AMBULATORY CARE PERFORMANCE: A SIMULATION STUDY OF THE ROLE OF APPOINTMENT SCHEDULING RULES, PATIENT CLASSIFICATION AND ENVIRONMENTAL FACTORS

by

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Abstract

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Tugba Cayirli

Advisor: Professor Emre A. Veral

This paper investigates the effects of patient classification on ambulatory care performance. Using a simulation model, two approaches to patient classification are evaluated: (i) patient classification used only for sequencing patient appointments at the time of booking, and (ii) patient classification used for both sequencing and appointment interval-adjustment. In the latter approach, appointment intervals are adjusted to match the consultation time characteristics of different patient classes. This paper uses the terminology "new/return" to differentiate patient classes. However, the results are applicable to any classification criteria based on consultation time length.

Several appointment systems which combine appointment rules, sequencing rules and interval-adjustment approaches are evaluated under various clinic environments, characterized by walk-ins, no-shows, patient punctuality, number of appointments per session, the percentage of new patients, and the ratio of the mean consultation time of

new patients to the mean consultation time of return patients. The effects of decision factors and environmental variables are analyzed by ANOVA. Apart from the primary measures of doctor idle time, doctor overtime and patient waiting time, two secondary measures are used to assess ambulatory care performance. These include the "fairness" measured by the uniformity of waiting times, and the percentage of patients seen within 30 minutes of their appointment times.

Results indicate that the major performance differences between appointment systems result from the choice of sequencing rules and interval-adjustment approaches. This finding suggests that when designing appointment systems, decisions pertaining to patient classification are more critical than the choice of an appointment rule, which determines the template for appointment slots. Appointment systems that use patient classification perform better than the traditional 'first-call-first-appointment' systems. The improvement is more significant when the percentage of new patients is high, and/or there is a greater dispersion among the mean consultation times of different patient classes. Furthermore, other environmental factors such as walk-ins, no-shows, patient punctuality, and overall session volume, largely affect the performance and the ultimate selection of an appointment system.

DEDICATION

To Rifat, in gratitude for years of encouragement, support, and understanding.

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LIST OF SYMBOLS AND ABBREVIATIONS

μ	Mean consultation times
μ_{New}	Mean consultation times for new patients
μ_{Ret}	Mean consultation times for return patients
σ	Standard deviation of consultation times
σ_{New}	Standard deviation of consultation times for new patients
σ_{Ret}	Standard deviation of consultation times for return patients
%New	Percentage of new patients
μ_{New}/μ_{Ret}	Ratio of the mean consultation time of new patients to the mean consultation time of return patients
β_i	Multipliers used in calculating OFFSET and DOME rules
a_i	Appointment interval-length
ADJ	Interval-adjustment for patient class
C_d	Cost of doctor's idle time
C_o	Cost of doctor's overtime
C_p	Cost of patient's waiting time
C_d/C_p	Relative ratio of the cost of doctor's idle time to the cost of patient's waiting time.
CV	Coefficient of variation of consultation times (σ/μ)
CV_{New}	Coefficient of variation of consultation times for new patients
CV_{Ret}	Coefficient of variation of consultation times for return patients
E(I)	Doctor's mean idle time per patient
E(O)	Doctor's mean overtime per patient
E(W)	Patients' mean waiting time
E(TC)	Expected total cost of the system
FAIR	Fairness of an appointment system (i.e. the uniformity of patients' waiting times)
k_i	Early/late breakpoint combinations used in formulating OFFSET and DOME rules

IDLE	Mean doctor idle time
LESS30	Percentage of patients seen within 30 minutes of their appointment times
m	Number of multiple patients assigned to each appointment slot (i.e. appointment batch size)
n_i	Number of patients scheduled to i^{th} block (i.e. block size)
n_1	Number of patients given an identical appointment time at the start of the session (i.e. initial block, also called "begin-block")
N	Number of patients per clinic session
OVER	Mean doctor overtime
P_N	Probability of no-shows
P_W	Probability of walk-ins
RULE	Appointment rule
SEQ	Sequencing rule
T	Clinic session length
t_b	Time begin session
TC1	Total cost of the system calculated using C_d/C_p ratio= 1
TC10	Total cost of the system calculated using C_d/C_p ratio= 10
TC100	Total cost of the system calculated using C_d/C_p ratio= 100
t_e	Time end session
t_i	Appointment time given to patient i
WAIT	Mean patient waiting time

CHAPTER I

INTRODUCTION

The current climate in the health care industry is typified by ever-increasing demands for efficiency in medical care delivery, and simultaneous demands for patient satisfaction. One vital point at which these two demands intersect is the scheduling of ambulatory care visits in private office group practices and in hospital clinics.

Most of the appointment-scheduling literature considers appointment systems (AS) with no patient classification, assuming that patients are homogeneous for scheduling purposes. This means that the scheduler assigns patients to available slots on a first-call-first-appointment basis. If there are certain classes of patients known to be distinct in terms of various attributes (i.e. service time characteristics, arrival patterns, costs of waiting), this raises the issue of whether or not an AS can be improved by recognizing such differences. In ambulatory care, some variables used for classifying patients include major problem, acute problem, acute problem follow-up, and chronic problem. (Arbitman, 1986).

Apart from outpatient services, patient classification has potential applications in equipment-related medical services. For example, when scheduling appointments for CAT scans, patients may be classified by procedure type (head, spine, brain, chest, etc.), or by age, if pediatric and geriatric patients are known to require longer times to prepare compared to adult patients. Implementation of sequence-based AS requires the scheduler to identify each appointment slot by patient type.

The goal of this study is to investigate the effect of using such information on patient class when designing an AS. Without loss of generality, our study uses a classification scheme of new/return patient to analyze the effects of sequencing at the time of booking. "New" patients are defined as those who are totally new to the clinic; "return" patients are old patients that arrive with new problems or for follow up of an old problem. Although other classification criteria such as 'pediatric / adolescent / geriatric', or 'difficult / easy' are possible, all pertain to a single common element, which has relevance for scheduling decisions: the length of consultation time. This research differs from earlier studies that consider patient classification in a number of ways. First, patient classification is not limited to sequencing only. This study examines the effects of tailoring appointment intervals to match the consultation time characteristics of different patient classes. Thus the combination effect of sequencing and interval-adjustment is investigated. Second, each sequencing rule is evaluated based on seven different underlying appointment rules, allowing us to investigate the possible interactions between sequencing rules and appointment rules. Third, the analysis is carried under a wider range of environments than previous studies, some of which focused on specific clinic applications. Apart from environmental factors that were identified as important by previous simulation studies, this study examines the effects of presence of walk-ins and unpunctual patients. Lastly, both the mean and the variability of consultation times of different patient classes are addressed when sequencing patients.

Another distinctive feature of this study is the use of a three-factor measure of ambulatory care performance. Unlike prior literature, a physician overtime measure is explicitly considered when comparing AS along with measures of patient and physician idle time. No matter how impressive the results may be in terms of waiting times of patients and idle time of doctor, an AS that leads to excessive overtime is unlikely to be implemented. Some secondary measures are also included for gaining more insight on clinic performance. These include the "fairness" of an AS, and the probability of patients seen within *x*-minutes of their appointment times.

The remainder of this dissertation is organized as follows: Chapter II provides a review of the literature on appointment scheduling. Chapter III discusses the research contribution, and Chapter IV presents the methodology. Results of the simulation experiments are reported in Chapter V. Lastly, Chapter VI presents a summary of the findings and practical considerations, followed by the limitations of this study and suggestions for future research.

CHAPTER II

LITERATURE REVIEW

2.1. INTRODUCTION

This chapter provides a review of the literature on appointment scheduling for outpatient services. This topic has attracted the interest of many academicians and practitioners over the last fifty years, starting with the pioneering works of Bailey (1952) and Lindley (1952). This review focuses on outpatient scheduling, with limited reference to the most relevant literature on surgical scheduling, as there is some overlap between the two topics. The interested reader is referred to reviews of Magerlein and Martin (1978) and Przasnyski (1986) on the latter topic. First, we define and formulate the problem of outpatient scheduling, and present performance criteria used to evaluate appointment systems. Next, we present a classification of AS that have been studied in the literature; followed by analysis methodologies used in the past.

2.2. PROBLEM DEFINITION AND FORMULATION

The objective of outpatient scheduling is to find an appointment system for which a particular measure of performance is optimized in a clinical environment- an application of resource scheduling under uncertainty. The underlying problem applies to a wide variety of environments such as general practice patient scheduling, scheduling patients for hemo-dialysis, radiology scheduling, surgical scheduling, etc. Literature on appointment scheduling can be classified into two broad categories: static and dynamic. In the static case, all decisions must be made prior to the beginning of a clinic session, which is the most common appointment system in health care. Thus, it is not surprising to see that most of the literature concentrates on the static problem. Some papers, however, also consider the dynamic case, where the schedule of future arrivals are revised continuously over the course of the day based on the current state of the system (Fries and Marathe 1981; Liao, Pegden and Rosenshine 1993; Liu and Liu 1998b). This is applicable when patient arrivals to the service area can be regulated dynamically, which generally involves patients already admitted to a hospital or clinic.

Outpatient clinics can be regarded as queuing systems, which represent unique set of conditions that must be considered when designing AS. The simplest case is when all scheduled patients arrive punctually at their appointment times and a single doctor serves them with stochastic processing times. The formulation gets more complicated as multiple doctors and multiple services are considered. Presence of unpunctual patients, no-shows, walk-ins and/or emergencies may intervene to upset the schedule. Furthermore, doctors may be late to start a clinic session or they may be interrupted during the course of the day due to activities not directly related to consultation. These environmental factors are discussed in detail next.

1. Number of Services

Almost all studies in the literature model a single-stage system where patients queue for a single service. A few simulation studies investigate clinic environments where a patient may pass through facilities such as registration, pre-examination, post-examination, x-ray, laboratory, checkout, etc. (Rising, Baron and Averill 1973; Cox, Birchall and Wong 1985; Swisher, Jacobson, Jun and Balci 2001). In such multi-stage models, the patient flow (transition) probabilities associated with each facility need to be specified for Markov Process modeling.

2. Number of Doctors

Most literature has focused on single-server systems for appointment scheduling. As simple as it may look at first glance, common practices indicate that doctors usually have their own list of patients in clinics. Although queuing theory proves that a single common queue results in shorter wait-times, in most medical services, systems designed around random assignment of doctors are undesirable, as they fail to provide a one-to-one doctor-patient relationship. Given this psychological effect, both practitioners and researchers generally employ independent queues for each doctor (Rising et al. 1973; Cox et al. 1985). On the other hand, some public clinics do not give appointments for specific patients, sending them to the first available doctor. This is the case in clinics studied by Babes and Sarma (1991) in Algeria and Liu and Liu (1998a, 1998b) in Hong Kong. Representing an even more complex system, Swisher et al. (2001) also model assignment of different types of medical staff members, assigning each patient category a probability of requiring a particular type/skill of staff.

3. Number of Appointments per Clinic Session

Vissers (1979), Heaney, Howie and Porter (1991) and Meza (1998) report a positive relationship between waiting times and the number of appointments in a clinic session (N). Also, studies by Welch and Bailey (1952), Vissers and Wijngaard (1979) and Ho and Lau (1992) cite the importance of including this factor when comparing scheduling rule performance. In addition, the Ho and Lau (1992) study finds that the effect of N is mitigated by no-shows and variability of consultation times, and thus cannot be easily generalized.

4. The Arrival Process

The arrival characteristics of patients to the clinic are comprised of the following factors, which affect appointment system performance:

i. Unpunctuality of patients can be defined as the difference between a patient's appointment time and actual arrival time. Empirical evidence suggests that patients arrive early more often than late (Fetter and Thompson 1966; Villegas 1967; Babes and Sarma 1991; O'Keefe 1985; Brahimi and Worthington 1991b; Klassen and Rohleder 1996; Lehaney, Clark, and Paul 1999). As Welch and Bailey (1952) point out, patient earliness may also be undesirable, since it creates excessive congestion in the waiting area.

Some authors model patient unpunctuality by fitting theoretical probability distributions to empirically derived histograms of patient arrival times relative to their appointment times (Blanco White and Pike 1964; Fetter and Thompson 1966; Swartzman 1970; Cox et al. 1985). Vissers and Wijngaard (1979) combine patient and doctor unpunctuality under one variable called "system earliness". In the queuing models of

Mercer (1960, 1973), patient lateness is modeled as an independent random variable with a certain limit on maximum lateness. In all these studies, it is assumed that patients' unpunctuality is independent of their scheduled appointment times.

ii. Presence of no-shows is moderately studied in the literature, using no-show probabilities that range from 5 to 30 percent. Empirical data suggest differences among specialties in terms of no-show probabilities observed (Nuffield Provincial Hospitals Trust 1965). As might be expected, studies find that larger no-show probabilities increase the risk that the doctor will stay idle and decrease the waiting time of patients. Ho and Lau's (1999) assessment of three environmental factors (no-show probability, variability of service times and number of patients per clinic session) reveals that among the three, no-show probability is the major one that affects the performance and the choice of an AS.

Given that no-shows pose important problems for health-care administrators, many studies have attempted to investigate possible variables (such as age, socioeconomic level, etc.) that might affect patient attendance, and some identify policies aimed at discouraging no-shows. Interested readers are referred to reviews of Deyo and Inui (1980) and Barron (1980). Schafer (1986) discusses some policies that are found to be useful in dealing with latecomers and no-shows in a private clinic.

iii. Presence of walk-ins (regular and emergency) is neglected in most studies. Reported walk-in rates are very low in the Nuffield studies of England (1965). In the U.K., hospital clinics are primarily used for consultation services for patients referred to them by the general practitioner outside the hospital. However, in the U.S., some clinics are the patient's general practitioner, and are responsible for the patient's total care, whether elective or emergent. Therefore, walk-ins must be anticipated and planned for in the administration of clinic sessions (Fetter and Thompson 1966). Similar to no-shows, walk-in probabilities are observed to vary across specialties (Fetter and Thompson 1966; Shonick and Klein 1977; Field 1980).

Swartzman (1970) presents a statistical analysis of the arrival pattern based on data collected from a Michigan Hospital, and finds that arrival rates of emergency patients and walk-ins differ significantly throughout the day, but not from day to day. He concludes that the Poisson distribution offers an acceptable representation (i.e. inter-arrival times are distributed negative-exponentially). Similarly, Rising et al. (1973) model walk-ins using negative exponential distribution to represent inter-arrival times, with the mean value changed on an hourly basis to reflect the seasonal pattern. Walter (1973) finds that when the proportion of patients with appointments increase (that is, the probability of walk-ins decrease), efficiency improves through the reduction in either the doctor's idle time, the patients' waiting time, or both, depending upon the number of patients seen in the session (N). Vissers and Wijngaard (1979) model the impact no-shows and walk-ins on the mean and variance of consultation times. Swisher et al. (2001) use exponential arrival rate for walk-ins based on their observation of a family clinic. None of these studies models balking or reneging behavior of walk-ins.

In the outpatient literature, there is even less focus on emergencies. These are special type of walk-ins that require immediate medical attention and may possibly preempt the current consultation. Fetter and Thompson (1966) and Rising et al. (1973) include non-preemptive emergencies in their simulation models.

iv. Presence of companions may also be included when modeling the arrival process. Companions are those who accompany a patient to the clinic (e.g. a patient's child, husband, wife, etc.). Although they do not receive the service, they do utilize the waiting room and disregarding them may lead to misleading results for determining the appropriate size of a clinic's waiting room area (Swisher et al. 2001). In that case, the probability of a patient arriving with companion(s) needs to be determined. Differences among specialties are highly possible; for example, in a pediatrics or mental health clinic, all patients are expected to arrive with at least one companion.

5. Service Times

Service (or consultation) time can be defined as the sum of all the times a patient is claiming the doctor's attention, preventing him/her from seeing other patients (Bailey 1952). The majority of the studies assume patients are homogeneous for scheduling purposes, and use independently and identically distributed (i.i.d.) service times for all patients. Other studies that consider AS with unique patient classes model independently and distinctly distributed (i.d.d.) service times. The general assumption of independence between the arrival and the service patterns may be questionable. In practice, doctors may increase their service rate, if only subconsciously, during peak hours knowing that there are many patients waiting. This is observed to be the case in a number of studies (Bailey 1952; Rockart and Hofmann 1969; Rising et al. 1973; Babes and Sarma 1991).

A variety of service time distributions are chosen in the studies. Some use empirical data collected from the clinics investigated, and the frequency distributions of observed service times display forms that are unimodal and right-skewed (Welch and

Bailey 1952; Jackson 1964; Rising et al. 1973; Buchan and Richardson 1973; Cox et al. 1985; Brahimi and Worthington 1991b; Meza 1998). Most analytical studies use Erlang or exponential service times to make their models tractable.

The coefficient of variation, which is the standard deviation divided by the mean ($CV = \sigma/\mu$), is a commonly used measure for the variability of consultation times. Empirical studies report *CV* values that range from approximately 0.35 to 0.85 (Bailey 1952; Blanco White and Pike 1964; Rising et al. 1973; O'Keefe 1985; Brahimi and Worthington 1991b; Meza 1998).

Denton and Gupta (2003) find that optimal solutions, although mostly dependent on mean and variance, may exhibit some dependence on higher moments such as skewness. On the other hand, some report that the *relative* performance of AS is not affected by skewness and kurtosis, but only by the mean and variance (Ho and Lau 1992; Yang, Lau and Quek 1998). Robinson and Chen (2003) show that the means of the service times can be removed from the formulation without affecting the problem.

A number of studies report that high variability of service times deteriorates both the patients' waiting times and the doctor's idle time (Bailey 1952; Blanco White and Pike 1964; Vissers and Wijngaard 1979; Ho and Lau 1992; Klassen and Rohleder 1996; Denton and Gupta 2003). Similarly, in his analysis of the effects of *CV*, Wang (1997) indicates that the larger the *CV*, the smaller the optimal appointment intervals, and the higher the costs due to uncertainty created in the system.

In general, studies that evaluate the effect of service-time duration find that shorter mean consultation times result in lower patient waiting times (Bailey 1952; Blanco White and Pike 1964; Walter 1973). Support mechanisms that provide rapid access to clinical information (internal medical records, lab reports, etc.) may be used to reduce the mean and the variability of consultation times (Dexter 1999).

Bailey (1952) reports that the performance of the system is very sensitive to even small changes in appointment intervals. Thus, it is also important to tailor AS's to individual doctors, as some studies find that doctor style is a predictor of consultation time.

6. Lateness and Interruption Level of Doctors

Doctors' unpunctuality, measured as lateness to first appointment, is considered by Blanco White and Pike (1964), Fetter and Thompson (1966), Vissers (1979), Mahachek and Knabe (1984), Babes and Sarma (1991), and Liu and Liu (1998a, 1998b). Agreement among all studies is that patient waiting times are highly sensitive to this factor. If the doctor does not start the clinic on time, a delay factor builds up from the start that ripples throughout the clinic session.

Another doctor-related factor is the interruption level (also called the "gap times"). These include all activities during the session that may require doctor's attention, such as interactions with support staff, phone calls, writing up notes, comfort breaks, etc., which interrupt consultation. Rising et al. (1973) and Lehaney et al. (1999) include non-preemptive gap times in their simulation model by assuming that interruptions occur only in between consultations.

Game theory may be useful in modeling patient and doctor arrivals by considering the conflicting interests of both parties. It is likely that patients arrive early to "beat" the system or arrive late knowing that they will have to wait anyway. Similarly, doctors may arrive late, being afraid that the first patient will be late. There should be either some sort of mechanisms to enforce punctuality, or the AS should be designed to account for all parties' behavior (Van Ackere 1990). One might expect that when clinics are run under more credible AS, both patients and doctors will become more punctual.

