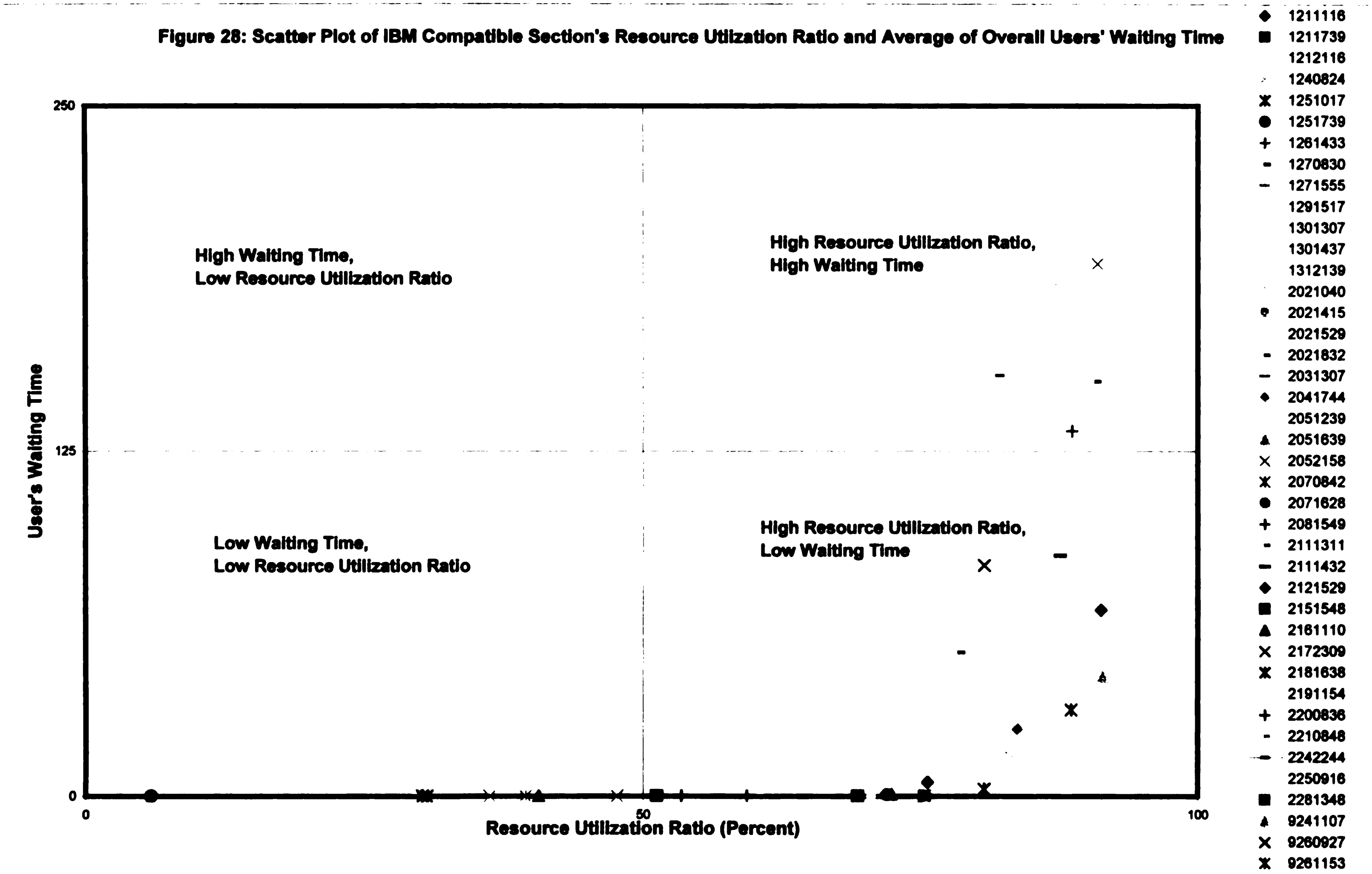


Figure 29: Scatter plot IBM Compatible section's resource utilization ratio and average of overall users' waiting time

The analysis of the relationship of the actual resource utilization ratio and overall users' waiting time in the IBM Compatible section indicates that the majority of the data sets (68.29%) fall in the "low waiting time, high resource utilization ratio" quarter. None of the data set falls in the area of "high waiting time, low resource utilization ratio". A fair amount of data sets (19.51%) fall in the "low waiting time, low resource utilization ratio" area. And the smallest number data sets (12.19%) fall in the area of "high waiting time, high resource utilization ratio."

The analysis of the actual system's resource utilization ratio and waiting time is very helpful when there is a need to determine the direction of system capacity improvement. For instance, after reviewing the distribution of the data sets in the scatter plot, the facility manager may want to increase the resource utilization ratio of the system, and decide that the number of data sets falling into the area of high resource utilization ratio, low waiting, time should be increased. The Computer-aided capacity-planing model can be used to explore potential alternatives towards achieving this goal. There are several ways to optimize the use of individual computer stations in the IBM compatible section. These alternatives include; 1) increase the number of stations in the section, 2) upgrade the computers, 3) limit computer usage time, etc.

In the following section, we use the validated model of the IBM Compatible section to generate forecasts of resource utilization in different scenarios. The first scenario is when we apply various numbers of computer stations in the IBM Compatible section. In the second scenario we reduce service time assuming that there is a limitation on computer usage time or the computer is upgraded and it works faster and the users can accomplish their work in shorter time. The last scenario models the different interarrival times versus the resource utilization ratio and users' waiting time. This scenario can be used when there is an increasing or reducing numbers of users who come to the use the IBM Compatible computers at this computer lab.

Figure 29 shows the resource utilization ratio forecasts generated by applying the different numbers of computers in the IBM Compatible section. The fixed values used in this scenario are average of service time and average of interarrival time from a large group of data sets (Cluster A) in the scatter plot. We assume that these values represent normal or everyday situation of the IBM Compatible section in the computer lab.

Figure 30 shows resource utilization ratios resulting from forecast generated by varying service times in the IBM Compatible section. The fixed values used in this scenario are the number of computer stations (30 stations) the average interarrival time (120 seconds) from the large group of data (Cluster A) in the cluster analysis for IBM Compatible section.

Figure 31 shows resource utilization and users' waiting time resulting from forecast generated by varying average interarrival times in the IBM Compatible section. The fixed values used in this scenario are number of the computer stations (30 stations) and the average service time (2100 seconds) from the large group of data (Cluster A) in the cluster analysis for IBM Compatible section.

The scenario testing above demonstrates the use of the Computer-Aided Capacity Planing model to generate different resource utilization ratios in different scenarios. However, to use the model to assist in decision making for capacity planing in a facility would be complete when the model can generate an accurate waiting time so that the facility manager can be able to balance the users' demand and the organization goal. Subsequent implementation of scatter plot, using model outputs' resource utilization and waiting times may be used to evaluate the effectiveness of the model.

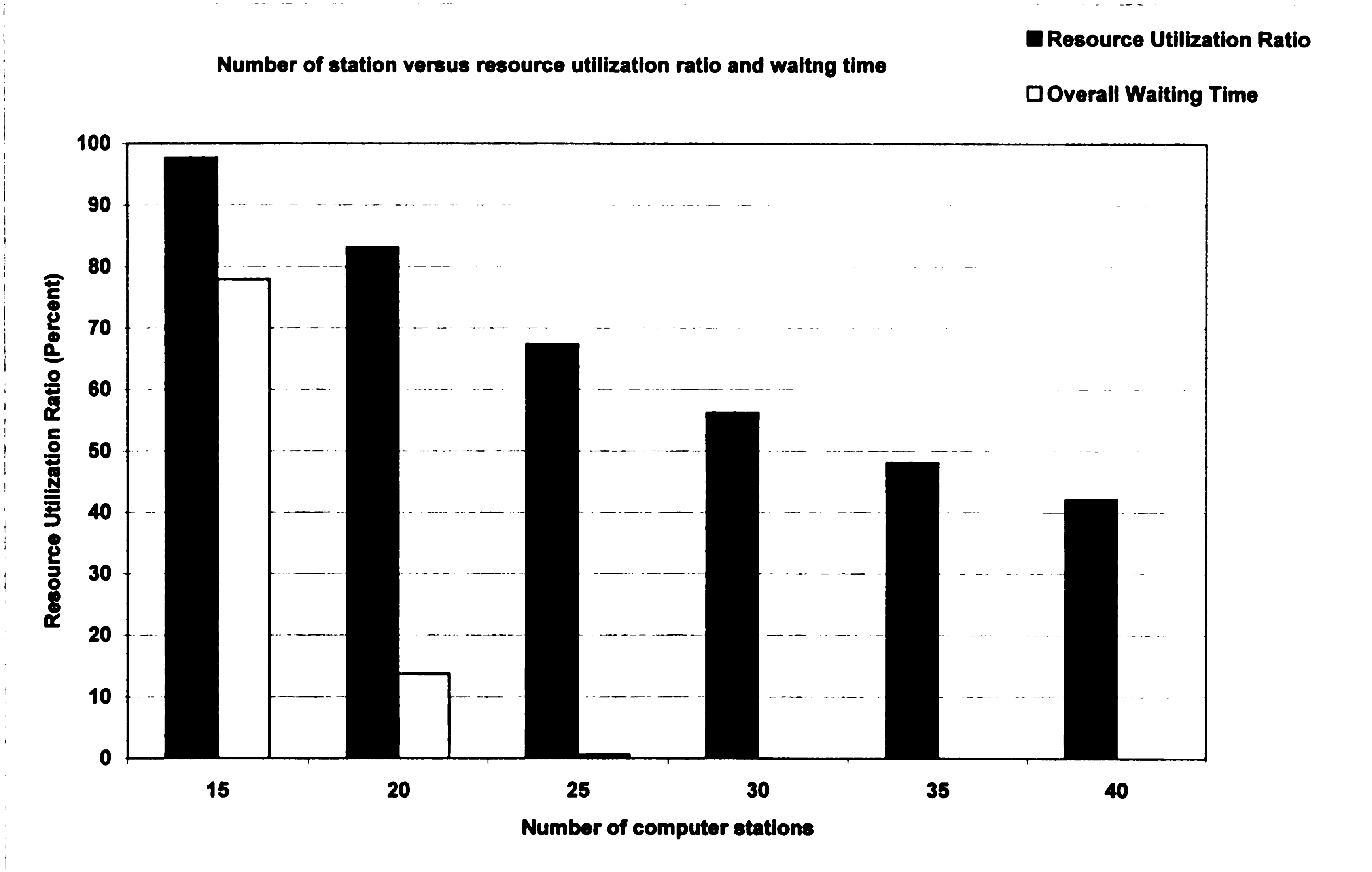