7. Queue Discipline

Almost in all studies, it is assumed that arriving patients are served on a first-come, first-served (FCFS) basis. Given punctual patients, this queue discipline is identical to serving patients in the order of their appointment times. However, unpunctuality may cause changes in the actual order of seeing patients, as doctors would not keep idle waiting for the next appointment in the presence of other waiting patients.

A clinic which deals with walk-ins, emergencies and/or second consultations, (i.e. those patients returning from the lab, x-ray, etc. visited after an initial consultation) needs to set a priority rule, which determines the order in which these patients will be seen. In general, the first priority is given to emergencies, followed by second consultations, then scheduled patients; the lowest priority is given to walk-ins that are seen on a FCFS basis (Rising et al. 1973; Cox et al. 1985). In practice, it is not uncommon for patients to be called in the order of arrival even when there is an AS, probably because of the ease of administration. However, this may destroy the whole purpose of an AS, and may lead to patients ignoring appointments and coming earlier than necessary. It is fairer if the scheduler maintains a policy of calling patients in the order of appointments, while trying to fit in walk-ins and late patients as early as possible.

Table I summarizes the relevant factors that are encountered in appointment scheduling environments:

Table I. Problem Definition and Formulation

1. Nature of Decision-Making
   - 1.1 Static
   - 1.2 Dynamic
2. Modeling of Clinic Environments
   - 2.1 Number of services (single or multi-stage)
   - 2.2 Number of doctors (single or multi-server)
   - 2.3 Number of appointments per clinic session
   - 2.4 Arrival process (deterministic or stochastic)
     - 2.4.1 Unpunctuality of patients
     - 2.4.2 Presence of no-shows
     - 2.4.3 Presence of regular and emergency walk-ins (preemptive or non-preemptive)
     - 2.4.4 Presence of companions
   - 2.5 Service times (empirical or theoretical distribution)
   - 2.6 Lateness of doctors and their interruption levels (preemptive or non-preemptive)
   - 2.7 Queue discipline (FCFS, by appointment time, by priority)

2.3. MEASURES OF PERFORMANCE

There are a variety of performance criteria used in the literature to evaluate AS's (see Table II). Studies often list results in terms of the mean waiting time of patients E(W), and the mean idle time of doctor E(I), and/or the mean overtime of doctor E(O), but a "reasonable" trade-off level between them is to be decided subjectively by the decision-maker. One can give them relative weights in terms of the cost of patients' waiting time (C_p), cost of doctor's idle time (C_d), and doctor's overtime (C_o). Then the objective becomes minimizing the expected total cost of the system represented as:

$$\text{Min } E(TC) = E(W)\, C_p + E(I)\, C_d + E(O)\, C_o \qquad [1]$$

1. Cost-Based Measures

Studies use different subsets or variations of the cost function shown in [1]. Majority includes only the patients' waiting time and the doctor's idle time. Others use patients' flow time instead of patients' waiting time. The general cost function assumes a linear relationship between the waiting cost and the waiting time of the patient. However, as pointed out by Klassen & Rohleder (1996), a system where one patient waits 40 minutes is not the same as one in which 20 patients wait two minutes each. And the fact that relative costs may differ from one patient to another complicates the issue further. In the literature, studies assume identical waiting costs for all patients. When modeling unpunctual patients and/or walk-ins, the assumption of homogeneous waiting costs may need to be relaxed. Late patients may consider some additional waiting as normal, being partly their own fault. Similarly, walk-ins may tolerate longer waits compared to scheduled patients. For regular patients, there might be a threshold over which patients' tolerance declines steeply. Some survey results indicate that tolerance diminishes after about 30 minutes (Westman et al. 1987; Huang 1994). In the U.K., hospitals are rated each year according to a national standard set by the Ministry of Health that requires 75 percent of the patients to be seen within 30-minutes of their appointment time (Department of Health 1991).

From a decision-making point of view, it is sufficient to come up with relative values for these costs. For example, estimates of C_d/C_p and/or C_o/C_p ratios, but not the actual monetary values of C_d, C_p, and C_o are needed. The relative cost ratios of C_d/C_p considered in the studies range from 1 to 100. As Fries and Marathe (1981) point out, it is easier to estimate the costs relative to the server, which are usually available via standard cost accounting, but the costs of waiting involve a different type of analysis where the issues of goodwill, service, and "costs to the society" place a value on patients' waiting time. Keller and Laughhunn (1973) divide the annual salary of the doctor by the hours worked per year to estimate C_d, and use the minimum wage to reflect the opportunity cost of the patients' waiting time. It is generally assumed that $C_d > C_p$; this is because C_d includes not only the cost of the idle doctor but also the cost of the idle facility (Yang et al. 1998).

2. Time-Based Measures

It is usually desirable to evaluate waiting time, idle time and overtime measures separately, as there may be a maximum acceptable level for each. A common approach is to calculate the "*true*" waiting time of patients by subtracting the greater of {appointment time, arrival time} from the consultation start-time. This excludes any waiting prior to appointment time, because additional waiting due to early arrival is voluntary and is not a consequence of the AS. True waiting times will be negative if patients are served before their appointment times, which may help the decision-maker to capture information regarding the benefit patients receive by being seen earlier. However, if one wants to focus on positive waiting times only, then negative values need to be truncated at zero. *Flow-time* is another patient-related measure, which is the total time a patient spends in the clinic, including the service time. Since, patients generally do not mind time spent in service, most of the literature focuses on waiting time, rather than the flow time.

Idle time of a doctor is the total time during the clinic session when s/he is not consulting because there are no patients waiting to be seen. *Overtime* is calculated as the positive difference between the "desired" completion time of the clinic session and the actual end of service for the last patient. The desired end time for the clinic may be set by accounting for the additional tasks the doctor needs to complete before s/he can leave the office (e.g. writing patient charts, meetings with colleagues, etc.). Yet, it is possible that these tasks are partially handled during the course of the day whenever the doctor stays idle. In general, the negative overtime value can be considered as a part of idle time.

3. Congestion Measures

Congestion in the clinic hurts service quality from many different perspectives. Apart from taking up valuable space, when queues get excessively long, doctors may increase their service rate or they may be forced to call back some patients at another time. Main measure of congestion is the mean number of patients in the queue (or system).

4. Fairness Measures

Some studies pay attention to the "fairness" issue, which is the uniformity of performance of an AS across patients. In fixed-interval AS's, each successive patient is expected to have, on average, a longer wait time due to the congestion that tends to build up over time. Not only do waiting times increase, but also consultation times tend to decrease as doctors speed up when they progressively fall behind schedule (Heaney et al. 1991). Therefore, patients at the end of the clinic session generally get the worst combination of long waiting times and truncated consultation times, unless an adjustment is made to the AS to account for this phenomenon. Bailey (1952) measures the mean waiting times of patients according to their place in the clinic session (1^{st}, 2^{nd}, etc.); Yang et al (1998) measures the uniformity of waiting times, and Cox et al. (1985) compares AS's based on the variance of queue sizes over the duration of the clinic session.

5. Other Measures

Other measures used to evaluate AS include doctor's productivity (i.e. number of patients seen in a session), mean doctor utilization, delays between requests and granted appointments, percentage of urgent patients served, and likelihood of patients receiving the slots that they requested. Swisher et al. (2001) use a measure called "clinic effectiveness" which encompasses both clinic profits (revenues and expenses) and patient waiting time on a dollar scale. Table II classifies the most commonly used performance measures used in the literature.

Table II. Performance Measurements Used in the Literature

1. Cost-Based Measures

   Mean total cost calculated using relevant combinations of:
   1.1 Waiting time of patients
   1.2 Flow time of patients
   1.3 Idle time of doctor(s)
   1.4 Overtime of doctor(s)

2. Time-Based Measures

   2.1 Mean, maximum, and frequency distribution of patients' waiting time
   2.2 Mean, variance, and frequency distribution of doctor's idle time
   2.3 Mean, maximum and standard deviation of doctor's overtime
   2.4 Mean and frequency distribution of patients' flow time
   2.5 Percentage of patients seen within 30-minutes of their appointment time

3. Congestion Measures

   3.1 Mean and frequency distribution of number of patients in the queue
   3.2 Mean and frequency distribution of number of patients in the system

4. Fairness Measures

   4.1 Mean waiting time of patients according to their place in the clinic
   4.2 Variance of waiting times
   4.3 Variance of queue sizes

5. Other

   5.1 Doctor's productivity
   5.2 Mean doctor utilization
   5.3 Delays between requests and appointments
   5.4 Percentage of urgent patients served
   5.5 Likelihood of patients receiving the slots they requested
   5.6 Clinic effectiveness

2.4. DESIGNING AN APPOINTMENT SYSTEM

The AS design can be broken down into a series of decisions regarding (1) the appointment rule, (2) the use of patient classification, if any, and (3) the adjustments made to reduce the disruptive effects of walk-ins, no-shows, and/or emergency patients.

2.4.1. Appointment Rules

The appointment rule used to schedule patients can be described in terms of three variables:

i. block size (n_i) is the number of patients scheduled to the i^{th} block. Patients can be called individually, in groups of constant size or in variable block sizes.

ii. begin-block (n_1), also called the *initial block*, is the number of patients given an identical appointment time at the start of a session.

iii. appointment interval (a_i) is the interval between two successive appointment times, also called *"job allowance"*. Appointment intervals can be constant or variable. A common practice is to set them equal to some function of the mean (and sometimes the standard deviation) of consultation times.

Any combination of these three variables (n_i, n_1, a_i) is a possible appointment rule. So far, the following appointment rules have been investigated in the literature (See Figure I).

Figure I. Appointment Rules Studied in the Literature

1. **Single-Block**
   $n_1 = N$
   No a_i

2. **Individual-Block/Fixed-Interval**
   $n_i = 1$ for all $i = 1, 2, 3, \ldots, N$
   a_i constant

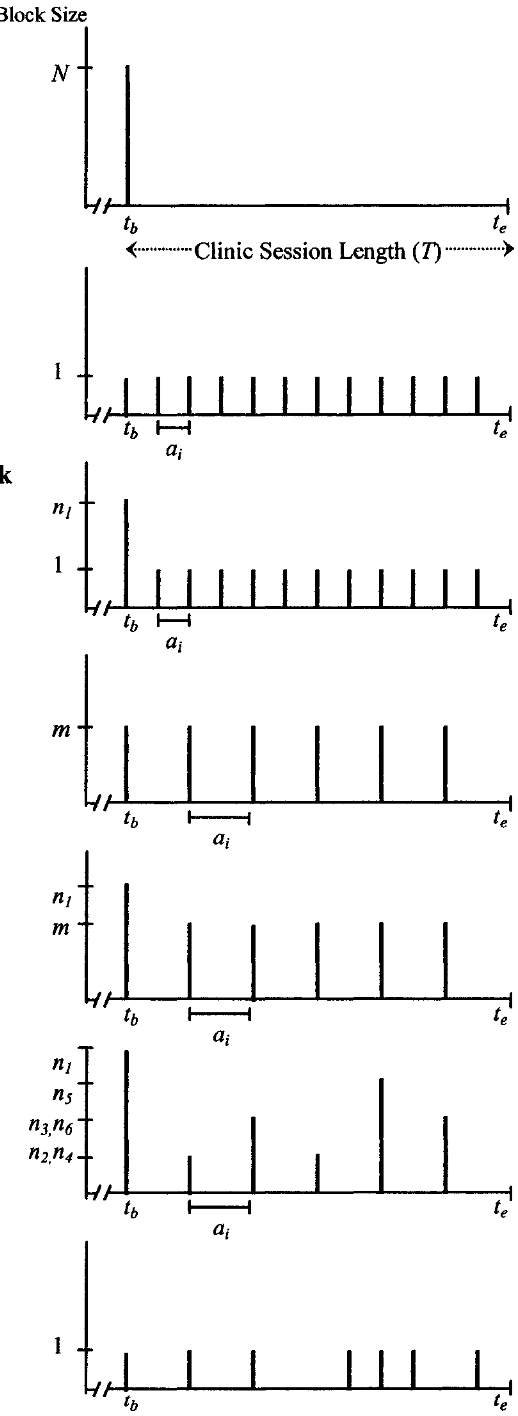
3. **Individual-Block/Fixed-Interval with an Initial Block**
   $n_1 > 1$; $n_i = 1$ for all $i = 1, 2, 3, \ldots, N$
   a_i constant

4. **Multiple-Block/Fixed-Interval (m-at-a-time)**
   $n_i = m > 1$ for all $i = 1, 2, 3, \ldots, N$
   a_i constant

5. **Multiple-Block/Fixed-Interval with an Initial Block**
   $n_1 > m$; $n_i = m > 1$ for $i = 2, 3, \ldots, N$
   a_i constant

6. **Variable-Block/Fixed-Interval**
   n_i variable for $i = 1, 2, 3, \ldots, N$
   a_i constant

7. **Individual-Block/Variable-Interval**
   $n_i = 1$ for all $i = 1, 2, 3, \ldots, N$
   a_i variable



a_i = appointment interval, t_b = time begin session, t_e = time end session
n_i = block size for i^{th} block, n_1 = initial block

(Adapted from Fries and Marathe, 1981)

*1. **Single-block rule*** assigns all patients to arrive as a block at the beginning of the clinic session. For example, all morning patients are scheduled for 9:00 a.m. and they are seen on a first-come, first-served basis. This is the most primitive form of AS, where patients are assigned a "date-only", rather than a specific appointment slot. Clearly, single-block systems will lead to excessive waiting times for patients, while ensuring that doctors do not stay idle. This was the common practice in most clinics in 1950's, when the research on outpatient scheduling initiated. Thus we see that most of the earlier studies praise the advantages of individual appointments, pioneering the shift from single-block to individual-block systems (Lindley 1952; Bailey 1952; Welch 1964; Fry 1964; Johnson and Rosenfeld 1968; Rockart and Hofmann 1969). Single-block systems are still used, mostly in public clinics, probably because they require the least administrative effort. Babes and Sarma (1991) investigate a public clinic in Algeria that uses a single-block AS.

2. Individual-block/Fixed-interval rule assigns each patient unique appointment times that are equally spaced throughout the clinic session. A number of studies investigate this type of an appointment rule (Fetter and Thompson 1966; Klassen and Rohleder 1996, 2000).

3. Individual-block/Fixed-interval rule with an initial block is a combination of the previous rule with an initial group of n_1 patients ($n_1 > 1$) called at the start of the clinic session. The goal is to keep an inventory of patients so that the doctor's risk of staying idle is minimized if the first patient arrives late or fails to show up. Bailey (1952, 1954) is the first to suggest an individual-block system with two patients assigned at the beginning of the session and the rest scheduled at intervals equal to the mean consultation time (n_1= 2, n_i= 1, a_i= μ). Jansson (1966), Blanco White and Pike (1964), Brahimi and Worthington (1991b), Ho and Lau (1992), and Klassen and Rohleder (1996) evaluate this rule in their comparative analyses.

*4. **Multiple-block/Fixed-interval rule*** is one in which groups of *m* patients are assigned to each appointment slot with appointment intervals kept constant. Soriano (1966) studies an appointment system, where patients are called two-at-a-time with intervals set equal to twice the mean consultation time (n_i = 2, a_i= 2μ). Blanco, White and Pike (1964) and Cox et al. (1985) find that multiple-block rules perform the best in their particular environments. There is also some practical advantage of multiple-block systems in terms of giving patients "rounded" appointment times, such as calling four patients every 15 minutes rather than one every 3.75 minutes (Walter 1973). More rigorous research is needed to investigate under what circumstances multiple-block rules might perform better than individual-block rules.

*5. **Multiple-block/Fixed-interval rule with an initial block*** is simply a variation of the above system with an initial block (n_1> *m*). Cox et al. (1985) is the only study that investigates this particular type of rule.

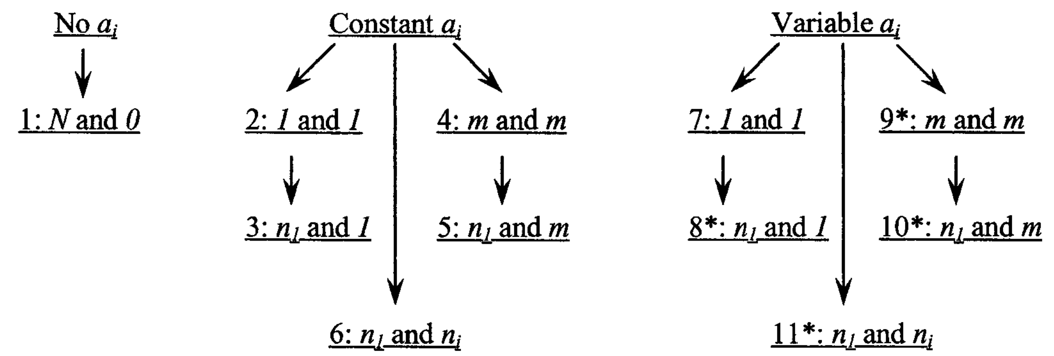
*6. **Variable-block/Fixed-interval rule*** allows different block sizes during the clinic session, while keeping appointment intervals constant. Villegas (1967), Rising et al. (1973), Fries and Marathe (1981), Liao et al. (1993), Liu and Liu (1998a, 1998b), and Vanden Bosch, Dietz and Simeoni (1999) investigate this rule in their studies.

*7. **Individual-block/Variable-interval rule*** is one in which customers are scheduled individually at varying appointment intervals. Ho and Lau (1992) introduce a number of variable-interval rules, and test their performance against traditional ones using simulation. They find that, among the rules they tested, increasing appointment intervals toward the latter part of the session improves performance the most. Some recent analytical studies show that for i.i.d. service times and uniform waiting costs for all patients, optimal appointment intervals exhibit a common pattern where they initially increase toward the middle of the session and then decrease. This is referred to as the "dome" shape, studied by Wang (1997), Robinson and Chen (2003), and Denton and Gupta (2003). In addition, Pegden and Rosenshine (1990), Yang et al. (1998) and Vanden Bosch and Dietz (2000) are some recent studies that analyze individual-block/variable-interval rules.

Figure II presents a generalization structure of appointment rules. Rules 1 through 7 are the ones examined in the literature (as summarized in Figure I). Appointment rules that have not yet been studied in the literature (to the best of our knowledge) include individual-block/variable-interval rule with an initial block, multiple-block/variable-interval rule with and without an initial block, and variable-block/variable-interval rule (Rules 8* through 11*). Note that rule 7 can be considered as subsuming the variable-block rules 6 and 11*, since it is possible to set $a_i = 0$. Also, there are special cases of rule

7, such as the ones studied in Ho and Lau (1992, 1999), which may be considered as an intermediate between rules 2 and 7, where $a_1 = a_2 = \ldots = a_k$ are different than $a_{k+1} = a_{k+2} = \ldots = a_{N-1}$ for $k < N-1$.

Figure II. Generalized Structure for Appointment Rules



Note: Notation in underlined entries in this figure is as follows:
For #: *A and B*, # is the appointment rule number in Figure I; *A* is the initial block, and *B* is the block size.
Rules 1-7 are studied in the literature. 8*-11* have not yet been studied in the literature.

2.4.2. Patient Classification

In the majority of the studies, patients are assumed to be homogeneous and they are scheduled on a first-call, first-appointment (FCFA) basis. When there are patient groups (classes) that are known to be distinct in terms of various attributes (e.g. service time characteristics, arrival patterns, costs of waiting, etc.), then this raises the issue whether an AS can be improved by recognizing such differences.

In outpatient scheduling, patient classification can be used for two purposes: to sequence patients at the time of booking; and/or to adjust the appointment intervals based on the distinct service time characteristics of different patient classes. Since the schedule has to be ready in advance and the arriving requests are handled dynamically, the use of patient classification in outpatient settings is somewhat limited. A realistic application requires that the patients are classified into a manageable number of groups and that they are assigned to pre-marked slots when they call for appointments. In the literature, some of the classification schemes used for scheduling purposes include new/return, variability of service times (i.e. low/high-variance patients) and type of procedure. These factors are discussed in Cox et al. (1985), Klassen and Rohleder (1996, 2000), Lehaney et al. (1999), Lau and Lau (2000), and Vanden Bosch and Dietz (2000). In an application to a radiology department, Walter (1973) investigates the possibility of improving the AS by dividing patients with similar exam times into different sessions. It is found that examination times depend on factors such as patient's age, physical mobility and type of service. For example, older patients with limited mobility (trolley, wheelchair) require, on average, considerably more time than the younger and walking patients (see Section 2.5 for detailed discussions of papers).

There is also relevant literature on surgical scheduling literature, which recognizes heterogeneous patients in the context of operating room. In this case, the scheduler estimates surgery durations for *every* procedure individually, and assigns them start times, given the desired sequencing rule (e.g. FCFS, random, in the order of increasing/decreasing mean or variance of service times, etc.). Unlike in outpatient scheduling, the scheduler has a complete list of all requests for the day, and patient availability is guaranteed. Nevertheless, some of the most pertinent papers such as Charnetski (1984) and Weiss (1990) are summarized in Section 2.5.

2.4.3. Adjustments for No-shows, Walk-ins, Urgent patients, Emergencies and/or Second Consultations

Whenever relevant, no-shows, walk-ins, urgent patients, and/or emergencies need to be planned for, during the design of an AS. In clinics where second consultations occur frequently, such as in orthopedics, some allowance should be made for the additional demand imposed on doctors (Older 1966). Even though many administrative mechanisms are found to be effective in reducing the likelihood of patients to break their appointments (such as reminders by mail or phone prior to appointment dates, fees for failed appointments, etc.), it is not possible to entirely eliminate no-shows (Barron 1980). On the other hand, strong links are found between a tendency to attend without an appointment and lower social class and perception of urgency by Taylor (1984) and Virji (1990). These findings suggest that a clinic that denies access to walk-ins may further disadvantage these groups. Therefore, in general, a better approach may be to anticipate no-shows and walk-ins, and adjust the AS in order to reduce their disruptive effects.

Blanco White and Pike (1964) consider adjustments for no-shows, only. They use simulation to analyze the effects of adding extra patients to make-up for the anticipated average number of no-shows, and find that such an adjustment can considerably improve system performance. Fetter and Thompson (1966) illustrate that it is dangerous to assume walk-ins and no-shows cancel out each other, since they rarely occur in the same volume or at the same time within a session. Therefore, they suggest that the patient load (i.e. percent of available appointments filled) be adjusted based on the expected number of walk-ins and no-shows. Vissers and Wijngaard (1979) introduce a procedure that finds the revised mean and the revised variance of consultation times based on the expected probabilities of no-shows and walk-ins. Using simulation, they illustrate that their method leads to an adequate approximation. In a later paper, Vissers (1979) simulates two options for dealing with no-shows: adding extra patients spread out evenly during the session (called overbooking) vs. shortening appointment intervals proportionally. He finds that the latter approach is slightly better perhaps because of its sustained effect throughout the clinic.

Pierskalla and Brailer (1994) suggest that an AS which considers the stochastic variation of walk-ins (regular/emergency) separately from the stochastic variation of no shows will better achieve improvements in performance. For unplanned walk-in patients, adjustment requires either leaving open slots or setting appointment intervals relatively longer. The former case requires a secondary decision to identify which particular slot(s) to leave open. In their case study, Rising et al. (1973) show that when walk-ins exist, scheduling appointments to complement the arrival pattern of walk-in patients can smooth the patient flow. They also model second consultations where patients may be sent for an x-ray before seeing the doctor again. Klassen and Rohleder (1996) investigate the best position for leaving open slots for "urgent" patients, who need to be seen within 24 hours. They find no conclusive results; if more urgent slots are left earlier in the session, average patient waiting time is lower and fewer urgent patients are served; whereas if more slots are left later, doctor idle time is lower and more urgent patients are served. Fetter and Thompson (1966) include emergency breaks in the AS. In practice, when the doctor leaves for an emergency, private clinics usually call patients who have appointments to reschedule (Schafer 1986). This is rarely an option for hospital clinics where patients usually end up waiting longer, unless emergencies are accounted for or handled with other resources.

Table III summarizes the relevant decision areas that need to be considered for designing appointment systems.

Table III. Designing an Appointment System

1. Appointment Rule
   - 1.1 Block size
     - 1.1.1 Individual
     - 1.1.2 Multiple
     - 1.1.3 Variable
   - 1.2 Appointment interval
     - 1.2.1 Fixed
     - 1.2.2 Variable
   - 1.3 Initial block
     - 1.3.1 With
     - 1.3.2 Without
   - 1.4 Any combination of the above
2. Patient classification
   - 2.1 None (i.e. all patients assumed homogeneous)
   - 2.2 Use patient classification for:
     - 2.2.1 Sequencing patients at the time of booking
     - 2.2.2 Adjusting appointment intervals to match the service time characteristics of patient classes
     - 2.2.3 Any combination of the above
3. Adjustments
   - 3.1 For no-shows
     - 3.1.1 None
     - 3.1.2 Overbooking extra patients to predetermined slots
     - 3.1.3 Decreasing appointment intervals proportionally
   - 3.2 For walk-ins, second consultations, urgent patients, and/or emergencies
     - 3.2.1 None
     - 3.2.2 Leaving predetermined slots open
     - 3.2.3 Increasing appointment intervals proportionally
   - 3.3 Any combination of the above

2.5. ANALYSIS METHODOLOGIES

Research methodologies in appointment scheduling literature can be classified as analytical, simulation-based or case study, depending on the health-care environment on which they focus, and the assumptions they make.

2.5.1. Analytical Studies

The analytical approaches to the study of AS include queuing theory and mathematical programming methods. Most of the earlier queuing models assume steady-state behavior, which is never reached in a real clinic environment with a small and finite number of patients. Lindley (1952) addresses a G/G/1-type queuing model with a single-server where inter-arrival times between customers and service times are given by arbitrary distributions. He establishes an elementary relationship between the waiting times of successive customers, which enables him to derive the waiting time distributions of customers. In the conclusion of his paper, he shows that the system improves dramatically when customer arrivals are scheduled at regular intervals as opposed to random arrivals. Jansson (1966) studies a D/M/1 queuing model and derives the total cost distribution function (i.e. waiting and idle costs) for the k^{th} customer. The optimal initial block (n_1) and the constant appointment interval (a_i) are determined for a given C_d/C_p ratio so that the mean total cost is minimized. Soriano (1966) compares the steady-state waiting time distribution functions of individual and multiple-block/fixed-interval AS for various load factors, assuming deterministic arrivals and gamma service times. Mercer (1960) allows for late arrivals, using a general distribution for lateness. He obtains the steady-state queue length distributions for a single-server system with exponential service times. It is assumed that the patient either arrives at her/his scheduled interval or not at all. Mercer (1973) extends the study to batch arrivals, multi-stage services, and general service times studying a number of different queuing models.

Fries and Marathe (1981) study variable-block/fixed-interval AS and compare results with single-block and multiple-block/fixed-interval systems. They use dynamic programming to determine the optimal block sizes (n_i) for the next period given that the number of patients remaining to be assigned is known. They present an approximate method to apply the dynamic results to generate a schedule for the static version. Weiss (1990) is the first to address the problem of jointly determining the optimal start times of surgical procedures and the optimal order of those procedures. He presents analytical results for general service times for N= 2 and a heuristic solution for larger problems when the goal is to minimize the weighted cost of surgeon waiting time and OR idle time. Regarding the sequencing problem, he proves that the optimal order of two procedures is in increasing variances when service times are exponential or uniform. For larger N-values, the study uses simulation to compare a number of sequencing rules using normally-distributed service times.

Brahimi and Worthington (1991a) study finite capacity multi-server queuing models with non-homogeneous arrivals (arrival rate dependent on time) and general discrete service time distributions. Their Markov-chain based algorithm computes time-dependent distributions of the number of customers in the system, from which several key performance measures can be derived. They extend the method to provide approximate results for continuous service time distributions, and present results for the transient behavior of systems with constant arrivals. Pegden and Rosenshine (1990) study an S(N)/M/1 model which assumes finite number of scheduled arrivals with distinct inter-arrival times and exponential service times. They prove that the total cost function is convex for $N \leq 4$ which allows them to compute optimal appointment intervals using a Markov-chain based procedure. In a later study, Liao et al. (1993) constrain customer arrivals to fixed lattice of times with k intervals and N number of patients. They use dynamic programming to determine the optimal block sizes when service times are Erlang. The dynamic solution is used as a lower bound to solve the static problem by a branch-and-bound algorithm, which is restricted to small-scale problems. Vanden Bosch et al. (1999) propose a fathoming approach to solve the same problem with customer arrivals constrained to lattice points. They show that their fathoming algorithm is more efficient than Liao et al.'s (1993) method for larger problems.

Wang (1993) considers both the static and the dynamic case for a single-server system with exponential service times where the goal is to minimize the weighted sum of customer flow time and system completion time. He shows that customer flow times can be represented by a phase-type distribution which enables using the matrix method to derive the expected flow times. The optimal appointment times are then calculated using a recursive procedure. The results show that the optimal appointment intervals are not constant, but dome-shaped. Wang (1997) extends the study to any service time distribution that can be approximated with a phase-type distribution.

Liu and Liu (1998b) study a queuing system with multiple doctors, where doctor arrival times are random. They develop a dynamic programming formulation to optimally find the block sizes and use the results from the dynamic case to solve the static problem.

They compare the performance of schedules obtained using the approximation method to the best ones found by exhaustive simulation. Lau and Lau (2000) address two problems relevant to outpatient and surgical scheduling: (i) How to determine the total system cost given a particular appointment scheduling rule; and (ii) How to determine the optimal schedule given a particular sequence of arrivals. They present an efficient procedure to solve the first problem when service times are non-identically and generally distributed. This leads to solving the second problem by examining a large number of AS and finding the optimal one using a search procedure. They evaluate the accuracy of this approximate method by comparing results to those obtained by simulation. As they note, solving the second problem efficiently can enable one to solve the relevant problem of finding the optimal sequence, which still remains an open issue.

Robinson and Chen (2003) study finding the optimal appointment times when the sequence of *N* patients has already been specified. They formulate the problem as a stochastic linear program, and solve it using Monte-Carlo integration. They use the "dome" structure of the optimal policy as the basis to develop a simple heuristic that adjusts appointment intervals by the relative valuation of C_d/C_p ratio. They show that its performance is robust with regards to distributional misspecification. Denton and Gupta (2003) present a two-stage stochastic linear programming model to determine the optimal appointment intervals, and apply a decomposition approach to solve it for general i.i.d. service times. Similar to Wang (1993, 1997) and Robinson and Chen (2003), they show that the optimal intervals are dome-shaped, and note that this is more pronounced for higher values of C_d/C_p ratio.

Analytical studies are summarized in Table IV.

Table IV. Summary of Analytical Studies in the Literature

Author(s)	**Service Time Distribution** μ= mean σ= standard deviation CV= coefficient of variation= σ/μ	**Patient Unpunctuality**	**No-shows & Walk-ins** P_N= no-show probability P_W= walk-in probability	**Doctors' Lateness and Interruption Level (Gap Times)**	**Number of doctors (S)** Number of patients per session (N) **Duration of session (T)**	**Queue Discipline**	**Performance Measurements**	**Appointment System** n_i= block size for i^{th} block n_1= initial block a_i= appointment interval
Lindley (1952)	General	Punctual	P_N= 0 P_W= 0	Punctual	S= 1	FCFS	(1) Mean and variance of patient wait times (2) Probability of not having to wait	**Individual-block/ fixed-interval AS** a_i= hμ where h ranges 1.2 to 4
Mercer (1960, 1973)	Exponential, General	General lateness distribution	P_N> 0 P_W= 0	Punctual	Multiple $S\geq 1$	FCFS	(1) Frequency distribution of queue length	**Individual-block/ fixed-interval AS**
Jannson (1966)	Exponential CV= 1	Punctual	P_N= 0 P_W= 0	Punctual	S= 1	FCFS	(1) Frequency distribution of total cost of patients' waiting and doctor's idle time	**Individual-block/ fixed-interval AS with an initial block** Solve for optimal n_1 and a_i= hμ where h ranges 1.1, 2, 3, 5
Soriano (1966)	Gamma CV= 0.50	Punctual	P_N= 0 P_W= 0	Punctual	S= 1 N= 8	FCFS	(1) Waiting time distributions of patients	**Multiple-block/ fixed-interval AS** n_i= 2 and a_i= 2hμ where h= 1.01 to 2
Fries and Marathe (1981)	Negative exponential	Punctual	P_N= 0 P_W= 0	Punctual	S= 1 N= 24	FCFS	(1) Mean waiting time of patients (2) Mean idle time (3) Mean overtime of doctor	**Variable-block/ fixed-interval AS** Solve for n_i given a_i constant
Pegden and Rosenshine (1990)	Exponential	Punctual	P_N= 0 P_W= 0	Punctual	S= 1 $N\leq 3$	FCFS	(1) Total cost of patients' waiting time and doctor's availability	**Individual-block/ variable-interval** Solve for optimal a_i
Liao, Pegden & Rosenshine (1993)	Erlang	Punctual	P_N= 0 P_W= 0	Punctual	S= 1 $N\leq 12$	FCFS	(1) Total cost of patients' waiting time and doctor's overtime	**Variable-block/ fixed-interval AS** Solve for optimal n_i given a_i constant

Table IV. Summary of Analytical Studies in the Literature (Cont'ed)

Brahimi and Worthington (1991a)	Discrete service time distribution is used to approximate general continuous service times	Punctual (for constant arrivals)	$P_N = 0$ $P_W = 0$	Punctual	Multiple $S = 4$	FCFS	(1) Frequency distribution of mean number of customers in the system (2) Frequency distribution of the probability of all servers being busy	No specific AS
Wang (1993)	Exponential	Punctual	$P_N = 0$ $P_W = 0$	Punctual	$S = 1$ $N = 2, 3, 4, 9$	FCFS	(1) Total cost of patients' flow times and doctor's completion time	**Individual-block/ variable-interval** Solve for optimal a_i where $n_i = 1$
Wang (1997)	Coxian, Exponential $CV = 0.85$, 1 and 1.27	Punctual Also, considers the lateness of the first and the last patient	$P_N = 0$ $P_W = 0$	Punctual	$S = 1$ $N < 50$	FCFS	(1) Total cost of patients' flow times and doctor's completion time	**Individual-block/ variable-interval** Solve for optimal a_i where $n_i = 1$
Liu and Liu (1998b)	Uniform $CV = 0.33$ Exponential $CV = 1$ Weibull $CV = 5$ $\mu = 10$ min.	Punctual	$P_N = 0, 0.10$ $P_W = 0$	Distribution for available service capacity is determined by (1) Poisson approximation, (2) Simulation	Multiple $S = 3$ N is a decision variable	FCFS	(1) Total cost of patients' waiting time, doctor's idle time and doctor's overtime $C_d/C_p = 0.5\text{-}1000$	**Variable-block/ fixed-interval AS** Solve for optimal n_i where a_i. constant What-if analysis to determine a_i
Vanden Bosch, Dietz & Simeoni (1999)	Erlang	Punctual	$P_N = 0$ $P_W = 0$	Punctual	$S = 1$ N general	FCFS	(1) Total cost of patients' waiting times and doctor's overtime	**Variable-block/ fixed-interval AS** Solve for optimal n_i given constant $a_i = \mu$
Lau & Lau (2000)	Generally and non-identically distributed	Punctual	$P_N = 0$ $P_W = 0$	Punctual	$S = 1$ $N < 30$	FCFS	(1) Total cost of patients' waiting & doctor's idle time $C_d/C_p = 10$	**Individual-block/ variable-interval** Solve for optimal a_i & optimal sequence
Robinson and Chen (2003)	Generalized Lambda distribution fitted to data collected on surgery times	Punctual	$P_N = 0$ $P_W = 0$	Punctual	$S = 1$ $N = 3, 5, 8, 12, 16$	FCFS	(1) Total cost of patients' waiting time and doctor's idle time $C_d/C_p = [1 \text{ to } 100]$	**Individual-block/ variable-interval** Solve for optimal a_i
Denton and Gupta (2003)	General; illustrated for Uniform, Gamma and Normal	Punctual	$P_N = 0$ $P_W = 0$	Punctual	$S = 1$ $N = 3, 5, 7$	FCFS	(1) Total cost of patients' waiting, server's idle and overtime	**Individual-block/ variable-interval** Solve for optimal a_i

2.5.2. Simulation Studies

An advantage of simulation modeling over analytical approaches is the ability to model complex outpatient queuing systems and represent environmental variables such as server or customer-related attributes. Studies conduct simulation experiments to evaluate the performance of alternative AS and/or understand the relationship between various environmental factors and various performance measures. Also, a number of generic simulation modeling packages are developed that enable health care planners and administrators to assess the effectiveness of alternative AS for their particular clinics (Katz 1969; Paul and Kuljis 1995).

Bailey's (1952) is the first study to analyze an individual-block AS at a time when most hospitals were still using single-block systems. He used a manual Monte-Carlo simulation technique in his search for the best initial block (n_1) and appointment interval (a_i) for clinics with a variety of N-values. As a result, he concludes that an individual-block/fixed-interval AS with an initial block of two patients leads to a reasonable balance between patient waiting time and doctor idle time. This is known as the "Bailey's rule", and it is widely studied in the literature. Blanco White and Pike (1964) relax the assumptions on patient and doctor punctuality when examining the effects of initial block (n_1), number of patients called together (n_i), and appointment interval (a_i). They find that different AS perform better for the two clinics investigated, which face different levels of patient unpunctuality. In their Yale studies, Fetter and Thompson (1969) conduct simulation experiments to analyze the effects of several key variables, such as unpunctuality of patients, lateness of doctors, no-show rates, walk-in rates, appointment scheduling intervals and patient loads. Their results confirm the importance of doctor punctuality, and stress the role of a realistic clinic load in the efficient operation of clinics. Vissers and Wijngaard (1979) reduce the variables essential for modeling AS to five: mean consultation time, coefficient of variation of consultation times, standard deviation of patient's punctuality, number of appointments per session, and mean "system earliness". "System earliness" includes all factors that decrease the risk of idle time of doctors, such as patients' earliness, doctor's lateness, block-booking (n_i> 1), initial block-booking (n_1> 1), and setting the appointment intervals smaller than the mean consultation time. In another related study, Vissers (1979) extends the analysis to various N-values, and develops a heuristic to select a suitable AS, given these five key variables and an acceptable balance between waiting time and idle time.

Charnetski (1984) uses simulation to study the problem of assigning time blocks to surgeons on a first-come, first-served basis when the goal is to balance the waiting cost of the surgeon and the idle cost of the facilities and operation room personnel. The proposed heuristic recognizes that different types of procedures have different service time distributions and sets job allowances based on the mean and the standard deviation of the *individual* procedure times.

Compared to earlier environmental assessment studies, Ho and Lau (1992, 1999) is the most comprehensive, where they evaluate fifty appointment rules under various operating environments. They introduce a number of individual-block/variable-interval AS, and test their performance against the traditional rules. Their best performing variable-interval rule allows patients to arrive in shorter intervals in a session's earlier part, and in larger intervals later on. They conclude that there is no rule that will perform well under all circumstances, and propose a simple heuristic to choose an appointment rule for a clinic given P_N, CV, N, and C_d/C_p ratio. Their procedure for finding the 'efficient frontier' provides a unified framework for comparing the performance of AS. They find that P_N, CV, and N affect AS performance in the order of decreasing importance.

Klassen and Rohleder (1996) introduce AS that classify patients based on their expected service time variability and use simulation to compare alternative ways of sequencing "low" and "high" variance patients when appointment intervals are kept constant. They find that the AS that schedules low-variance patients at the beginning of the session (called the LVBEG rule) performs better than Ho and Lau's (1992) best performing rules. They also model urgent patients. In a later study, Rohleder and Klassen (2000) consider the possibility that the scheduler can make an error when classifying patients, and moreover the possibility that s/he cannot sequence patients perfectly when some patients insist on particular slots. They find that the LVBEG rule still performs well under these more realistic assumptions.