Figure 29: Number of station versus resource utilization ratio and waiting time

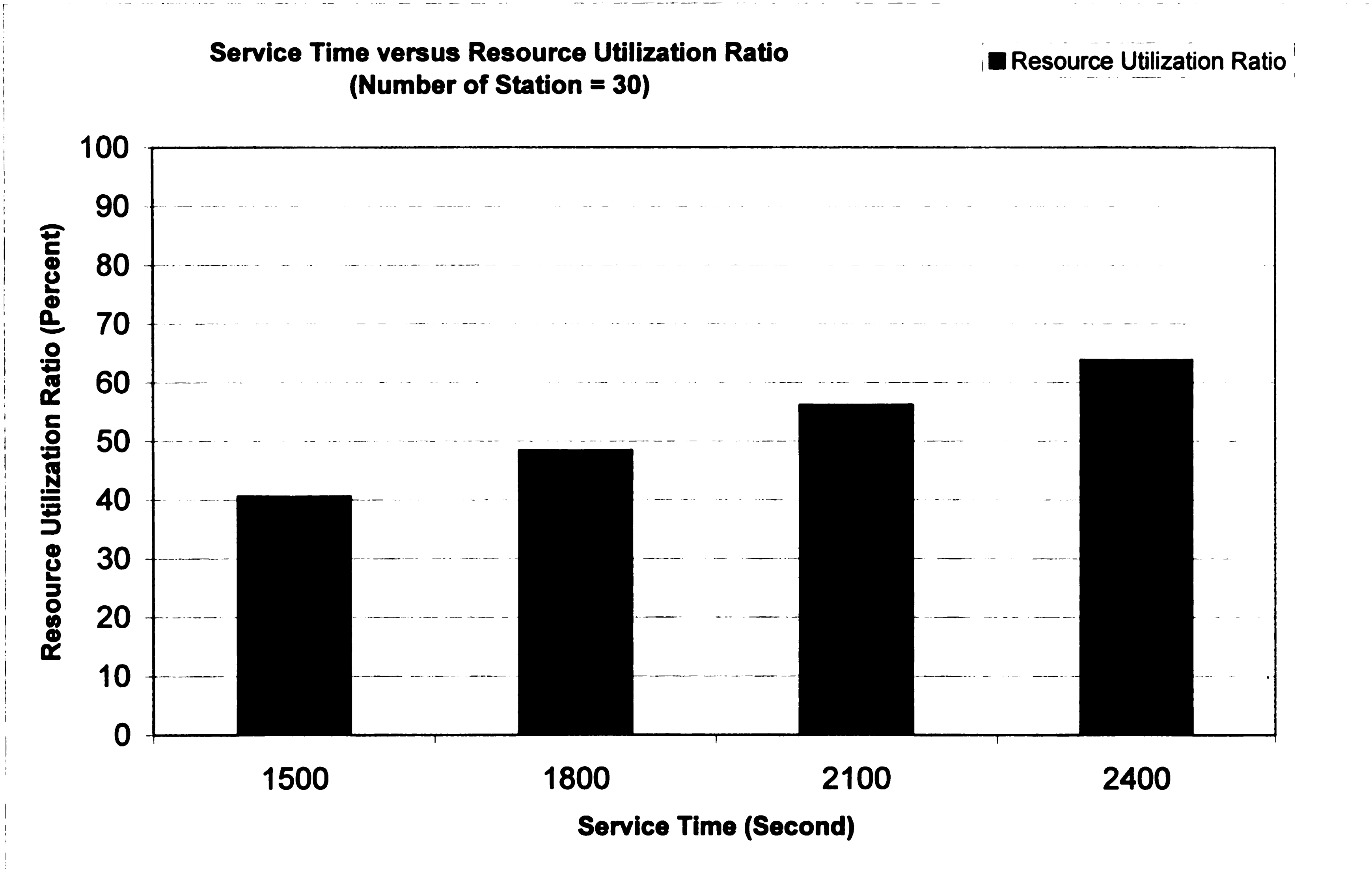


Figure 30: Service time versus resource utilization ratio

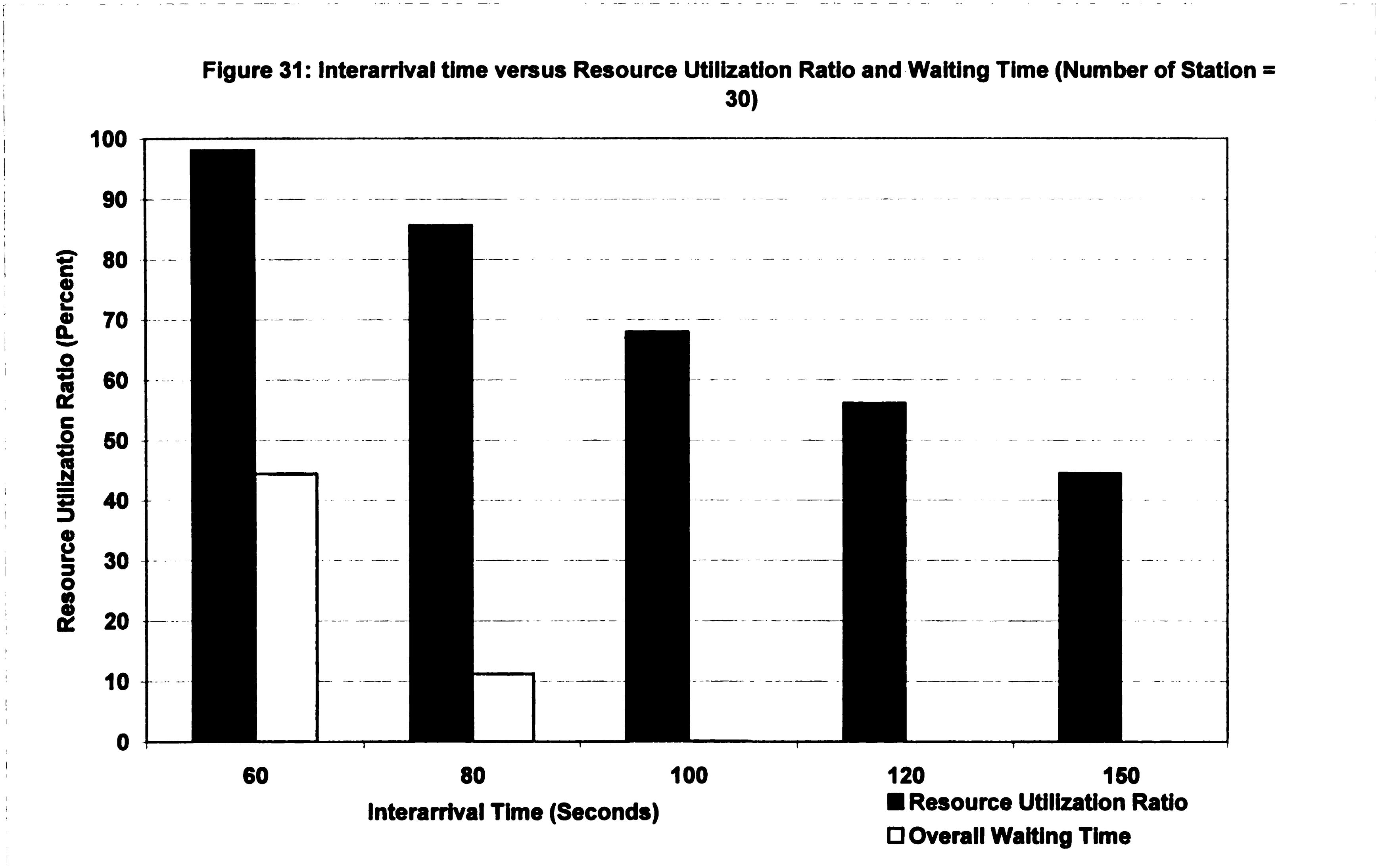


Figure 31: Interarrival time versus resource utilization ratio

Summary

In conclusion, the paired *t*-test of no mean difference of the historical outputs and model outputs reveals that the model for predicting the resource utilization ratio for the IBM compatible section works and produce a reliable outputs. The model for predicting the Macintosh section' resource utilization ratio and the model for predicting the IBM compatible waiting time do not work and generate inaccurate results. On the other hand, the test proved that the model worked once and did not work twice. The causes for the shortcoming of these models are from different factors including the planning of data collection, inappropriate devices and misinterpretation of the data.