Liu and Liu (1998a) study a variable-block/fixed-interval AS for a multi-server queuing system where doctors may arrive late. They develop a simulation search procedure to determine the number of patients to schedule to each block (n_i) that will minimize the total cost of patient flow-time and doctors' idle time. Using the properties of the best rules, derived after simulating various environmental factors (number of doctors, no-show probability, number of appointment blocks, and C_d/C_p), they propose a simple procedure to find an appointment rule for a given environment. Yang et al. (1998) propose a heuristic that is presented as a mathematical function of the mean and the standard deviation of consultation times, and the "planning constant k", where k is calculated for a particular clinic environment (i.e. combination of CV, P_N, N, and C_d/C_p) using a regression model. This rule explicitly tries to be more "fair" by increasing appointment intervals towards the end of the session to avoid compounded waiting times. They use simulation to compare the performance of the heuristic to the best rules proposed by Ho and Lau (1992).

Swisher et al. (2001) provide a discrete-event (visual) simulation model, which can be utilized for decision-making in outpatient services. They apply this model to a family practice clinic and show that the results are very sensitive to changes in the patient mix, patient scheduling and staffing levels. Regarding scheduling, they only study the effect of changing the time of day a certain patient category is scheduled, rather than comparing different appointment rules.

Our review reveals that, in general, simulation research fails to report the variance-reduction techniques employed and/or the statistical significance of the results. Other simulation studies, although not directly addressing the problem on hand, also offer useful insights on the general design and analysis of outpatient clinics in regards to staffing requirements, facility size/layout etc. (Stafford and Aggarwal 1979; Taylor III and Keown 1980).

Table V provides a summary of the simulation studies in the literature in terms of environmental factors addressed, performance measures used, and the type(s) of appointment systems evaluated.

Table V. Summary of Simulation Studies in the Literature

Author(s)	**Service Time Distribution** μ= mean σ= standard deviation CV= coefficient of variation= σ/μ	**Patient 1Unpunctuality**	**No-shows & Walk-ins** P_N= no-show probability P_W= walk-in probability	**Doctors' Lateness and Interruption Level (Gap Times)**	**Number of doctors (S)** Number of patients per session (N) **Duration of session (T)**	**Queue Discipline**	**Performance Measurements**	**Appointment System** n_i= block size for i^{th} block n_1= initial block a_i= appointment interval
Bailey (1952) Welch & Bailey (1952)	Pearson Type III fitted to empirical data CV= 0.51-0.62 μ= 5 min for N= 25 μ= 6.25 for N= 20 μ= 8.33 for N= 15 μ= 12.5 for N= 10	Punctual	P_N= 0 P_W= 0	Punctual	S= 1 N= 10, 15, 20, 25 T= 125 min.	FCFS	(1) Frequency distribution (FD) of patients' waiting times, (2) FD of doctor's idle time (3) FD of number of patients in queue (4) Mean and standard deviation of clinic end time (5) Mean waiting time of patients according to their place in the clinic. C_d/C_p= 37.5	**Individual-block/ fixed-interval AS w/ an initial block** n_1= 2 n_2= 1 for i= 2, .., N a_i= μ
Blanco White and Pike (1964)	Pearson Type III fitted to empirical data CV= 0.44-0.70 μ= 2.5 min for N= 60 μ= 3 for N= 50 μ= 5 for N= 30 μ= 7.5 for N= 20 μ= 15 for N= 10	Pearson Type VII fitted to empirical distribution for unpunctuality (mean= 0) based on empirical data	P_N= 0, 0.09, 0.19 Patient load is adjusted according to the observed no-shows. P_W= 0	Doctor is late to first appointment 0, 5, 10, 15, 20 min.	S= 1 N= 10, 20, 30, 40, 50, 60 T= 150 min.	FCFS	(1) Mean waiting time of patients (2) Mean idle time of doctors (3) % of patients seen within 30 min. of appointment time	For punctual case: **Individual-block/ fixed-interval AS w/ an initial block** n_1= 2 or 3, a_i= μ For unpunctual case **Multiple-block/ fixed-interval AS** a_i= T/10, n_i= m
Fetter and Thompson (1966)	Empirically collected service times for walk-ins (μ= 9.8 min.) and scheduled patients (μ= 12.6 min.)	Early-late times are allowed to go to maximum 5 minutes.	Observed P_N range 0.04 to 0.22 (mean 0.14) Observed P_W range 0.07 to 0.58 (mean 0.38)	Doctor is late to first appointment 0, 30, 60 min.	S= 3 N= 26	FCFS Walk-ins are assigned to first available doctor, Emergencies are nonpre-emptive	(1) Mean waiting time of patients (walk-ins vs scheduled patients) (2) Mean idle time of doctors (3) Productivity (# of patients seen per session)	**Individual-block/ fixed-interval AS** a_i= 15 min. and a_i= 20 min.

Table V. Summary of Simulation Studies in the Literature (Cont'ed)

Vissers and Wijngaard (1979) Vissers (1979)	General CV = 0.25, 0.5, 0.75, 1, 1.25	Modeled under a new variable called "system earliness" Mean punctuality= 0 to 3μ.	This factor is incorporated by revising the mean and variance of service times	Doctor lateness is modeled under "system earliness"	S= 1 N= 10, 20, 30, 40, 50, 60	FCFS	(1) Mean waiting time of patients (2) Mean idle time of doctors	**Individual-block & Multi-block/ fixed-interval AS's with or without an initial block**
Ho and Lau (1992, 1999)	Uniform CV= 0.2, 0.5 Exponential CV= 1	Punctual	P_N= 0, 0.10, 0.20 P_W= 0	Punctual	S= 1 N= 10, 20, 30	FCFS	(1) Mean waiting time of patients (2) Mean idle time of doctors	**Individual-block/ variable-interval** n_i= 1 a_i is variable
Klassen and Rohleder (1996, 2000)	Lognormal dist μ= 8, 10, 12 min. σ= 5, 10 CV= 0.5, 1.0 In the later study, a client's service time variance is randomly chosen from a lognormal distribution (mean 7.5 min. standard deviation 3.75, 7.5 min.)	Punctual	P_N= 0.05 P_W= 0	Punctual	S= 1 T= 210 min. N varies from 19 to 21, depending on urgent calls received	FCFS for regular patients Poisson distribution is used to generate urgent calls	(1) Total cost of patients' waiting and doctor's idle time (C_d/C_p= 1) (2) Mean waiting time of patients (3) Mean idle time of doctor (4) Mean and max. completion times (5) % of urgent clients served (6) Mean and max. waiting time (7) % of waits less than 10 min. (8) % of patients who received the slot requested	**Individual-block/ fixed-interval** a_i= 10 min. Two slots left open for urgent calls Use patient classification to sequence low and high-variance patients in various ways
Liu and Liu (1998a)	Uniform CV= 0.58 Exponential CV= 1 Weibull CV= 2.236 μ= 10 min.	Punctual	P_N= 0, 0.10, 0.20 P_W= 0	Doctors' arrival times uniform over [0, 0] and [0, 6]	Multiple S= 2, 3, 5 N= 46	FCFS	(1) Total cost of patients' flow times and doctor's idle time	**Variable-block/ fixed-interval AS** Solve for optimal n_i given a_i
Yang, Lau & Quek (1998)	Gamma CV= 0.2, 0.4, 0.6, 0.8, 1.0 μ= 1	Punctual	P_N= 0, 0.05, 0.10, 0.15, 0.20 P_W= 0	Punctual	S= 1 N= 10, 15, 20, 25, 30	FCFS	(1) Total cost of patients' waiting and doctor's idle time C_d/C_p= 1-100 (2) Variance of doctor idle time (3) Variance of patients' waiting times	**Individual-block/ variable-interval** Solve for a_i
Swisher, Jacobson, Jun & Balci (2001)	Exponential	Punctual	P_N= 0 Exponential walk-ins	Punctual	Multiple $S \geq 1$	FCFS	(1) Clinic effectiveness (2) Mean doctor utilization (3) Mean overtime	Scheduling various patient categories on different periods of the day

2.5.3. Case Studies

In case studies, the researchers analyze a particular outpatient clinic, make recommendations for improving the existing system, and sometimes evaluate the results of actual implementation. Even though case studies offer valuable insights into how real outpatient clinics function, their major drawback is the lack of generalization.

Villegas (1967) reports a study in the general medicine clinic of an outpatient department, where he experiments with actual practices. He compares the performance of a number of variable-block/fixed-interval AS in terms of patients' waiting times and doctor's idle time. Williams, Covert and Steel (1967) use simulation to analyze a university clinic to improve patient and doctor scheduling. They show that when a multiple-block schedule is used, as opposed to a single-block system, patient waiting times decrease substantially with no decrement in staff utilization. Johnson and Rosenfeld (1968) study factors affecting patient waiting times in eight New York City Hospitals using an observational approach. They conclude that the AS in use is a major determinant of waiting times, and both individual and multiple-block systems outperform single-block systems. In their analysis of Massachusetts General Hospital, Rockart and Hofmann (1969) observe that when clinics shift to individual-block systems, where patients are given unique appointments and are assigned to specific doctors, both doctors and patients behave more punctually and no-show rates decline. Based on the data collected from the same hospital, Hofmann and Rockart (1969) study variables that affect no-show rates in outpatient clinics. One key factor is the "request to appointment" interval; the more time patients have to wait for an appointment, in general, the greater the percentage of no-shows.

Walter (1973) uses simulation to model the queuing system in a radiology department, and explores the effects of varying n_1, m, N, CV, and the ratio of patients with appointments. He also investigates the effects of dividing the clinic session into more homogeneous groups, and finds that even a simple grouping of inpatients and outpatients results in substantial improvement in doctors' idle time. Rising et al. (1973) use simulation modeling to investigate an outpatient clinic at the University of Massachusetts, with the goal of improving patient and physician scheduling. They suggest scheduling patients in a way that complements the daily and hourly arrival pattern of walk-ins, resulting in a smoothing of the actual arrival rate. Their implementation results suggest improvements in terms of reduced clinic overtime and less waiting time for walk-ins. In a simulation model of an ear, nose, and throat clinic, Cox et al. (1985) evaluate a number of AS with alterations of parameters (a_i, n_1, n_i) and various ways of sequencing new/return patients at the time of booking. They validate their simulation model by comparing results with those observed in real life. When implemented, their proposed rules achieve improved patient flow times, uniform queue sizes, and uniform work rates for doctors. Mahachek and Knabe (1984) use simulation to analyze alternative operational decisions with respect to patient scheduling, staffing requirements, patient-mix, and facility size. The rules evaluated involve a patient classification scheme of new vs. return patients.

O'Keefe (1985) uses a mainly qualitative approach in his analysis of the operations of three outpatient departments in the U.K. The proposed AS which uses a patient classification of new vs. return patients is rejected by staff who prefer to keep AS simple and uniform across the institution. Similarly, the author faces an enormous resistance by doctors who refuse to change their old habits. This case study is a good illustration of the fact that the real appointment-scheduling problem is primarily a "political" one. Babes and Sarma (1991) investigate a clinic in Algeria which uses a single-block AS, where patients are assigned a certain date with no appointment times specified. Under these conditions, the problem is reduced to determining the number of patients per clinic session (*N*) and the number of doctors (*S*) that will optimize the cost performance of the system. They initially apply steady-state queuing theory models of type M/G/S. However when results turn out to be very different than those observed in real operation, they use simulation modeling. They examine the sensitivity of performance parameters to *N*, *S*, the lateness of doctors, and the mean service time. Brahimi and Worthington (1991b) apply their previous work on time-dependent-queuing model (1991a) to the problem of improving AS in seven clinics in the U.K. They compare alternative systems based on a number of performance measures, and as a result, they suggest an individual-block/fixed-interval system with an initial block of three patients. They observe an improvement in patients' waiting times after the new AS is implemented. Huarng and Lee (1996) use simulation to model the outpatient department of a local hospital in Taiwan that uses no AS, with the goal of improving waiting times and doctor utilization. The authors report that they could not implement an individual-block AS because of staff resistance. Instead, they recommend extending the doctor's work hours in order to better match demand and supply.

Bennett and Worthington (1998) use a systems approach where they consider the interaction of outpatient department with other units in the hospital. They observe that overbooking and scheduling of excessive follow-up appointments create a major capacity problem. Authors' recommendations could not be implemented successfully as the required changes in the behavior of doctors could not be enforced. Lehaney et al. (1999) propose an AS that sorts patients in ascending order of consultation times, similar to sequencing jobs by the shortest processing time (SPT) rule in job shop scheduling. Even though they discuss this approach in the context of an outpatient setting, in a real application the scheduler has to assign a slot to a calling patient without knowing whether the next one will require a shorter or a longer consultation time (Strict-ordering schemes are more suited to surgical scheduling, as discussed previously in Section 2.4.2). As the authors acknowledge, it is also not practical to come up with reliable estimates of *individual* consultation times. Authors encourage end-user participation in simulation model building in order to increase acceptability of the model, its results, and eventually its implementation. This approach is called "soft-simulation", which combines simulation and soft systems methodology. When implemented as suggested, the new AS improves the performance of the clinic in terms of patient waiting times.

Vanden Bosch and Dietz (2000) examine scheduling/sequencing policies for a specific primary clinic, which uses a classification scheme based on patients' past appointment history or type of procedure (called type A, B, or C-patients). This is the first attempt to study the best patient-mix and sequence over several days. They present an analytical approach to solve the static problem where all patients that need to be scheduled for the day are known in advance. They find that there is no easy rule for the optimal sequence; it is difficult to generalize any results on ordering patients by service time means or variances. Furthermore, due to enumeration required, the optimal solution cannot be determined except for very small problems. For the more complex problem of finding the schedule/sequence when requests arrive dynamically, they develop a heuristic policy and test its performance using simulation.

In Table VI, the reader will find a summary of case studies in the appointment-scheduling literature. Table VII summarizes the various research methodologies that address appointment scheduling problems as observed in the literature.

Table VII. Analysis Methodologies

1. Analytical Studies
    - 1.1 Queuing Theory
    - 1.2 Mathematical Programming
        - 1.2.1. Dynamic Programming
        - 1.2.2. Nonlinear Programming
        - 1.2.3. Stochastic Linear Programming
2. Simulation Studies
    - 2.1 Environmental assessment (Which factors affect which performance measures?)
    - 2.2 Comparison of the performance of alternative AS
3. Case Studies
    - 3.1 Observational
    - 3.2 Real-life experimentation of alternative AS
    - 3.3 Quantitative modeling (simulation, queuing model, etc.) for alternative systems design with or without after-implementation analysis

Table VI. Summary of Case Studies in the Literature

Author(s)	**Service Time Distribution** μ= mean σ= standard deviation CV= coefficient of variation= σ/μ	**Patient Unpunctuality**	**No-shows & Walk-ins** P_N= no-show probability P_W= walk-in probability	**Doctors' Lateness and Interruption Level (Gap Times)**	**Number of doctors (S)** Number of patients per session (N) **Duration of session (T)**	**Queue Discipline**	**Performance Measurements**	**Appointment System** n_i= block size for i^{th} block n_1= initial block a_i= appointment interval
Walter (1973)	Gamma fitted to actual data CV= 0.31-0.86 μ= 2.5 min for N= 60 μ= 15 for N= 10	Punctual	P_N= 0 P_W= 0.33, 0.50, 0.67	Punctual	N= 10, 20, 30, 40, 50, 60 T= 150 min.	FCFS	(1) Mean waiting time of patients (2) Mean idle time of doctors	**Individual-block/ fixed-interval AS w/ an initial block** n_1= 2, 3, 4; a_i= μ **Multiple-block/ fixed-interval AS** m = 2, 3 Patient classification as outpatients and inpatients
Rising, Baron & Averill (1973)	Separate empirical distributions are derived for scheduled patients (μ= 13, CV= 0.75), walk-ins, and (μ= 10, CV= 0.51), second-consultations (μ= 5, CV= 0.84).	Punctual	P_N= 0 Negative exponential interarrival times for walk-ins and non-preemptive emergencies	Gap times per day per doctor (in min) 0, 20, 40, 60, 80	Number of doctors scheduled hourly is a decision variable Maximum S= 7 N is around 100 T= 480 min.	1st priority given to emergencies or patients returning from X-ray, 2nd priority to scheduled patients, and 3rd walk-ins.	(1) Mean waiting time of scheduled patients, walk-ins, and second-service patients (2) Frequency distribution of waiting times for all types of patients	**Variable-block/ fixed-interval AS** Find n_i that best complement the observed arrival pattern of walk-ins a_i= 60 min.
Mahachek & Knabe (1984)	Poisson μ= 11 min.	Punctual	P_N= 0 P_W= 0	Doctor lateness is modeled based on actual times observed	S and N are decision variables S = 1, 2, 3 N = 20-35	FCFS	(1) Average flow time of patients (2) Doctor utilization (3) Clinic end time	**Individual-block/ fixed-interval AS** that uses new/return classification
O'Keefe (1985)	The distribution for one department is close to lognormal. CV's range from 0.58-0.75.	Observe that 75% of the patients arrive early	Observed P_N= 0.05 P_W= 0	Observe that doctors are usually late	Multiple S= 1, 2, 3 Three clinics: N_1= 68, N_2= 41 N_3 = 132	FCFS	(1) Mean waiting time of patients	**Individual-block/ fixed-interval AS w/ an initial block** a_i= 15 min.

Table VI. Summary of Case Studies in the Literature (Cont'ed)

Cox, Birchall, Wong (1985)	Empirical distributions: X^2_5 for new patients, X^2_3 for return patients, and truncated Normal distribution for the hearing test N (8,12)	Empirical distribution for unpunctuality; Exponential is fitted for late patients, and a probability density function of form $(a + bx)$ is fitted for early patients.	$P_N = 0$ Empirically observed no-show probabilities range from 0.10 to 0.30 $P_W = 0$	Increase service times to allow for "gap times"	Multiple 2 doctors, and 2 audio-metricians $T = 210$ min. Two clinics: $N_1 = 40$, $N_2 = 63$	For consultation: Highest priority is given to patients returning from a hearing test, For hearing test: FCFS	(1) Queue sizes at each time of session (2) % doctor is busy (3) Frequency distribution (FD) of patients' flow time (4) FD of patients' waiting time (5) FD of idle time of doctors	**Multiple-block/ fixed-interval AS** that sequences new/return patients $n_i = 3$, $a_i = 15$ min. **Multiple-block/ fixed-interval AS w/ an initial block** $a_i = 15$ min. $n_1 = 3$, $n_i = 5$ for $i = 2, .., N$
Babes and Sarma (1991)	Weibull	Arrivals are Poisson	$P_N = 0$ $P_W = 0$	Punctual vs. when doctors start 30 min. late to first appointment	S and N are decision variables Multiple S=1, 2, 3	FCFS	(1) Mean number of patients in queue (2) Mean waiting times in queue (3) Time clinic session ends (4) % doctor busy	**Single-block AS** Patients are scheduled no appointment times, just the date.
Brahimi and Worthington (1991b)	Discrete approximation to empirical distributions $CV = 0.36\text{-}0.61$ $\mu = 5.4\text{-}7.2$ min.	Punctual	$P_N = 0, 0.10$ $P_W = 0$	Punctual	$S = 1$ Seven clinics: N ranges from 11 to 23	FCFS	(1) Mean # of patients in system (2) Mean waiting time in the system (3) % doctor busy	**Individual-block/ fixed-interval AS w/ an initial block** $n_1 = 3$, $a_i = 5$ min. $n_i = 1$ for $i = 2, .., N$
Huarng and Lee (1996)	Exponential Dermatology: $\mu = 1.82$ min., General surgery: $\mu = 2.82$ min., General medicine: $\mu = 2.78$ min.	Punctual	$P_N = 0$ $P_W = 0$	None	Multiple $S = 2$ $N = 80\text{-}335$ $T = 240\text{-}480$ min.	FCFS	(1) Mean waiting time (2) Mean and maximum idle time (3) Mean and max. # patients in queue (2) Mean doctor utilization (3) Mean number of patients served	**Individual-block/ variable-interval** $a_i = 1.05\mu$ vs. **Single-block system** used
Lehaney, Clarke & Paul (1999)	Not specified $\mu = 11$ min.	Punctual	$P_N = 0$ $P_W = 0$	Gap times modeled as nonpreemptive	Multiple $S = 3$ $N = 11$	FCFS	(1) Mean patient waiting time (2) FD of waiting times (3) # of patients in queue	AS that sequences patients in ascending order of processing times
Vanden Bosch & Dietz (2000)	Truncated Erlang & gamma based on actual service times. $CV = 0.046, 0.139$, and 0.163. $\mu = 18.75, 21.94$, and 25.56 min.	Punctual	$P_N = 0.05, 0.08$, and 0.11 for three different classes of patients. $P_W = 0$	Punctual	$S = 1$ $T = 170$ min. $N = 6$	FCFS	(1) Total cost of patients' waiting times and doctor's overtime $C_d/C_p = 3$ (2) # of vacant slots (3) delays between requests and appointments	**Individual-block/ variable-interval** a_i variable, multiples of 10 min. Use patient classification based on problem type

CHAPTER III

RESEARCH CONTRIBUTION

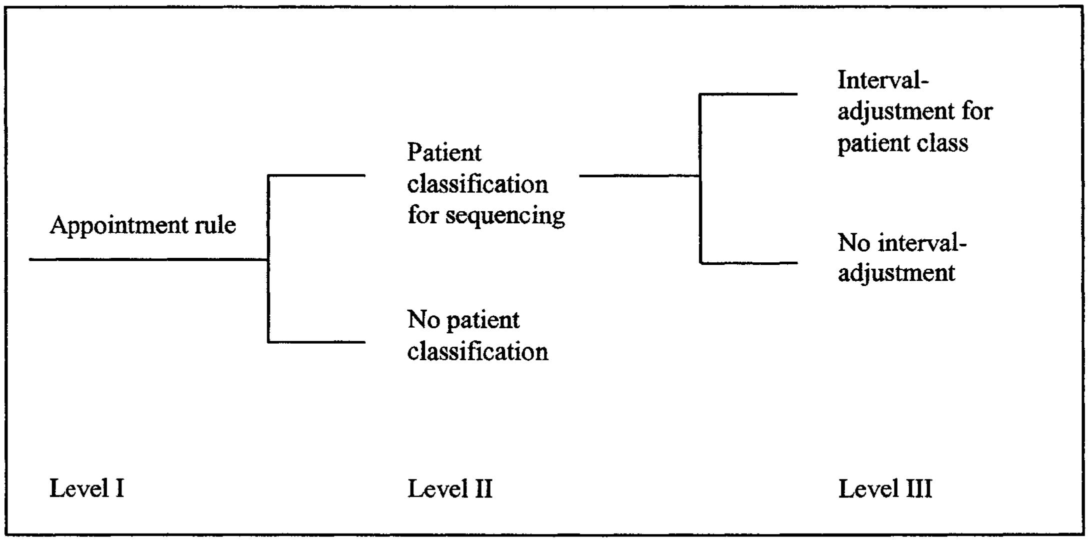
3.1. RESEARCH OBJECTIVES

The first objective of this study is to introduce new appointment systems (AS) and evaluate their effectiveness in comparison to traditional ones in the literature. Compared to previous research, the appointment-scheduling problem is considered within a broader framework that includes a series of decisions regarding (i) appointment rules, (ii) sequencing rules, and (iii) interval-adjustment for patient class.

A review of the literature reveals that the majority of the studies concentrate on the first problem of finding the best appointment rule. These studies assume patients are homogeneous for scheduling purposes. A number of studies consider the second-level decision, which is to use patient classification for sequencing purposes at the time of booking. In these studies, appointment intervals are not adjusted for patient category (See Chapter II). One of the objectives of this study is to take patient classification to the next logical step, which is to adjust appointment intervals to match the consultation time characteristics of different classes of patients. To the best of our knowledge, there is no study in appointment-scheduling literature that addresses this third-level decision, called "interval-adjustment". Figure III illustrates the three-level decision making in AS design.

The second objective of this study is to expand the previous environmental assessment studies by analyzing a wider range of environmental factors and determining how and in what manner these affect the performance of AS. Apart from environmental factors that were identified as important by previous simulation studies (i.e. clinic size, service time variability, presence of no-shows), this study examines the effects of presence of walk-ins and unpunctual patients. Furthermore, two new factors are hypothesized to be important when patient classification is used: the probability of each patient class, and the ratio of the service times of different patient classes.

Figure III. Three Decision Levels in Appointment System Design



3.2. RESEARCH QUESTIONS

The present study is concerned with the following primary research questions. Since each appointment system is a combination of three levels of decision factors, research questions can be further broken down as follows:

1. Does the choice of an appointment system affect clinic performance?
    - Does the choice of an appointment rule affect clinic performance?
    - Does the choice of a sequencing rule affect clinic performance?
    - Does interval-adjustment for patient class affect clinic performance?
2. Does the choice of an appointment system differ for different clinic environments?
3. What impact do the environmental factors have on clinic performance?

3.3. RESEARCH HYPOTHESES

$H_0 1$: There will be no significant difference among the mean performances of appointment systems.

$H_0 2$: There will be no significant difference in the choice of an appointment system for different environments.

$H_0 3$: There will be no significant effect of environmental factors on clinic performance.

CHAPTER IV

METHODOLOGY

This chapter develops a framework within which research hypotheses will be tested. First, we present decision factors related to appointment systems (AS). Next, we list environmental factors that are hypothesized to affect the performance of AS. Lastly, we specify measures of performance that will be used for evaluation.

The experimental methodology for this study is implemented with a simulation model written in GPSS/H language to investigate various decision factors and environmental factors (See Appendix A). Through simulation, real-life complexities of clinic environments can be easily represented. By changing inputs into the simulation model, the performance of alternative AS and their interactions with various environmental factors are measured. When simulating alternative system configurations, common random numbers was used as a variance reduction technique.

4.1. DECISION FACTORS

There are three decision factors in the experimental model: (1) *appointment rule* determines the basic template of the AS by specifying the number of patients scheduled to each appointment slot (i.e. block size) and the length of appointment intervals, (2) *sequencing rule* determines the order in which calling patients are assigned to blocks based on a particular patient classification scheme, and (3) *interval-adjustment* specifies whether an adjustment is made to appointment intervals to match the distinct service time characteristics of different patient classes. This is only relevant if patient classification is used for sequencing purposes.

4.1.1. Appointment Rule (RULE)

Seven appointment rules are tested in this study:

1. **IBFI** (individual-block/fixed-interval) rule calls patients individually at intervals equal to the mean consultation times of patients.

$t_1 = 0$; then for $i > 1$, set $t_i = t_{i-1} + \mu$ [2]

where t_i is the appointment time given to patient i, and μ is the mean consultation time.

2. **OFFSET**, introduced by Ho and Lau (1992), is an individual-block/variable-interval rule where the initial (k-1) patients are scheduled to arrive earlier and the rest are scheduled to arrive later compared to the IBFI rule.

$t_i = (i-1)\mu - \beta_1(k-i)\sigma$ for $i \leq k$, and [3]

$t_i = (i-1)\mu + \beta_2(i-k)\sigma$ for $i > k$.

where σ is the standard deviation of consultation times.

OFFSET rule results in variable intervals that are relatively shorter for the first (k-1) patients compared to the rest for $\beta_1 < \beta_2$ and vice versa for $\beta_1 > \beta_2$. (Note that the rule results in fixed intervals when $\beta_1 = \beta_2$). As a result of a pre-study which evaluated a range of β_1, and β_2 values, parameters in this study are set at β_1= 0.15, β_2= 0.30 and k= 5 for simulated clinics with 10 patients (k= 10 for clinics with 20 patients). The reader will find the details on pilot runs in Appendix C.

3. **DOME** is another individual-block/variable-interval rule, which is included because recent analytical studies report that in optimal solutions, appointment intervals gradually increase toward the middle and then decrease slightly at the end of the session (Wang 1997, Robinson and Chen 2003, and Denton and Gupta 2003). This study tests the following rule that results in "dome-shaped" appointment intervals:

$$t_i = (i-1)\mu - \beta_1(k_1-i)\sigma \qquad \text{for } i \leq k_1, \qquad [4]$$

$$t_i = (i-1)\mu + \beta_2(i-k_1)\sigma \qquad \text{for } k_1 < i \leq k_2, \text{ and}$$

$$t_i = (i-1)\mu - \beta_3(i-k_2)\sigma \qquad \text{for } i > k_2.$$

Patients 1 through (k_1-1) are called earlier, (k_1+1) through (k_2-1) are called later, and the rest are called earlier compared to IBFI. In pilot runs, we tested various multipliers β_i and early/late breakpoint combinations of k_i (see Appendix C). As a result, the DOME rule with β_1= 0.15, β_2= 0.30, β_3= 0.05, k_1= 5, and k_2= 9 is chosen for the main experiments for clinics with N= 10. Similar to the OFFSET rule, k-values are adjusted to clinic size; k_1= 10, and k_2= 18 are used for clinics with 20 patients.

4. **2BEG**, commonly referred to as "Bailey's Rule" (1952), is an individual-block/fixed-interval rule with an initial block of two patients. This can be represented as:

$$t_1 = t_2 = 0; \text{ then for } i > 2, \text{ set } t_i = t_{i-1} + \mu \qquad [5]$$

5. **2BEG_DOME** rule is a combination of the 2BEG and the DOME rules.

$t_1 = t_2 = 0$ for $i = 1, 2$ [6]

$t_i = (i-1)\mu - \beta_1(k_1-i)\sigma$ for $3 \leq i \leq k_1$,

$t_i = (i-1)\mu + \beta_2(i-k_1)\sigma$ for $k_1 < i \leq k_2$, and

$t_i = (i-1)\mu - \beta_3(i-k_2)\sigma$ for $i > k_2$.

6. **MBFI** (multiple-block/fixed-interval) rule calls patients two-at-a-time with appointment intervals set equal to twice the mean consultation time.

$t_i = t_{i+1} = (i-1)\mu$ for $i = 1, 3, 5, 7, \ldots$ [7]

In the literature, performance evaluations for the MBFI rule are varied. Soriano (1966), Blanco White and Pike (1964), and Cox et al. (1985) find that multiple-block rules perform better for the particular clinics they studied. Ho and Lau (1992) report that multiple-block rules perform worse than OFFSET and 2BEG rules for the operating environments investigated in their simulation experiments. This paper investigates the performance of MBFI rules under a wider range of environmental factors, using multiple performance measures.

7. **MB_DOME** is a combination of MBFI and DOME rules. The result is a multiple-block/variable-interval rule, investigated for the first time in the literature.

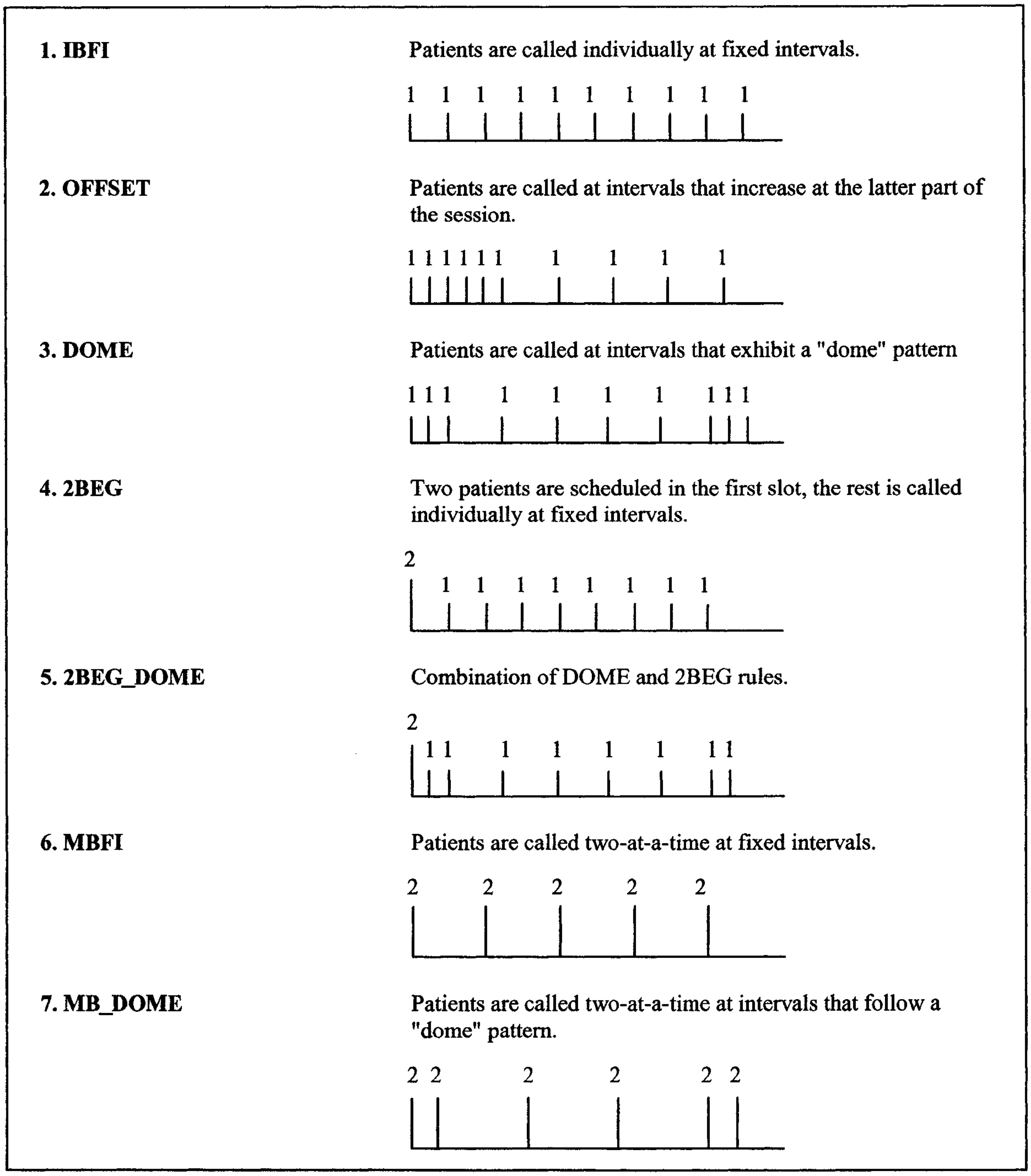
$t_i = t_{i+1} = (i-1)\mu - \beta_1(k_1-i)\sigma$ for $i = 1, 3, 5, 7, \ldots, k_1$ [8]

$t_i = t_{i+1} = (i-1)\mu + \beta_2(i-k_1)\sigma$ for $k_1 < i \leq k_2$, and

$t_i = t_{i+1} = (i-1)\mu - \beta_3(i-k_2)\sigma$ for $i > k_2$; where i, k_1, k_2 are odd integers.

Since outpatient scheduling is a static problem, the formulae are used only once when designing the AS. Figure IV provides a graphical representation of all the appointment rules tested in this study.

Figure IV. Appointment Rules Tested in This Study



4.1.2. Sequencing Rule (SEQ)

This paper uses a patient classification scheme of "new" and "return" patients, which is one of the most common classification schemes used for scheduling purposes in practice. Empirical data collected in a variety of specialties reveal that the mean consultation time of new patients is usually higher than that of return patients (Nuffield Provincial Hospitals Trust 1965; Partridge 1992; Hart 1995). The wide range of applications of this scheme in practice, as well as the availability of empirical support, made this classification the best candidate for our analysis. However, the results of this study can be generalized to any classification scheme based on consultation time length. This scheme may also be called "short" and "long" consultation times.

Six sequencing rules are evaluated:

1. **FCFA** represents the base experimental setting with 'no sequencing rule', patients receiving appointment slots on a first-call, first-appointment basis,

2. **ALTER** orders new and return patients in an alternating pattern (RNRNRNR….),

3. **NEW_BEG** schedules new patients in the beginning, and return patients in the remaining part of the session, based on the expected percentage of each patient class (NNN….RRRR),

4. **RET_BEG** schedules return patients in the beginning (RRRR….NNN),

5. **NEW_BEG_END** schedules new patients in the beginning and in the end (NN..RRR..NN), and

6. **RET_BEG_END** schedules return patients in the beginning and in the end (RR..NNN..RR).

These sequencing rules have a pattern that is identical to those tested by Klassen and Rohleder's (1996) study when they addressed a patient classification scheme of "low" and "high-variance" patients. The seven appointment rules discussed in Section 4.1.1 can be combined with any of the six sequencing rules, resulting in forty-two AS.

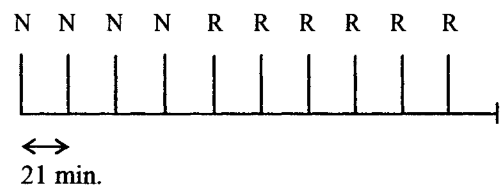
4.1.3. Interval-Adjustment for Patient Class (ADJ)

When patient classification is used for sequencing purposes, an issue is whether or not to adjust the appointment intervals for patient class. For new/return classification, this means longer slots are assigned to new patients and shorter slots to return patients, based on their distinct consultation time characteristics. If no adjustment is made, then appointment intervals are determined based on the mean consultation times of *all* patients. Figure V illustrates the two approaches for the NEW_BEG sequencing rule performed on the IBFI rule.

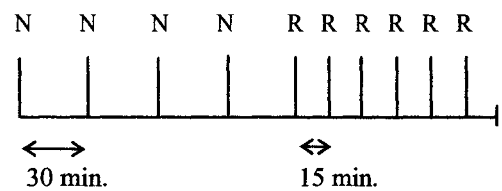
Figure V. Two Approaches to Interval-Adjustment When Sequencing is Used

Example: Appointment system: IBFI/NEW_BEG, 10 patients (4 new, 6 return)
Mean consultation times: μ_{New}= 30 min., μ_{Ret}= 15 min., weighted average of all patients: μ= 21 min.

1. Sequencing Without Interval-Adjustment



2. Sequencing With Interval-Adjustment



4.2. ENVIRONMENTAL FACTORS

This study investigates eight environmental factors. These include the number of patients per ambulatory care session, or the 'clinic size' (N), the coefficient of variation of consultation times for return patients (CV_{Ret}), the coefficient of variation of consultation times for new patients (CV_{New}), the probability of no-shows (P_N), the probability of walk-ins (P_W), the unpunctuality of patients (Unp), the percentage of new patients ($\%New$), and the ratio of the mean consultation time of new patients to the mean consultation time of return patients (μ_{New}/μ_{Ret}).

1. Number of Patients per Clinic Session (N)

When studies investigate an ambulatory care session with a fixed number of appointments, they ignore the possible effect of N on the performance of an appointment system. Simulation studies cite the importance of including this factor when comparing AS (Bailey 1952; Blanco White and Pike 1964; Vissers and Wijngaard 1979; Yang, Lau & Quek 1998). In their extensive environmental assessment studies, Ho and Lau (1999) find that different AS might be suitable for different values of N.

2-3. Coefficient of Variation of Consultation Times for Return (CV_{Ret}) and New Patients (CV_{New})

This study investigates the effects of service time variability for both new and return patients. Similar to previous studies, the coefficient of variation is used as measure for the variability of service times ($CV = \sigma/\mu$). Findings of Bailey (1952), Blanco White and Pike (1964), Vissers and Wijngaard (1979), Ho and Lau (1999), and Klassen and

Rohleder (1996) all demonstrate that *CV* is an important factor effecting the performance of AS.