As Shannon (1975) notes that there is a constant interplay between the construction of the model and the collection of the needed input data. Planning of data collection is considered a crucial part of the simulation project in this study. The data collection of this research begins together with the early stage of the model building. The assumptions for the data collecting frequency are based on the facility cycle of operation. The cluster analysis of the characteristic of the interarrival time and the service time shows insignificant difference of the workload characteristic between different times of a day. Hence, the frequency of the data collection should be reduced and observation session should be expanded. Longer observation helps the modeler to obtain a precise service time of any users who occupy the computer at a greater length of time.

A lesson learned from the data collection planning is the preliminary data collection should be implemented before outlining the actual data collection schedule. The preliminary data collection will provide the information necessary to construct a data collection framework. Since the data collection stage consumes a large portion of time, it is important to invest this great length of time to collect sufficient data that represents the true characteristic of the system.

The customized Visual Basic program, which is the data collecting device used in this study, produces reliable information and is able to record the correct the data collection of the IBM Compatible section. For the case of Macintosh section, the program is not able to trace the total service time of the users who move around and the users who occupy multiple computer stations. Hence the service time of the Macintosh users which is derived from this method are neither reliable nor valid. The waiting time collecting program also has the same deficiency as well. The design deficiencies of the program along with human error of the observers contribute to the inaccuracy of the data interpretation. Some other instrument such as a time lapse video or a computer based users' service log can be used as the alternative data-collecting tools.

At the early stage of data collection planning for simulation model, we hope to use the same sets of data to generate a trend of the workload characteristic of this facility, and use this trend to help predicting the anticipate system behavior. However, the data-collecting schedule is designed to be randomly distributed to be able to cover different workload characteristics from the different period of time within the cycle of operation. The randomly distributed observation periods do not have equal space between each other therefore the results of time series plot of the data are irregular and can not be described by a periodic mathematical function.

Ideally, data collection for short-term trend forecasting requires a high frequency and regular data collection at schedule. It is advisable to perform extensive study for trend analysis of the workload characteristic to obtain a pertinent reading, and then used to construct time series components.

When the model works, it can be used as a flexible tool in decision making to forecast resource needs. From the example of the IBM compatible model, we are able to adjust the number of computer stations provided for the users to forecast the resource utilization ratio. The advantage of the simulation model is that it can be used again and again, without spending time collecting the data all over again, whenever the administrative staff of the facility wants to readjust the resource allocation to meet the users' demand or meet the criteria of the organization

CHAPTER 5

CONCLUSION

Research Contribution

Continuous competitive pressures drive most contemporary businesses to improve performance. To meet this demand, facility management professionals continuously devise and challenge methods to measure and improve facility performance. The shared space facility is a common and potentially winning strategy. However, the complex multi-factorial dynamics of shared space facilities complicate efforts to describe and analyze these systems. Traditional opinion models used to evaluate and predict system performance prove particularly inadequate in describing these systems. The major weakness of this approach is that important decisions are based upon insufficient or subjective observations. Decisions based on beliefs and biases have uncertain accuracy and no precision. With the cost-driven high stakes decisions of today's facility operation, the potential analytical and predictive superiority of computer-aided simulation models justifies their development. The objectively quantifiable nature of computer-aided simulation models permits the potential to describe and forecast shared space facilities with accuracy and precision.

The computer-aided capacity planning model for facility management can be broken down into three phases. The first phase is the initial statement of the problem or problem formulation. Often, the initial objective has to be reset and fine-tuned to correspond with the nature of the system being studied. Preliminary observations help recalibrate and clarify the orientation of the project. The second phase includes model building, data collection, coding, and statistical analysis. This process resulted in the selection of a discrete-event simulation model described as a statistical experiment by Banks and Carson II (1984). The last phase is comprised of verification and validation of the model using a statistical inference from the results of the simulation tested against the observed data.

Study of the computer-aided capacity planning model reveals the benefits and pitfalls using this method to describe and predict the dynamics of the space sharing facility. The collection of data by field observations was an essential but exhaustingly laborious component of this investigation. From the study log I calculated that data collection and descriptive analysis consumed approximately 70% of the time spent on this investigation. Planning data collection, fitting the model, and validation expended the remaining 30% the total investigation time.

In perspective, this investigation of a computer-aided capacity planning model for the shared space facility was applied to two separate systems(the IBM compatible section and the Macintosh section). For the Macintosh section, the erroneous results and the misinterpretation of the data arise from a discordance of the system behavior and the instrumentation along with the design for data collection. By the same token, the problem due to the instrumentation occurs with the *waiting time* data collection for the IBM compatible section.

Operating cycles of the facility is another important factor to consider in implement a simulation model for capacity planing. It is advisable that the preliminary data collection should be conducted in the early stage of the data collection planing to determine the appropriate data collecting schedule, device and length of each observation period. The lesson learned from this study is that the device used in recording the data should conform to the pattern of user' behavior of the system. Otherwise it would lead to the misinterpretation of the variables derived from the process. The preliminary study of the workload characteristics will prepare the modeler for an appropriate course of action required for the design of the simulation model. Then a sufficient data collection design for the simulation project should cover a whole operation cycle to be able to use as the inputs to generate a valid model projection. However, this great length of data collection period can be laborious and costly.