4. Probability of No-shows (P_N)

Ho and Lau's (1999) assessment of environmental factors (P_N, *CV*, and *N*) reports that among the three factors, no-show probability has the major effect on performance of an AS. Since our AS design considers new/return patients, one issue is whether to consider the possible differences in no-show rates between the two patient classes. King, David, Jones and O'Brien (1995) report negligible difference for new and return patients (11.9 and 12.8 percent, respectively). On the other hand, Partridge (1992) finds that the overall no-show rate is lower among new patients compared to returns in forty-seven clinics investigated (13 vs. 22 percent).

5. Probability of Walk-ins (P_W)

The probability of walk-ins (P_W) is measured as the number of patients who walk-in without appointments as a percentage of all appointments. This factor is neglected in most studies. Similar to no-shows, walk-in probabilities are known to vary across specialties (Fetter and Thompson 1966; Field 1980). Studies use exponential inter-arrival times to model walk-ins either on theoretical or empirical grounds (Swartzman 1970; Swisher et al. 2001). Some also reflect seasonality effects by changing the mean value on an hourly basis (Rising et al. 1973). In their simulation study, Vissers and Wijngaard (1979) model the impact of no-shows and walk-ins through an adjustment to the mean and variance of consultation times.

6. Unpunctuality of Patients (Unp)

Unpunctuality of patients can be defined as the difference between a patient's appointment time and actual arrival time. This is a factor largely neglected in the literature. There are a number of empirical studies that provide histograms of patient arrival times relative to their appointment times (Welch and Bailey 1952; Blanco White and Pike 1964; Nuffield Provincial Hospitals Trust 1965, p.30; Fetter and Thompson 1966; Cox et al. 1985).

7. Percentage of New Patients (%New)

This study includes the percentage of new patients as a potential factor that may affect the performance of AS when patient classification is used. Empirical evidence from the literature suggests that the percentage tends to be different for various practices, ranging from approximately 15 to 40 percent (Nuffield Provincial Hospitals Trust 1965, p.5; Partridge 1992; King et al. 1995).

8. Ratio of Mean the Consultation Time of New Patients to the Mean Consultation Time of Return Patients (μ_{New}/μ_{Ret})

Lastly, this factor is included because of its likely effect on ambulatory care performance when patient classification is used. Empirical studies report μ_{New}/μ_{Ret} ratios that range from 1.2 to 2.9 (Nuffield Provincial Hospitals Trust 1965, p. 52; Partridge 1992).

4.3. SIMULATION MODEL

Empirical data were collected from a primary health care clinic in the metropolitan New York area with the intent of establishing the validity of our input parameters. This was vital for modeling arrival patterns of patients (unpunctuality), and service time distributions of new/return patients. These factors had little empirical evidence in prior literature. Secondary data on no-show, and walk-in rates observed in various clinics of the hospital, provided useful information when setting factor levels (See Appendix B for details on the statistical analysis of empirical data). For the rest of the factors, further support came from earlier empirical studies, which led to realistic environments in the simulated clinics.

All combinations of factors were simulated for 100 replications, each of which represented averages of 100 days (i.e. 10,000 clinic sessions simulated for each environment). Pilot runs showed that for this sample size, primary performance measures of doctor's idle time, doctor's overtime, and patients' waiting times were accurate within an average ±2.06% at the 95 percent confidence level.

4.3.1. Basic Assumptions

In our simulation model, the clinics represent single-server, single-phase queuing systems where patients are served only once per visit. This single-server assumption holds for most ambulatory care settings, because sharing patients among multiple doctors is generally avoided in order to maintain continuity of care, and to enhance the doctor-patient relationship.

A realistic arrival pattern is modeled, including unpunctual patients, no-shows and walk-ins. Patient unpunctuality, which includes both earliness and lateness of patients, is modeled using normal distribution based on actual data collected from the metropolitan hospital clinic. It is assumed that patients' unpunctuality is independent of their appointment times. On theoretical grounds, exponential distribution (time-independent) is used to model inter-arrival times of walk-ins. In our simulation model, all walk-ins are admitted to the clinic, regardless of the current congestion in the clinic. A walk-in can be either a new or a return patient based on the overall expected probability of new patients. For simplification, we assumed that no-show probabilities of new and return patients are identical. Furthermore, no-show probability is assumed to be independent of a patient's place in the clinic.

A lognormal distribution is used to model consultation times after goodness-of-fit test was conducted on actual service time data collected. Some of the earlier studies have also reported that a lognormal distribution is the best approximation to their empirical data (O'Keefe 1985; Klassen and Rohleder 1996). During our pilot runs, we observed that unrealistically short or long service times were simulated. To represent this factor more realistically, service times were truncated at a minimum of 2 minutes and maximum of 60 minutes. This resulted in left and right-tail truncations of 0.02% and 3.46%, respectively, over 5000 simulated service times for the worst-case scenario when both CV_{New} and CV_{Ret} are high.

The simulated clinics use a queue discipline where patients are seen in the order of their appointment times. This is fairer than first-come-first-served priority rule. When a patient does not show up, the doctor sees the next available patient with the nearest appointment time. The presence of unpunctual patients and walk-ins complicates the administration of patient flow in real life situations. Setting up rules on how to squeeze in late arrivals and walk-ins is a subjective decision, and is more complex than it may at first appear. It is natural to assume that late patients and walk-ins may tolerate longer waiting times. Yet penalizing a late patient may sometimes be undesirable, especially if the patient is late only a few minutes and/or when the doctor is running late anyway. In short, the effect of lateness is circumstantial and the risk of it becoming a problem increases with the magnitude of lateness. For this reason, our simulation model mimics a clerk's decision-making process by using a rule where the penalty is directly proportional to a patient's lateness. Walk-ins are given the lowest priority, yet within the limits of a reasonable waiting time. The simulation model uses a common sense rule for balancing these two conflicting goals. Unless a walk-in patient arrives to an empty clinic, s/he is forced to wait for at most three scheduled patients.

4.3.2. Environmental Factor Levels

In order to investigate the possible effects of *%New*, μ_{New}/μ_{Ret}, and N, eight hypothetical clinics are simulated with the characteristics summarized in Table VIII. The percentage of new patients (*%New*) is set at 20% and 40%, and the μ_{New}/μ_{Ret} ratio is set at 1.33 and 2. The choices for these input parameters are in line with empirical data on new and return patients published in the literature (See Sections 4.2.7-4.2.8). The resulting durations of clinic sessions range from 160 to 210 minutes, representing half-day periods. In practice, the total number of patients that can be seen in a session (N) will depend on the mean consultation times (μ). For this reason, our simulation model keeps clinic session length fixed while varying N. This helps us represent a range of medical disciplines whose mean consultation times vary by their nature (e.g. short x-rays versus longer MRI scans).

Experimental CV_{Ret} and CV_{New} values are set at two levels: "low" 0.35, and "high" 0.70. These values are in line with the empirical CV-values reported in the literature, which range from about 0.35 to 0.85 (Bailey 1952; Blanco White and Pike 1964; Rising et al. 1973; O'Keefe 1985; Brahimi and Worthington 1991b). Our empirical data collected from the hospital clinic also fall within this range (CV_{Ret}= 0.325, CV_{New}= 0.36, from Tables 1 and 2 in Appendix B).

Unpunctuality, in this study, is modeled by a normal distribution with means of 0 and -15 minutes, determined by our primary data collection. Negative values indicate earliness. These choices are consistent with prior research, which also suggests that

Table VIII. Hypothetical Clinics Simulated

Environmental Factor	**Clinic 1**	**Clinic 2**	**Clinic 3**	**Clinic 4**	**Clinic 5**	**Clinic 6**	**Clinic 7**	**Clinic 8**
Number of patients per clinic session (*N*)	10	20	10	20	10	20	10	20
Percentage of new patients (*%New*)	0.40	0.40	0.40	0.40	0.20	0.20	0.20	0.20
Ratio of the mean consultation time of new patients to the mean consultation time of return patients (μ_{New}/μ_{Ret})	2	2	1.33	1.33	2	2	1.33	1.33
Mean consultation time of return patients (μ_{Ret})	15 min.	7.5 min.	15 min.	7.5 min.	15 min.	7.5 min.	15 min.	7.5 min.
Mean consultation time of new patients (μ_{New})	30 min.	15 min.	20 min.	10 min.	30 min.	15 min.	20 min.	10 min.
Mean consultation time of all patients (μ)	21 min.	10.5 min.	17 min.	8.5 min.	18 min.	9 min.	16 min.	8 min.
Clinic session length (*T*)	210 min.	210 min.	170 min.	170 min.	180 min.	180 min.	160 min.	160 min.

patients arrive early more often than late. The standard deviation is fixed at 25 minutes, which was determined by our empirical data.

In the literature, studies generally report empirical no-show rates that range from 5 to 30 percent (Blanco White and Pike 1964; Fetter and Thompson 1966; Cox et al. 1985; O'Keefe 1985; Vanden Bosch and Dietz 2000). Our investigation of no-show probabilities, observed in the hospital clinic in New York, revealed major differences among specialties with an overall average of 38 percent (see Table 10 in Appendix B). As for walk-ins, average P_W was 16 percent across all clinics, and a few of the clinics had zero walk-ins. Excessive no-show rates may alert the clinic administration to consider policies aimed at discouraging no-shows, such as reminders by phone, or penalties for failed appointments. Nevertheless, it is not possible to eliminate no-shows entirely. Likewise, walk-ins may be encouraged to make appointments instead of simply showing up. Some clinics may totally deny access to walk-ins. In consideration of real life situations, we set P_W and P_N at two levels of 0 and 15 percent. Table IX lists a summary of the levels chosen for each of the environmental factors simulated in this study.

Table IX. Environmental Factors Simulated

Environmental Factor	**Symbol**	**Levels**	**Settings**
Number of patients per clinic session	N	2	10, 20
Coefficient of variation for return patients	CV_{Ret}	2	0.35, 0.70
Coefficient of variation for new patients	CV_{New}	2	0.35, 0.70
Probability of walk-ins	P_W	2	0, 0.15
Probability of no-shows	P_N	2	0, 0.15
Mean unpunctuality of patients	*Unp*	2	-15, 0 min.
Percentage of new patients	*%New*	2	0.20, 0.40
Ratio of the mean consultation times of new patients to the mean consultation times of return patients	μ_{New}/μ_{Ret}	2	1.33, 2

4.4. MEASURES OF PERFORMANCE

The primary performance measure used is the expected total cost of the system represented as [1], discussed in Section 2.3. The formula is repeated here for the ease of reference:

$$E(TC) = E(W)\,C_p + E(I)\,C_d + E(O)\,C_o \qquad [1]$$

A "reasonable" trade-off level among these measures will be decided subjectively by the decision-maker, based on the relative valuation of the cost of patient's waiting time (C_p), cost of doctor's idle time (C_d), and cost of doctor's overtime (C_o).

Since our simulation model includes unpunctual patients, we use "true" waiting times, calculated by subtracting the greater of {appointment time, arrival time} from the consultation start time. This is because extra waiting due to early arrival is voluntary. Negative true waiting times obtained for early patients, were truncated at zero when calculating overall averages.

A common approach in the literature is to compare performance of AS by plotting alternatives on 'efficient frontiers'. A major advantage of this approach is that there is no need to quantify the exact values of C_d and C_p, but only their relative valuation. Strictly inferior AS can be identified as those that remain inside the efficient frontier, and the final choice among "corner" AS that comprise the best-performing options, depends on the desirable C_d/C_p ratio. Unlike previous studies, this study includes overtime explicitly when comparing AS. Idle time and overtime are combined in one doctor-related measure, called IDLE/OVER by fixing C_d/C_o ratio at 1.5. This assumes doctors' overtime costs to be 50 percent higher than their idle time cost. This approximate valuation reflects the fact that overtime is a greater concern in practice, since doctors may use idle time more productively during the day, with tasks such as consulting with colleagues, or reviewing patient charts. As a result, the total system cost equation [1] is revised as follows:

$$E(TC) = E(W)\, C_p + [E(I) + 1.5 * E(O)]\, C_d \qquad [9]$$

Two secondary measures are included in our study. “Fairness” of an AS is measured by the standard deviation of patients’ waiting times. It is desirable that an AS is “fair” in terms of achieving uniform waiting times across appointment slots. Lastly, AS are compared based on the percentage of patients seen within 30-minutes of their appointment times. Inclusion of this measure is supported by survey results which indicate that patient tolerance generally diminishes after 30 minutes (Westman et al. 1987; Huang 1994). The U.K. Ministry of Health requires 75 percent of the patients to be seen within 30-minutes of their appointment time (Department of Health 1991). Table X lists all the performance measures used in this study.

Table X. Performance Measures (PM)

Primary Measures	**Symbol**
Expected total cost of the system	E(TC)
Mean patients’ waiting time	WAIT
Mean doctor’s idle time	IDLE
Mean doctor’s overtime	OVER

Secondary Measures	**Symbol**
Fairness (standard deviation of patients’ waiting times)	FAIR
Percentage of patients seen within 30 minutes of their appointment times	LESS30

4.5. STATISTICAL HYPOTHESES

4.5.1. Decision Factors

The following hypotheses correspond to three decision levels in appointment system design: (1) the choice of appointment rules, (2) the choice of sequencing rules, and (3) the choice of adjusting appointment intervals to match the consultation time characteristics of different patient classes.

1. There will be no significant difference among the mean performances of different appointment rules.

$\mu_{Rule1} = \mu_{Rule2} = \mu_{Rule3} = \mu_{Rule4} = \mu_{Rule5} = \mu_{Rule6} = \mu_{Rule7}$ for $PM_1, \dots PM_5$

2. There will be no significant difference among the mean performances of different sequencing rules.

$\mu_{FCFA} = \mu_{ALTER} = \mu_{RET\_BEG} = \mu_{NEW\_BEG} = \mu_{RET\_BEG\_END} = \mu_{NEW\_BEG\_END}$

for $PM_1, \dots PM_5$

3. There will be no significant difference among the mean performances of appointment systems with or without interval-adjustment for patient class.

$\mu_{No\_Adj} = \mu_{With\_Adj}$ for $PM_1, \dots PM_5$

4.5.2. Environmental Factors

1. There will be no significant effect of the clinic size on ambulatory care performance.

$\mu_{N1} = \mu_{N2}$ for $PM_1, \dots PM_5$

2. There will be no significant effect of the coefficient of variation of the consultation times for new patients on ambulatory care performance.

$\mu_{CVNew1} = \mu_{CVNew2}$ for $PM_1, \dots PM_5$

3. There will be no significant effect of the coefficient of variation of the consultation times for return patients on ambulatory care performance.

$\mu_{CVRet1} = \mu_{CVRet2}$ for $PM_1, \dots PM_5$

4. There will be no significant effect of the probability of no-shows on ambulatory care performance.

$\mu_{PN1} = \mu_{PN2}$ for $PM_1, \dots PM_5$

5. There will be no significant effect of the probability of walk-ins on ambulatory care performance.

$\mu_{PW1} = \mu_{PW2}$ for $PM_1, \dots PM_5$

6. There will be no significant effect of the unpunctuality of patients on ambulatory care performance.

$\mu_{Unp1} = \mu_{Unp2}$ for $PM_1, \ldots PM_5$

7. There will be no significant effect of the percentage of new patients on ambulatory care performance.

$\mu_{\%New1} = \mu_{\%New2}$ for $PM_1, \ldots PM_5$

8. There will be no significant effect of the ratio of the mean consultation times of new patients to the mean consultation times of return patients.

$\mu_{\mu New/\mu Ret1} = \mu_{\mu New/\mu Ret2}$ for $PM_1, \ldots PM_5$

4.5.3. Interactions Between Decision Factors

1. There will be no significant interaction effect of appointment rules and sequencing rules (RULE*SEQ).

2. There will be no significant interaction effect of sequencing rules and interval-adjustment (SEQ*ADJ).

3. There will be no significant interaction effect of appointment rules and interval-adjustment (RULE*ADJ).

4.5.4. Interactions Between Decision Factors and Environmental Factors

1. There will be no significant interaction effect of appointment rules and environmental factors (RULE*N, RULE*CV_{NEW}, RULE*CV_{RET}, RULE*P_N, RULE*P_W, RULE*Unp, RULE*$\%New$, RULE*μ_{New}/μ_{Ret}).

2. There will be no significant interaction effect of sequencing rules and environmental factors (SEQ*N, SEQ*CV_{NEW}, SEQ*CV_{RET}, SEQ*P_N, SEQ*P_W, SEQ*Unp, SEQ*$\%New$, SEQ*μ_{New}/μ_{Ret}).

3. There will be no significant interaction effect of interval-adjustment and environmental factors (ADJ*N, ADJ*CV_{NEW}, ADJ*CV_{RET}, ADJ*P_N, ADJ*P_W, ADJ*Unp, ADJ*$\%New$, ADJ*μ_{New}/μ_{Ret}).

CHAPTER V

RESULTS

This chapter analyzes results in two sections, corresponding to a two-stage hierarchical experimental design used to address the research questions. The hierarchical approach helps us explore a wider range of decision factors and environmental factors then would be possible otherwise.

In Part I, two decision factors are investigated, namely "appointment rules", and "sequencing rules". The effect of the third factor, interval-adjustment for patient class, is not investigated. Thus, patient classification is limited to sequencing, only. The resulting forty-two appointment systems are tested under sixty-four operating environments, combinations of six environmental factors. The formulations of these appointment systems can be found in Appendix D. Table XI lists all the experimental factors and their factor levels simulated at this first stage of our analysis. The percentage of new patients (*%New*) and the μ_{New}/μ_{Ret} ratio are fixed at one level; 40% and 2, respectively. Each setting is measured using the five performance criteria as shown in Table X.

Part II of our analysis addresses a more comprehensive approach to patient classification, including the third decision factor, "interval-adjustment for patient class". Patient classification is used for sequencing, and at the same time appointment intervals are adjusted to match the consultation time characteristics of different patient classes. Note that this does not imply real-time adjustment. In outpatient-scheduling, the schedule is "static", with each appointment slot premarked for a particular patient type. The scheduler identifies a calling patient's type (e.g. new or return), and assigns the patient to the next available slot reserved for that particular class. The investigation will be carried on with the most important environmental factors identified in Part I, along with two additional factors that include the percentage of new patients, and the ratio of the mean consultation time of new patients to the mean consultation time of return patients.

Table XI. Summary of Factors Explored in Part I

Decision Factor	**Symbol**	**Levels**	**Settings**
Appointment rule	RULE	7	See Section 4.1.1
Scheduling rule	SEQ	6	See Section 4.1.2
Interval-adjustment for patient class	ADJ	1	No adjustment (0)
		42 Total	

Environmental Factor	**Levels**	**Levels**	**Settings**
Number of patients per clinic session	N	2	10, 20
Coefficient of variation for return patients	CV_{Ret}	2	0.35, 0.70
Coefficient of variation for new patients	CV_{New}	2	0.35, 0.70
Probability of walk-ins	P_W	2	0, 0.15
Probability of no-shows	P_N	2	0, 0.15
Mean unpunctuality of patients	*Unp*	2	-15, 0 min.
Percentage of new patients	*%New*	1	0.40
Ratio of the mean consultation times of new patients to the mean consultation times of return patients	μ_{New}/μ_{Ret}	1	2
		64 Total	

5.1. ANALYSIS PART I

The simulation results are analyzed by Analysis of Variance (ANOVA), which evaluates the effect of main experimental factors and their interaction effects on each performance measure. ANOVA results listed for dependent variables of IDLE, OVER, WAIT, LESS30, and FAIR are based on average performance statistics across the sixty-four simulated environments (see Table XII). Discussion of results focuses on the main effects of decision factors and environmental factors, and the two-way interactions with decision factors.

5.1.1. Effects of Decision Factors

For all performance measures, both decision factors prove to be significant at alpha 0.05. Yet, the choice of sequencing rule (SEQ) explains a much larger proportion of variability compared to appointment rules (RULE) as shown by the F-values in ANOVA tables (Table XII). Analyzing the differences in means between the sequencing rules and comparing them to the observed differences between the appointment rules also confirm this finding. These results suggest that the choice of sequencing rule is more critical than the choice of appointment rule when designing appointment systems.

Table XII. ANOVA on Performance Measures - Part I

IDLE	DF	F-value	Sign.
Corrected Model	493	26484	0.000
Intercept	1	52442119	0.000
PN	1	5472576	0.000
PW	1	2824256	0.000
UNP	1	815230	0.000
CVNEW	1	383321	0.000
N	1	370925	0.000
SEQ	5	364479	0.000
RULE	6	126556	0.000
CVRET	1	76625	0.000
SEQ * UNP	5	13566	0.000
SEQ * PW	5	3611	0.000
SEQ * RULE	30	3001	0.000
SEQ * PN	5	2615	0.000
SEQ * N	5	1921	0.000
SEQ * CVNEW	5	470	0.000
SEQ * CVRET	5	18	0.000
RULE * N	6	9166	0.000
RULE * UNP	6	4054	0.000
RULE * PW	6	1402	0.000
RULE * PN	6	215	0.000
RULE * CVNEW	6	126	0.000
RULE * CVRET	6	20	0.000
PW * PN	1	161908	0.000
PW * N	1	14690	0.000
CVNEW * N	1	12390	0.000
CVRET * N	1	4370	0.000
CVNEW * PW	1	3025	0.000
UNP * PW	1	2686	0.000
PN * N	1	2267	0.000
UNP * N	1	2016	0.000
CVRET * PN	1	1140	0.000
UNP * PN	1	1091	0.000
CVRET * CVNEW	1	154	0.000
CVNEW * UNP	1	115	0.000
CVRET * PW	1	89	0.000
CVNEW * PN	1	24	0.000
CVRET * UNP	1	1	0.350*
R-SQUARE		.980	

OVER	DF	F-value	Sign.
Corrected Model	493	16672	0.000
Intercept	1	34788047	0.000
PW	1	3470925	0.000
PN	1	1555113	0.000
UNP	1	628917	0.000
SEQ	5	284307	0.000
RULE	6	97633	0.000
CVRET	1	55805	0.000
N	1	34259	0.000
CVNEW	1	26900	0.000
SEQ * UNP	5	10466	0.000
SEQ * PW	5	2788	0.000
SEQ * RULE	30	2315	0.000
SEQ * PN	5	1774	0.000
SEQ * N	5	1665	0.000
SEQ * CVNEW	5	352	0.000
SEQ * CVRET	5	14	0.000
RULE * N	6	7071	0.000
RULE * UNP	6	3128	0.000
RULE * PW	6	1082	0.000
RULE * PN	6	166	0.000
RULE * CVNEW	6	97	0.000
RULE * CVRET	6	16	0.000
PW * PN	1	124905	0.000
CVNEW * N	1	35627	0.000
PW * N	1	13241	0.000
PN * N	1	4896	0.000
CVNEW * PW	1	2500	0.000
UNP * PW	1	2072	0.000
UNP * N	1	1555	0.000
CVRET * PN	1	901	0.000
UNP * PN	1	842	0.000
CVNEW * PN	1	656	0.000
CVRET * N	1	545	0.000
CVRET * PW	1	158	0.000
CVRET * CVNEW	1	119	0.000
CVNEW * UNP	1	89	0.000
CVRET * UNP	1	1	0.411*
R-SQUARE		.968	

* Insignificant at alpha 0.05.

Environmental Factors: N: number of patients per session; PN: probability of no-shows; PW: probability of walk-ins; UNP: unpunctuality of patients; CVNEW: coefficient of variation for new patients; CVRET: coefficient of variation for return patients

Decision Factors: SEQ: sequencing rule; RULE: appointment rule

Table XII. ANOVA on Performance Measures - Part I (Cont'ed)

WAIT	DF	F-value	Sign.	LESS30	DF	F-value	Sign.
Corrected Model	493	18718	0.000	Corrected Model	493	13289	0.000
Intercept	1	42770429	0.000	Intercept	1	464353535	0.000
PW	1	3417546	0.000	PN	1	1221998	0.000
PN	1	1507383	0.000	PW	1	1022778	0.000
N	1	501255	0.000	SEQ	5	453999	0.000
SEQ	5	467019	0.000	N	1	398423	0.000
RULE	6	106082	0.000	RULE	6	89788	0.000
CVRET	1	53372	0.000	CVRET	1	54984	0.000
CVNEW	1	19389	0.000	CVNEW	1	41231	0.000
UNP	1	11700	0.000	UNP	1	26183	0.000
SEQ * PN	5	36244	0.000	SEQ * PN	5	42405	0.000
SEQ * PW	5	14990	0.000	SEQ * UNP	5	11644	0.000
SEQ * UNP	5	9689	0.000	SEQ * PW	5	11591	0.000
SEQ * RULE	30	3896	0.000	SEQ * RULE	30	6730	0.000
SEQ * N	5	1301	0.000	SEQ * N	5	4563	0.000
SEQ * CVNEW	5	748	0.000	SEQ * CVNEW	5	3796	0.000
SEQ * CVRET	5	679	0.000	SEQ * CVRET	5	961	0.000
RULE * N	6	12698	0.000	RULE * N	6	13076	0.000
RULE * PN	6	5602	0.000	RULE * PN	6	6077	0.000
RULE * UNP	6	5061	0.000	RULE * UNP	6	4559	0.000
RULE * PW	6	1001	0.000	RULE * CVNEW	6	903	0.000
RULE * CVNEW	6	247	0.000	RULE * PW	6	456	0.000
RULE * CVRET	6	20	0.000	RULE * CVRET	6	82	0.000
PW * PN	1	65955	0.000	PW * PN	1	52039	0.000
CVNEW * N	1	40292	0.000	CVNEW * N	1	49699	0.000
PW * N	1	5050	0.000	PW * N	1	31217	0.000
CVNEW * PW	1	2102	0.000	CVNEW * PW	1	6904	0.000
UNP * PW	1	1870	0.000	CVNEW * PN	1	3204	0.000
UNP * PN	1	1794	0.000	UNP * PW	1	1622	0.000
CVNEW * PN	1	789	0.000	CVRET * N	1	1232	0.000
CVRET * PN	1	780	0.000	PN * N	1	1092	0.000
CVRET * N	1	453	0.000	CVRET * PN	1	863	0.000
CVRET * PW	1	152	0.000	UNP * PN	1	415	0.000
PN * N	1	145	0.000	CVRET * CVNEW	1	326	0.000
UNP * N	1	120	0.000	UNP * N	1	175	0.000
CVRET * CVNEW	1	37	0.000	CVRET * PW	1	32	0.000
CVNEW * UNP	1	23	0.000	CVRET * UNP	1	4	0.043
CVRET * UNP	1	0	0.775*	CVNEW * UNP	1	0	0.535*
R-SQUARE		.972		R-SQUARE		.961	

* Insignificant at alpha 0.05.

Environmental Factors: N: number of patients per session; PN: probability of no-shows; PW: probability of walk-ins; UNP: unpunctuality of patients; CVNEW: coefficient of variation for new patients; CVRET: coefficient of variation for return patients
Decision Factors: SEQ: sequencing rule; RULE: appointment rule

Table XII. ANOVA on Performance Measures - Part I (Cont'ed)

FAIR	DF	F-value	Sign.
Corrected Model	493	9613	0.000
Intercept	1	19322272	0.000
PN	1	959075	0.000
PW	1	765453	0.000
SEQ	5	276680	0.000
N	1	96932	0.000
RULE	6	50794	0.000
UNP	1	18800	0.000
CVRET	1	4709	0.000
CVNEW	1	59	0.000
SEQ * PW	5	55951	0.000
SEQ * PN	5	25931	0.000
SEQ * UNP	5	22815	0.000
SEQ * N	5	8588	0.000
SEQ * RULE	30	8117	0.000
SEQ * CVNEW	5	2070	0.000
SEQ * CVRET	5	890	0.000
RULE * PW	6	9248	0.000
RULE * N	6	6165	0.000
RULE * UNP	6	5395	0.000
RULE * PN	6	4398	0.000
RULE * CVNEW	6	594	0.000
RULE * CVRET	6	388	0.000
PW * PN	1	101189	0.000
CVNEW * N	1	21019	0.000
UNP * PW	1	11880	0.000
CVNEW * PN	1	3331	0.000
CVRET * PW	1	1974	0.000
UNP * N	1	1517	0.000
CVNEW * PW	1	410	0.000
CVRET * PN	1	329	0.000
CVNEW * UNP	1	323	0.000
UNP * PN	1	230	0.000
CVRET * UNP	1	194	0.000
CVRET * N	1	123	0.000
PN * N	1	122	0.000
PW * N	1	74	0.000
CVRET * CVNEW	1	7	0.009
R-SQUARE		.946	

* Insignificant at alpha 0.05.

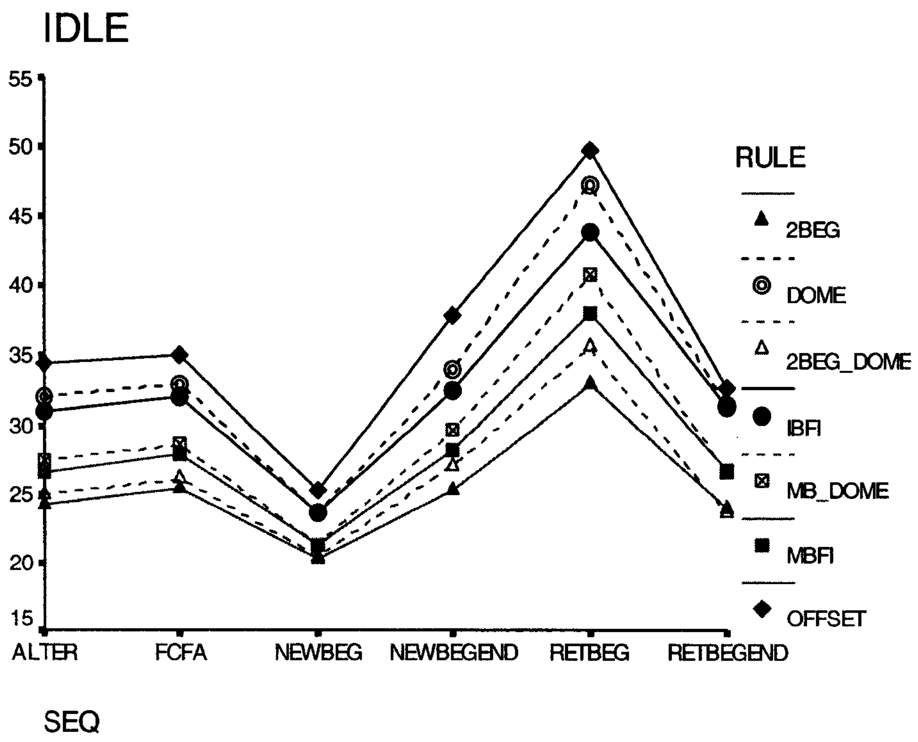
Environmental Factors: N: number of patients per session; PN: probability of no-shows; PW: probability of walk-ins; UNP: unpunctuality of patients; CVNEW: coefficient of variation for new patients; CVRET: coefficient of variation for return patients
Decision Factors: SEQ: sequencing rule; RULE: appointment rule

5.1.2. Interactions Between Decision Factors

SEQ*RULE interaction is significant for all dependent variables at $\alpha = 0.05$ (see Table XII). Interaction plots reveal that the nature of SEQ*RULE interactions are infatuating effects, not cross effects (Figure VI). This means the effect of SEQ is similar on all appointment rules, and the effect of RULE is similar on all sequencing rules. The only exception is the secondary measure of FAIRness, where the existence of cross effects implies that rankings of appointment rules differ across different sequencing approaches (or rankings of sequencing rules change based on the underlying appointment rule used). Detailed analysis of interaction plots leads to several significant conclusions that have a bearing on further analysis:

- In terms of doctor-related measures of IDLE and OVER, sequencing rule NEW_BEG is the best, and RET_BEG is the worst, regardless of the appointment rule on which sequencing is performed. Appointment rule 2BEG is the best and OFFSET is the worst across all sequencing rules for the same measures.
- The exact opposite rankings are observed for the patient-related measures of WAIT and LESS30. The percentage of patients seen within less than 30 minutes of appointment time drops below the threshold value of 75 percent when NEW_BEG sequencing rule is combined with appointment rules that utilize multiple-block approach (2BEG and MBFI and their dome variations).
- The SEQ*RULE interaction has cross effects for FAIRness measure. There seems to be no sequencing rule or appointment rule that is the overall best, but rather the combination of SEQ and RULE determines performance in terms of fairness.

Figure VI. Two-Way Interactions Between Decision Factors SEQ*RULE



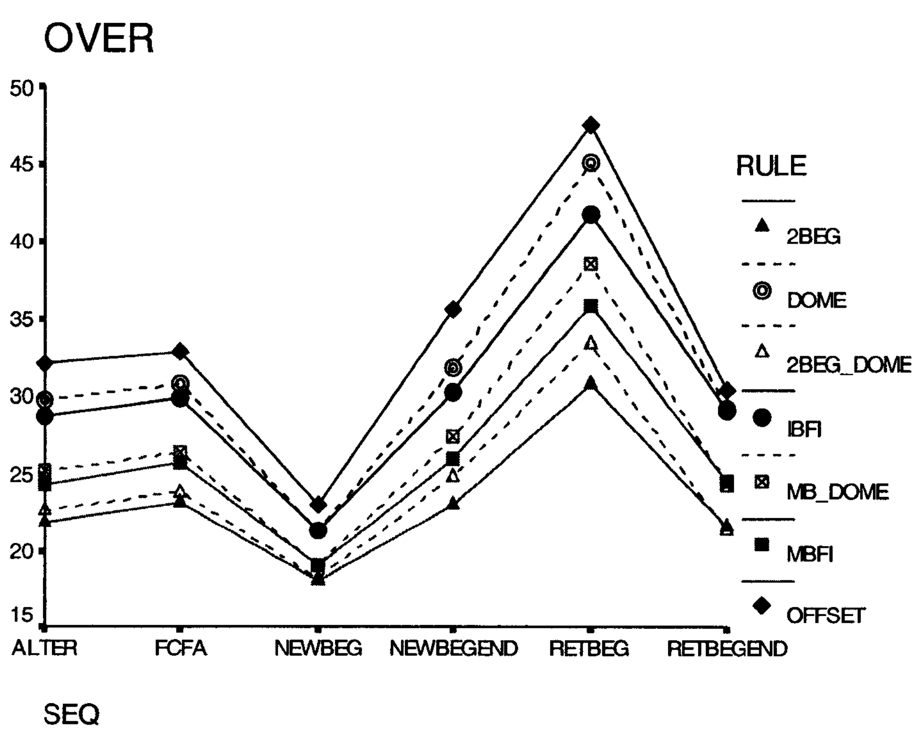
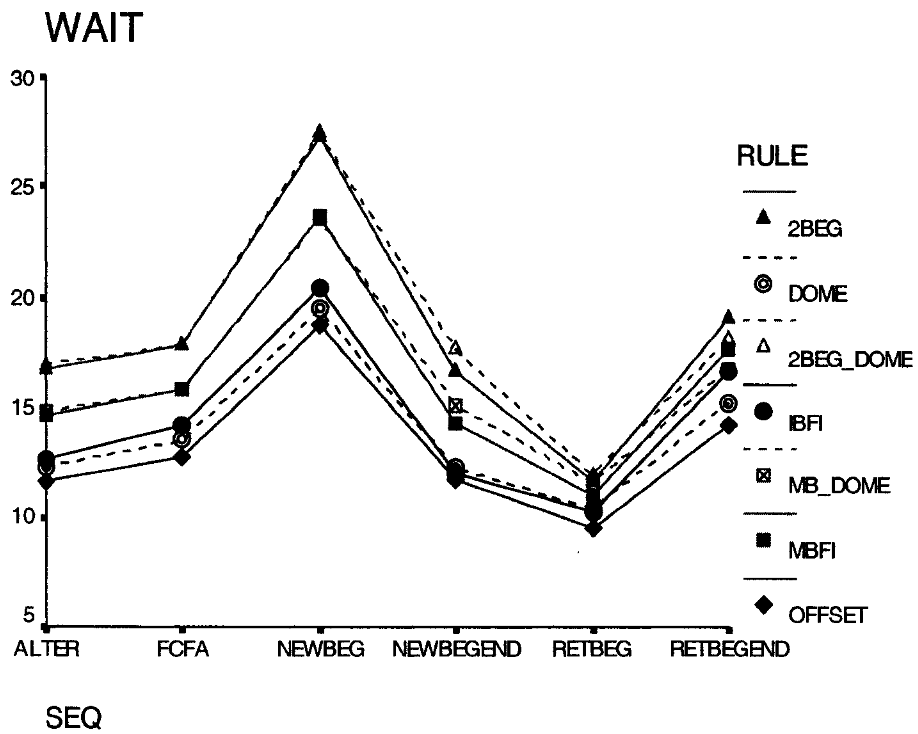


Figure VI. Two-Way Interactions Between Decision Factors SEQ*RULE (Cont'ed)



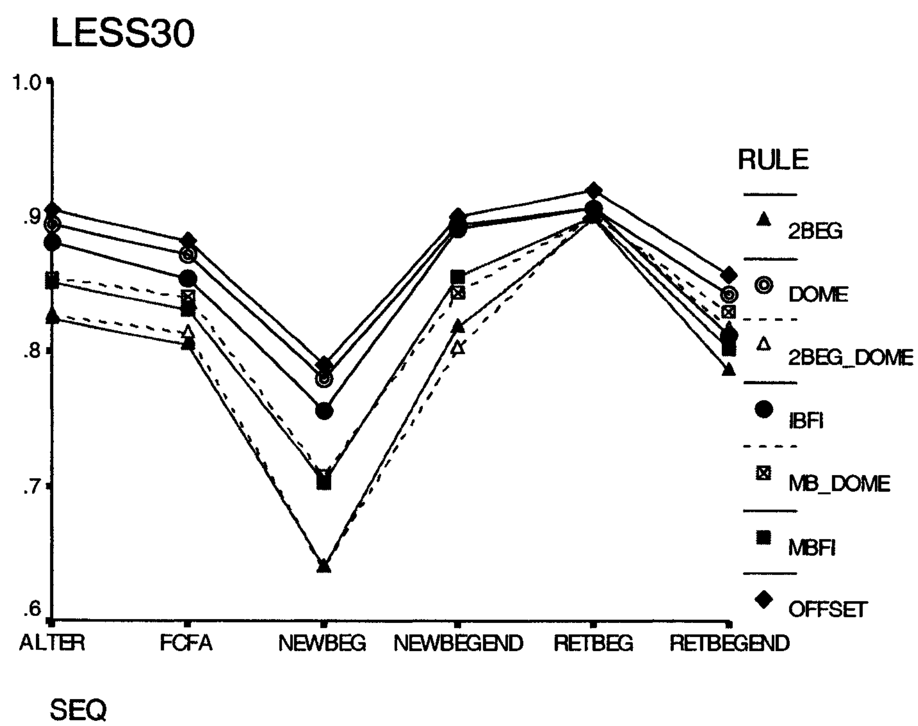
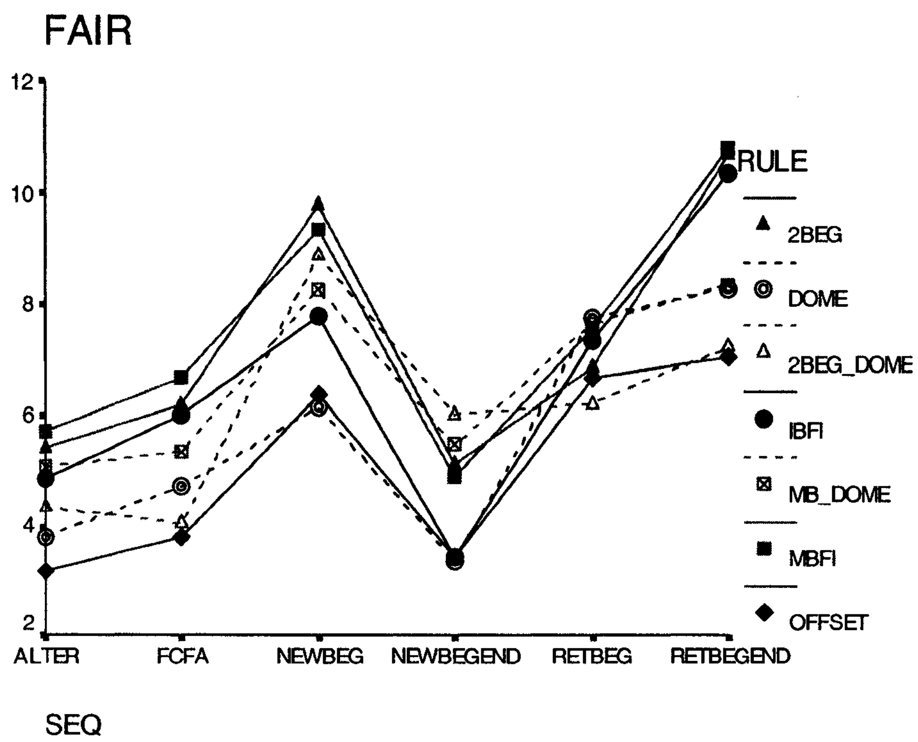


Figure VI. Two-Way Interactions Between Decision Factors SEQ*RULE (Cont'ed)



5.1.3. Environmental Factor Effects

ANOVA results show that all main environmental effects are significant at α= 0.05 (Table XII). The most powerful environmental factors are P_N and P_W, whereas CV_{Ret} and CV_{New} remain as the weakest factors. The effect of *Unp* is strong for doctor-related measures of IDLE and OVER, and the effect of *N* is strong for patient-related measures of WAIT, LESS30, and FAIRness.