In the real world, time and capital investment is at the core of the facility operation, the decision to implement the simulation project to help forecast the capacity planning should be taken into consideration. In a smaller scale facility or a small project, the return of time and capital investment to conduct the data collection and perform the data analysis may be unsatisfactory. The first alternative for this problem can be overcome by using an electronic or digital data-collecting device that is able to trace the interarrival time and the total service time of the user in the system. This method will help reduce the cost associated with contracting the observer to collect the data for a long duration of time. The second alternative is to construct the model based on a record obtained from the facility that has a closed system operation and distribution of a workload characteristic.

When initiating the simulation project, the collaboration of the modeler and the in-house facility manager is very important. Some organizations may have significant detail on some aspects of their operations, and yet have some sketchy information in other areas. These sorts of information can be very useful for the modeler to achieve a more accurate detail of data to create a simulation model that represents the true system characteristic.

To assess the benefit from a simulation investment, the simulation impact can be categorized as Manpower and Operation (Harrel, 1996). However, productivity and quality improvement can be achieved through the implementation of the simulation. The organization should evaluate the benefit and financial costs associated with the project including: 1) model building or purchasing the software, 2) outside consulting, 3) over/under capacity, 4) carrying cost and wait time, and 5) training.

In summary, the computer-aided capacity planing is an appropriate tool to use in forecasting the resource requirement in shared space for facility management incorporate with an opinion model. The successful implementation depends on how well the phases in the simulation has been developed and performed. It is also contingent upon how thoroughly the system analyst has involved the facility management profession of that system during the entire project. The system analyst and the facility manager should exchange the knowledge of the nature of the workload characteristic, the model-building process and the interpretation of inputs and outputs data. Therefore the likelihood of a vigorous implementation is enhanced.

Further Investigation

A further study of computer-aided capacity planning model would be more accurate when being narrowed down to study a single type of system. The extensive study of a single system would enable us to monitor the distribution and of the interested variables in the system, thus it would lead to a fully developed model. Furthermore, the preliminary data collection is recommended to perform in the early stage of model development. As noted earlier, the preliminary data collection will help determines the appropriate model for planing of data collection.

Further research is needed to study the underlying characteristic of the users in the queue line. The understanding of characteristic of the users in waiting line including leave characteristic will create a model that represent a system true characteristic. Specifically, there is a need for studies aimed at determining the actual distribution of the leave characteristic to be used as the leave criteria for the simulation model.

Although this study was performed on the computer lab of an educational setting, the same application can be replicated and tested in different types of setting such as shared office in a corporate facility or shared resource in the department store. The replication of this method will help investigate the applicability of this method in diverse environment.

Considering the purpose of the simulation used in this study, the two important factors generated from the computer-aided capacity planning model are resource utilization ratio and waiting time. In turn the administrative staff and facility manager can use these two factors to evaluate the performance critique the policy of this facility. Despite the resource utilization ratio, the user's waiting time is used to indicate user' s satisfaction, and is very subjective in nature. A further study using the combination of qualitative methods such as observation of behavior trace using time lapse video to study the behavior and the response of the users in different system condition should be taken into consideration. Relative to the unobtrusive observation of the behavior trace, user's inputs from interview or questionnaire are the best indication of a users' satisfaction toward the system operation.

Appendices

APPENDIX A

Appendix A

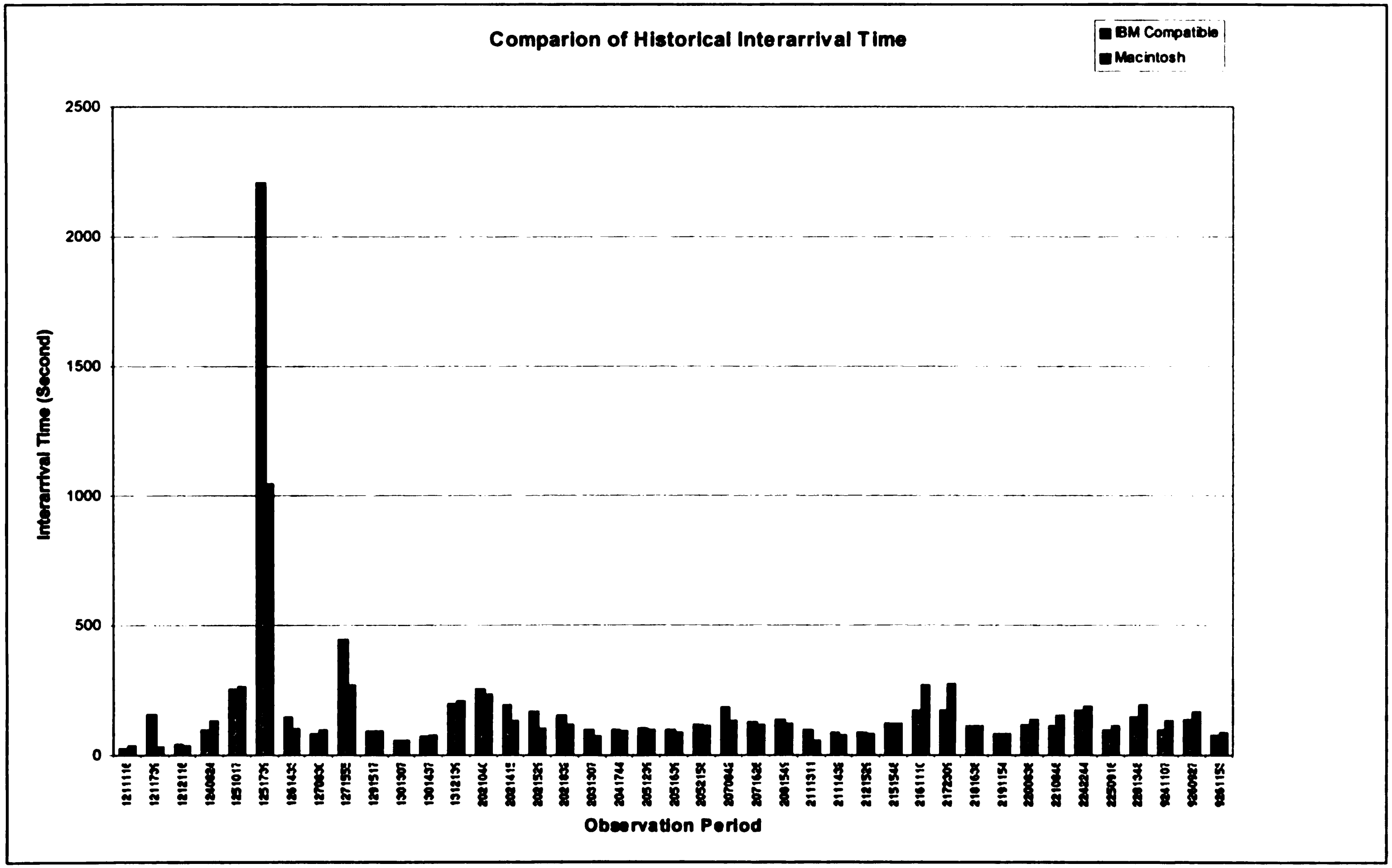


Figure 32: Comparison of Historical Outputs: Interarrival Time (IBM compatible versus Macintosh)

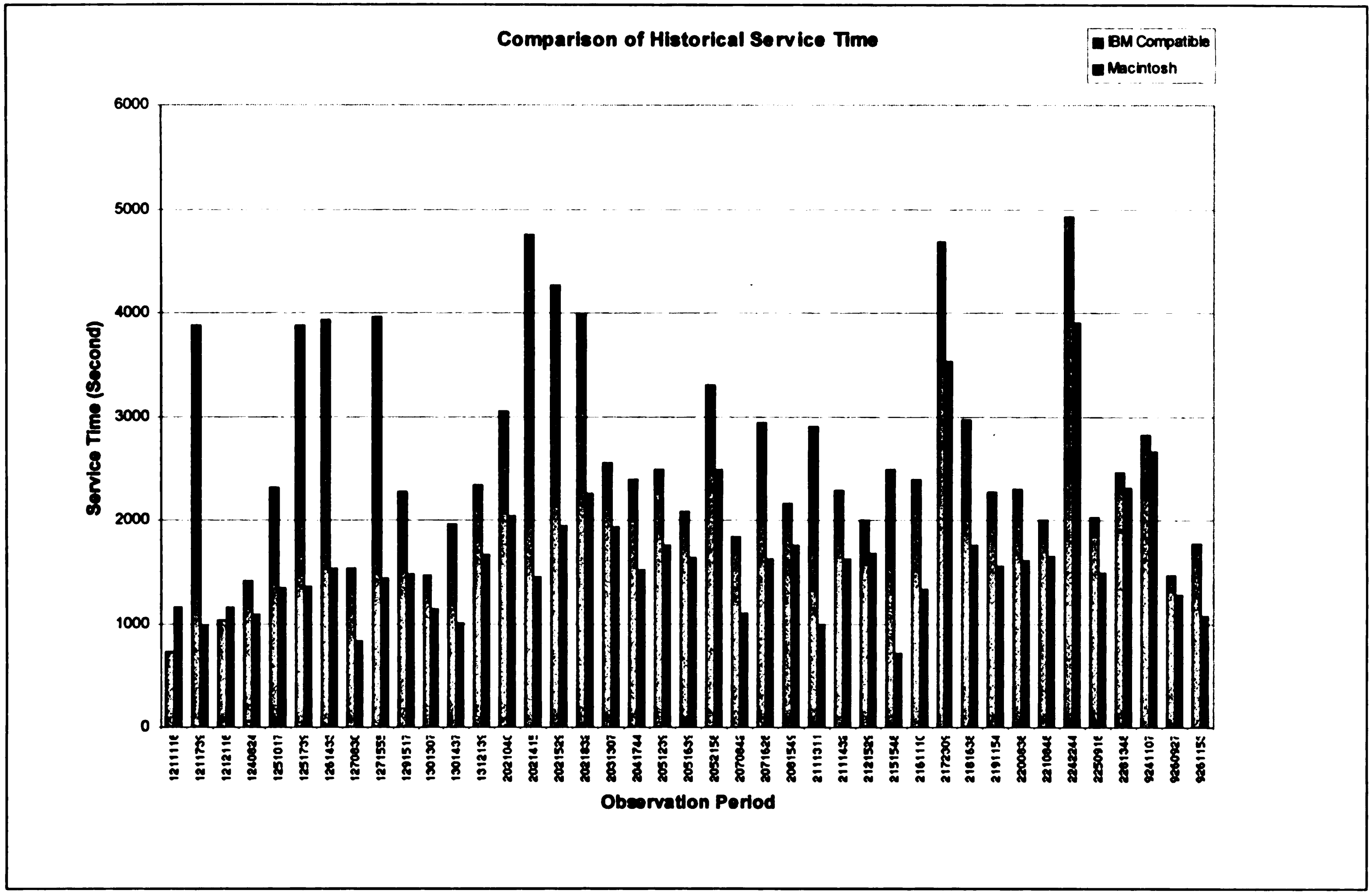


Figure 33: Comparison of Historical Outputs: Service Time (IBM Compatible versus Macintosh)

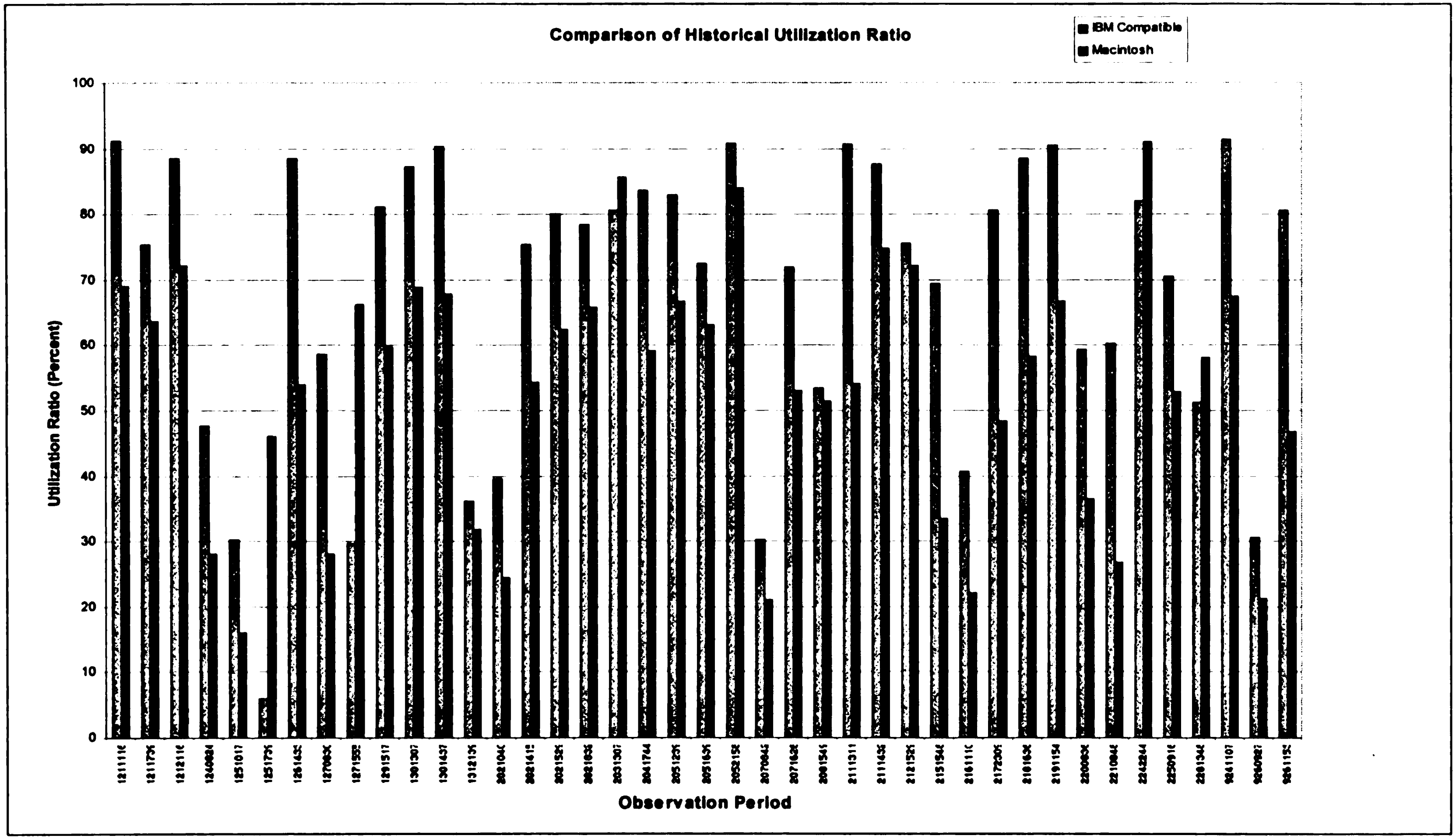


Figure 34: Comparison of Historical Outputs: Resource Utilization Ratio (IBM Compatible versus Macintosh)

APPENDIX B

Appendix B

Observation Session	IBM Compatible Utilization Ratio		Difference
	Historical Outputs (Second)	Model Outputs (Second)	Di (Second)
1211116	91.215	91.87	-0.655
1211739	82.534	75.18	0.14
1212116	90.728	90.87	-2.447
1240824	47.718	46.74	0.978
1251017	30.234	26.24	3.994
1251739	5.8472	6.1	-0.2528
1261433	90.846	82.65	5.923
1270830	61.8	61.2	-2.59
1271555	29.716	25.23	4.486
1291517	81.183	78.65	2.533
1301307	87.207	84.89	2.317
1301437	90.356	88.12	2.236
1312139	39.9	35.54	0.67
2021040	40.493	34.87	4.623
2021415	83.445	72.75	2.695
2021529	85.974	76.57	3.404
2021832	87.355	79.54	-1.185
2031307	88.353	84.85	-4.309
2041744	83.621	80.89	2.731
2051239	82.828	80.1	2.728
2051639	72.402	70.3	2.102
2052158	94.974	86.87	4.003
2070842	34.096	31.17	-0.975
2071628	77.928	72.6	-0.672
2081549	53.431	50.17	3.261
2111311	98.666	90.35	0.316
2111432	87.518	84.86	2.658
2121529	75.577	73.97	1.607
2151548	69.345	66.39	2.955
2161110	46.184	42.16	-1.537
2172309	90.641	79.73	0.911
2181638	90.059	85.06	3.429
2191154	92.798	88.86	1.65
2200836	66.113	63.96	-4.619
2210848	60.265	58.82	1.445
2242244	95.031	82.86	-0.829
2250916	70.518	68.51	2.008
2281348	56.36	53.21	-1.97
9241107	99.368	91.16	0.208
9260927	35.858	33.95	-3.337
9261153	80.635	78.6	2.035

Table 6: Comparison of Historical Outputs and Model Outputs: Utilization Ratio (IBM compatible)

file	Macintosh Utilization Ratio		Difference
	Historical Outputs (Second)	Model Outputs (second)	di (Second)
1211116	69.129	69.129	0
1211739	63.7	63.9	-0.2
1212116	72.092	71.15	0.942
1240824	28.029	16.58	11.449
1251017	15.918	9.43	6.488
1251739	46.092	2.74	43.352
1261433	53.896	31.66	22.236
1270830	28.136	18.3	9.836
1271555	66.194	10.18	56.014
1291517	59.717	35.1	24.617
1301307	68.971	41.88	27.091
1301437	67.893	28.32	39.573
1312139	31.754	15.03	16.724
2021040	24.438	16.35	8.088
2021415	54.402	22.18	32.222
2021529	62.359	39.43	22.929
2021832	65.747	40.86	24.887
2031307	85.696	55.99	29.706
2041744	59.11	34.06	25.05
2051239	66.799	38.53	28.269
2051639	63.175	33.59	29.585
2052158	83.979	45.66	38.319
2070842	21.081	16.89	4.191
2071628	53.047	38.92	14.127
2081549	51.515	29.76	21.755
2111311	54.063	11.01	43.053
2111432	74.789	29.52	45.269
2121529	72.045	44.23	27.815
2151548	33.434	12.59	20.844
2161110	22.074	9.42	12.654
2172309	48.386	24.1	24.286
2181638	58.276	42.56	15.716
2191154	66.691	40.67	26.021
2200836	36.459	23.92	12.539
2210848	26.741	22.27	4.471
2242244	90.993	40.06	50.933
2250916	52.863	28.32	24.543
2281348	58.121	22.67	35.451
9241107	67.516	39.89	27.626
9260927	21.251	15.02	6.231
9261153	46.799	27.11	19.689

Table 7: Comparison of Historical Outputs and Model Outputs: Resource utilization Ratio (Macintosh)

file	IBM Compatible Waiting Time		Difference
	Historical Outputs (Second)	Model Outputs (Second)	di (Second)
1211116	11.9	67.32	-55.421
1211739	3.075	0	3.075
1212116	13.572	100.3	-86.769
1240824	0	0	0
1251017	0	0	0
1251739	0	0	0
1261433	16.549	132.3	-115.76
1270830	0.002	0	0.002
1271555	0	0	0
1291517	4.13	8.649	-4.519
1301307	7.678	94.37	-86.687
1301437	19.341	184.8	-165.45
1312139	0	0	0
2021040	0	0	0
2021415	1.335	0	1.335
2021529	2.147	71.631	-69.484
2021832	10.144	52.022	-41.878
2031307	13.966	0	13.966
2041744	7.222	24.12	-16.898
2051239	6.778	15.143	-8.365
2051639	0.232	0.658	-0.426
2052158	23.39	193.1	-169.67
2070842	0	0	0
2071628	1.165	0.571	0.594
2081549	0	0	0
2111311	26.646	150.2	-123.56
2111432	12.218	87.024	-74.806
2121529	1.229	4.963	-3.734
2151548	0.039	0	0.039
2161110	0	0	0
2172309	7.065	83.58	-76.517
2181638	19.657	31.239	-11.582
2191154	19.233	82.922	-63.689
2200836	0	0	0
2210848	0	0	0
2242244	14.712	152.4	-137.72
2250916	0.089	0	0.089
2281348	0	0	0
9E+06	27.32	43.089	-15.769
9E+06	0	0	0
9E+06	3.07	2.574	0.496

Table 8: Comparison of Historical Outputs and Model Outputs: Waiting Time (IBM Compatible)

APPENDIX C

Appendix c

Comparison of system and Model outputs measures when using identical historical outputs.

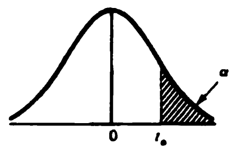
Input Data Set	*System Output,* Z_{ij}	*Model Output,* W_{ij}	*Observed Difference,* d_j	*Squared Deviation from Mean,* $(d_j - \bar{d})^2$
1	Z_{i1}	W_{i1}	$d_1 = Z_{i1} - W_{i1}$	$(d_1 - \bar{d})^2$
2	Z_{i2}	W_{i2}	$d_2 = Z_{i2} - W_{i2}$	$(d_2 - \bar{d})^2$
3	Z_{i3}	W_{i3}	$d_3 = Z_{i3} - W_{i3}$	$(d_3 - \bar{d})^2$
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
K	Z_{iK}	W_{iK}	$d_K = Z_{iK} - W_{iK}$	$(d_K - \bar{d})^2$
			$\bar{d} = \frac{1}{K} \sum_{j=1}^{K} d_j$	$S_d^2 = \frac{1}{K-1} \sum_{j=1}^{K} (d_j - \bar{d})^2$

Figure 35: Source Banks & Carson II (1984)

APPENDIX D

Appendix D

PERCENTAGE POINTS OF THE STUDENTS t
DISTRIBUTION WITH v DEGREES OF FREEDOM



v	$t_{0.005}$	$t_{0.01}$	$t_{0.025}$	$t_{0.05}$	$t_{0.10}$
1	63.66	31.82	12.71	6.31	3.08
2	9.92	6.92	4.30	2.92	1.89
3	5.84	4.54	3.18	2.35	1.64
4	4.60	3.75	2.78	2.13	1.53
5	4.03	3.36	2.57	2.02	1.48
6	3.71	3.14	2.45	1.94	1.44
7	3.50	3.00	2.36	1.90	1.42
8	3.36	2.90	2.31	1.86	1.40
9	3.25	2.82	2.26	1.83	1.38
10	3.17	2.76	2.23	1.81	1.37
11	3.11	2.72	2.20	1.80	1.36
12	3.06	2.68	2.18	1.78	1.36
13	3.01	2.65	2.16	1.77	1.35
14	2.98	2.62	2.14	1.76	1.34
15	2.95	2.60	2.13	1.75	1.34
16	2.92	2.58	2.12	1.75	1.34
17	2.90	2.57	2.11	1.74	1.33
18	2.88	2.55	2.10	1.73	1.33
19	2.86	2.54	2.09	1.73	1.33
20	2.84	2.53	2.09	1.72	1.32
21	2.83	2.52	2.08	1.72	1.32
22	2.82	2.51	2.07	1.72	1.32
23	2.81	2.50	2.07	1.71	1.32
24	2.80	2.49	2.06	1.71	1.32
25	2.79	2.48	2.06	1.71	1.32
26	2.78	2.48	2.06	1.71	1.32
27	2.77	2.47	2.05	1.70	1.31
28	2.76	2.47	2.05	1.70	1.31
29	2.76	2.46	2.04	1.70	1.31
30	2.75	2.46	2.04	1.70	1.31
40	2.70	2.42	2.02	1.68	1.30
60	2.66	2.39	2.00	1.67	1.30
120	2.62	2.36	1.98	1.66	1.29
∞	2.58	2.33	1.96	1.645	1.28

Source: Robert E. Shannon, *Systems Simulation: The Art and Science*, © 1975, p. 375. Reprinted by permission of Prentice-Hall, Inc., Englewood Cliffs, N.J.

Figure 36: Percentage of the Students t Distribution With υ Degree of Freedom (Source: Bank & Carson II, 1984)

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