High service time variability deteriorates clinic performance on all measures. Doctors' idle/overtimes increase, patients tend to wait longer, and fairness declines. As one would expect, an increase in no-shows increases idle time, while improving the rest of the measures. The exact opposite effect is observed for walk-ins. Performance declines on all measures except idle time, as the percentage of walk-ins increases. Earliness of patients (*Unp*) improves all measures, yet the effect is weaker on WAIT (Note that the WAIT measure ignores the portion of a patients' waiting time prior to the appointed time). Lastly, an increase in clinic size, which corresponds to shorter mean consultation times, improves clinic performance for all criteria. This observation highlights the importance of designing effective AS for clinics/practices with relatively longer consultation times.

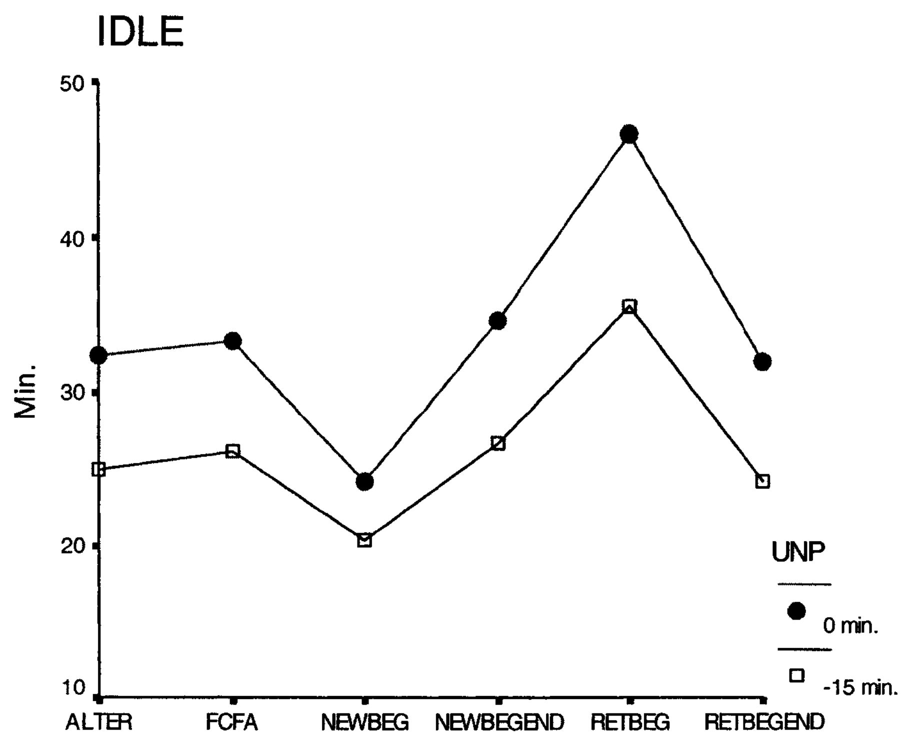
5.1.4. Interactions Between Decision Factors and Environmental Factors

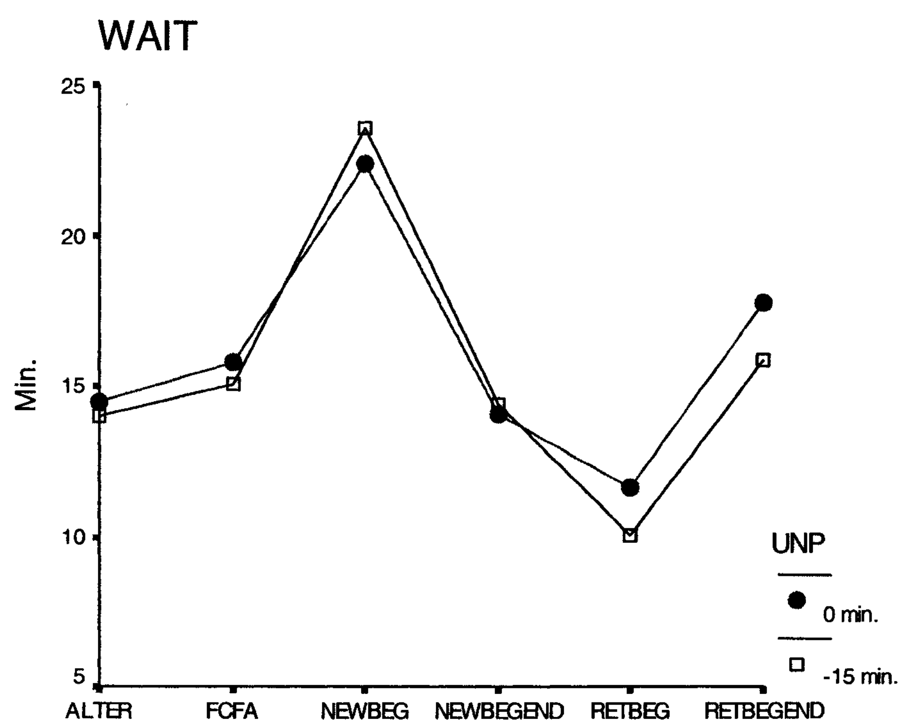
All two-way interactions of environmental factors with SEQ and RULE are significant at $\alpha = 0.05$ (Table XII). Generally, interactions of environmental factors with SEQ are more powerful than interactions with RULE. For sequencing rules, interactions with *Unp*, P_W, and P_N emerge as the strongest. For appointment rules, clinic size, *N*, results in a particularly high interaction effect. Two-way interactions with CV_{Ret} and CV_{New} are the weakest, although they are significant at the 0.05 levels. Interaction plots depict an identical picture to the SEQ*RULE interactions discussed earlier. The majority of the interactions are infatuating effects, not cross effects.

(a) *Interaction Effects with SEQ*

The SEQ*Unp interaction in Figure VII reveals that in terms of idle time, patient earliness has the least positive impact on the NEW_BEG sequencing rule, and the most on RET_BEG, leading to statistically significant interaction effects. For WAIT measure, the SEQ*Unp interaction indicates a slight cross effect, although insignificant. Increased earliness in patient arrivals generally improves waiting times and fairness, with the exceptions of NEW_BEG and NEW_BEG_END.

Figure VII. Two-Way Interactions Between Environmental Factors and SEQ



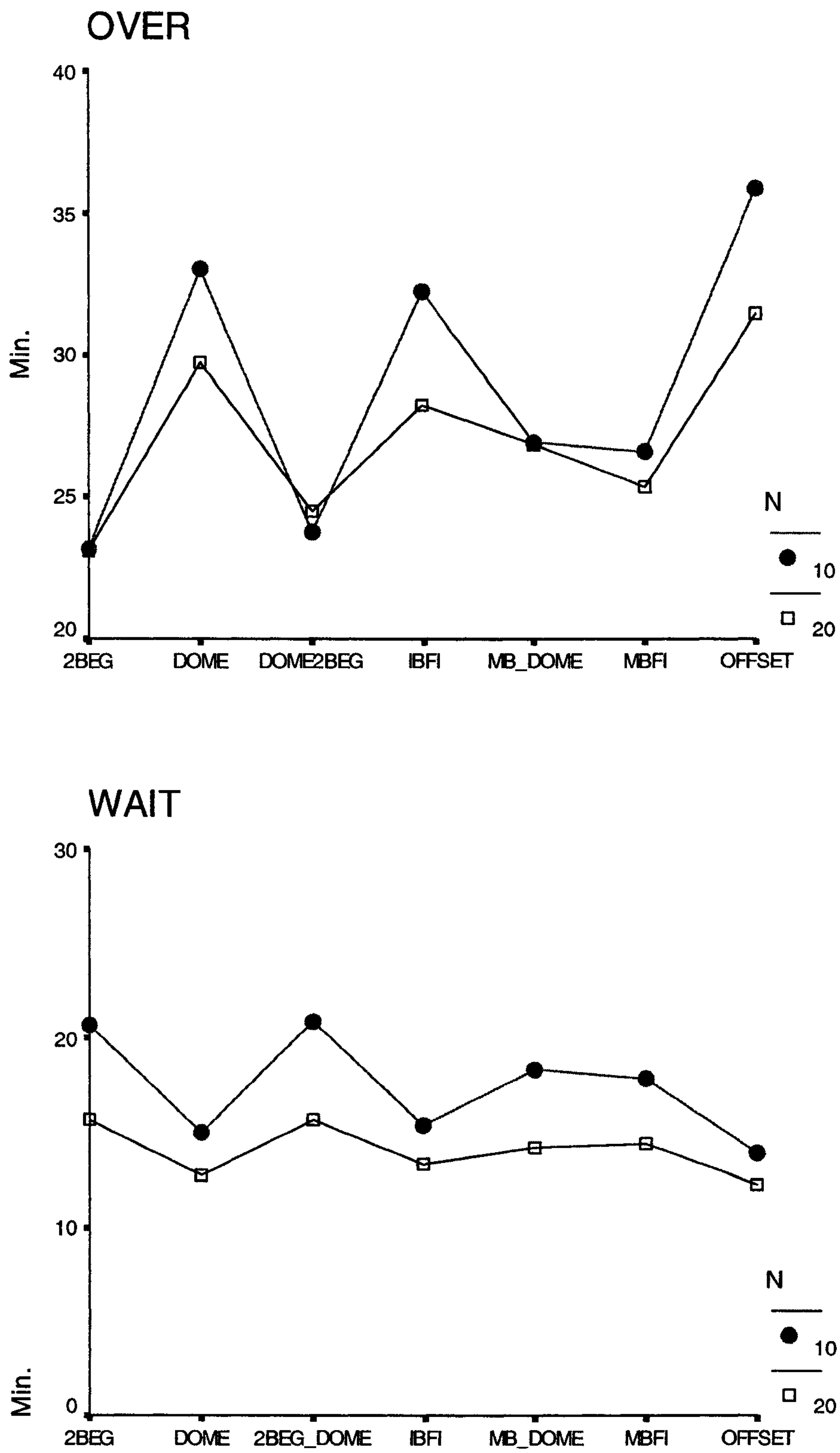


(b) *Interaction Effects with RULE*

The RULE*N interaction is the strongest and the most interesting one for appointment rules, as illustrated in Figure VIII for primary measures of doctor's overtime and patients' waiting time (See Table XII). A larger clinic size (shorter consultation times) generally reduces the risk of overtime, and the effect is more pronounced on individual-block rules that include IBFI, DOME, and OFFSET. As N increases, patient waiting time improves for all appointment rules, yet the impact is less on individual-block rules compared to 2BEG and multiple-block rules.

Discussion of these findings serves to further illustrate the general nature of interaction effects between environmental factors and decision variables. We omit a detailed discussion (for the sake of brevity) of the statistical significance of remaining interactions. However, we determined that they are due to the extent to which environmental factors affect the performance of sequencing and appointment rules. More importantly, they are not due to a cross effect, which would signify that some rules perform better than others under different environmental conditions.

Figure VIII. Two-Way Interactions Between Environmental Factors and RULE



5.1.5. Comparison of Appointment Systems

As a result of our analysis of the main and interaction effects of environmental factors and decision factors in Sections 5.1.2-5.1.4, CV_{Ret} and CV_{New} prove to have relatively less effects on the performance of AS. In the interests of (1) developing a more parsimonious model, (2) creating an actionable set of guiding principles for the practitioners, and (3) focusing on data ordinarily available to the practitioner, CV_{Ret} and CV_{New} are excluded from further analysis. Thus the total number of environments is reduced to sixteen (2 P_W x 2 P_N x 2 *Unp* x 2 *N*).

Forty-two AS combinations of six sequencing rules and seven appointment rules are ranked for measures of IDLE/OVER and WAIT in Tables XIII and XIV, respectively. As we discussed in Section 4.4, IDLE/OVER combines doctor's idle time and overtime in one measure. Given that SEQ*RULE interactions were identical for the two doctor-related measures, this simplification does not change the rankings of AS. Tukey's honestly significant difference test is conducted for pairwise multiple comparisons. Appointment systems joined by the same superscript are not significantly different at alpha 0.05. However, it should be noted that in general, when multiple measures are used, the actual confidence level may be lower than 95 percent (Law and Kelton, 1991).

Table XIII. Rankings of AS by IDLE/OVER - Part I[1]

ENV	# 1	ENV	# 2	ENV	# 3	ENV	# 4
N= 10	Unp= 0	N= 10	Unp= -15	N= 10	Unp= 0	N= 10	Unp= -15
P_N= 0	P_W= 0	P_N= 0	P_W= 0	P_N= 0	P_W= 0.15	P_N= 0	P_W= 0.15
2D-NB	3.751 [a]	2-NB	3.288 [a]	2D-NB	5.534	2D-NB	5.172 [a]
2-NB	3.791 [a]	2D-NB	3.294 [a]	2-NB	5.650	2-NB	5.182 [a]
MD-NB	4.099	MD-NB	3.393 [a]	MD-NB	5.842	MD-NB	5.267 [ab]
M-NB	4.239	M-NB	3.421 [a]	M-NB	6.037	M-NB	5.310 [b]
2D-RBE	4.776	2D-RBE	3.609 [b]	2D-RBE	6.497 [a]	2D-RBE	5.499 [c]
2-RBE	4.926	2-RBE	3.650 [bc]	2D-AL	6.521 [a]	2-RBE	5.562 [cd]
2-AL	5.065 [b]	2-AL	3.784 [cd]	2-AL	6.581 [ab]	2-AL	5.567 [cd]
2D-AL	5.145 [b]	2D-AL	3.856 [de]	2-NBE	6.645 [bc]	2D-AL	5.590 [cd]
D-NB	5.280 [c]	D-NB	3.900 [de]	2-RBE	6.719 [cd]	2-NBE	5.645 [de]
2-NBE	5.356 [c]	I-NB	3.944 [e]	D-NB	6.740 [cd]	D-NB	5.652 [de]
I-NB	5.409 [c]	2-NBE	3.955 [e]	2D-NBE	6.815 [de]	I-NB	5.731 [ef]
2-FC	5.583 [d]	MD-RBE	4.200 [f]	2D-FC	6.916 [ef]	2D-NBE	5.796 [fg]
2D-FC	5.691 [de]	2D-NBE	4.229 [f]	2-FC	6.956 [fg]	O-NB	5.895 [h]
2D-NBE	5.805 [e]	M-RBE	4.233 [f]	I-NB	6.981 [fg]	M-AL	5.968 [hi]
O-NB	5.976 [f]	M-AL	4.279 [fg]	O-NB	7.069 [g]	2-FC	5.976 [hi]
MD-RBE	6.062 [fg]	O-NB	4.388 [gh]	MD-AL	7.355 [h]	2D-FC	6.013 [hi]
M-AL	6.110 [fg]	MD-AL	4.403 [gh]	M-AL	7.377 [hi]	MD-AL	6.014 [hi]
M-RBE	6.166 [gh]	2-FC	4.429 [h]	M-NBE	7.493 [ij]	MD-RBE	6.022 [hi]
MD-AL	6.256 [h]	2D-FC	4.522 [hi]	MD-NBE	7.498 [ij]	M-RBE	6.093 [ij]
M-NBE	6.637 [i]	M-NBE	4.653 [ij]	MD-RBE	7.532 [j]	M-NBE	6.115 [j]
M-FC	6.678 [i]	MD-NBE	4.766 [j]	MD-FC	7.722 [k]	MD-NBE	6.173 [j]
MD-FC	6.705 [i]	M-FC	4.965 [k]	M-RBE	7.726 [k]	M-FC	6.417 [k]
MD-NBE	6.779 [i]	MD-FC	5.019 [k]	M-FC	7.807 [k]	MD-FC	6.425 [k]
2-RB	7.682	2-RB	5.220	2-RB	8.556	2-RB	6.712
I-AL	8.055	I-RBE	5.575 [l]	I-AL	8.777 [l]	I-AL	6.894 [l]
I-RBE	8.210 [j]	I-AL	5.607 [l]	D-AL	8.827 [lm]	D-AL	6.985 [lm]
D-RBE	8.293 [j]	D-RBE	5.633 [l]	I-NBE	8.860 [lm]	2D-RB	7.001 [m]
D-AL	8.334 [j]	2D-RB	5.723 [lm]	2D-RB	8.865 [lm]	I-NBE	7.020 [mn]
2D-RB	8.342 [j]	D-AL	5.814 [m]	D-NBE	8.919 [m]	D-NBE	7.126 [no]
I-FC	8.490 [k]	O-RBE	5.999 [n]	I-FC	9.218 [n]	D-RBE	7.202 [o]
I-NBE	8.554 [k]	I-NBE	6.016 [n]	D-FC	9.224 [n]	I-RBE	7.225 [op]
O-RBE	8.690 [l]	I-FC	6.128 [no]	O-AL	9.251 [n]	I-FC	7.335 [pq]
D-FC	8.702 [l]	D-NBE	6.237 [op]	D-RBE	9.316 [no]	O-RBE	7.381 [q]
D-NBE	8.838	D-FC	6.298 [p]	I-RBE	9.389 [op]	D-FC	7.396 [q]
O-AL	9.182	O-AL	6.651 [q]	O-RBE	9.501 [p]	O-AL	7.408 [q]
O-FC	9.485	M-RB	6.767 [q]	O-FC	9.628 [q]	O-FC	7.770 [r]
M-RB	9.778	O-FC	7.006	O-NBE	9.695 [q]	O-NBE	7.850 [r]
O-NBE	10.283 [m]	MD-RB	7.301	M-RB	10.083	M-RB	7.852 [r]
MD-RB	10.393 [m]	O-NBE	7.591	MD-RB	10.403	MD-RB	8.168
I-RB	12.103	I-RB	8.819	I-RB	11.836	I-RB	9.356
D-RB	13.008	D-RB	9.632	D-RB	12.342	D-RB	9.850
O-RB	13.889	O-RB	10.563	O-RB	12.835	O-RB	10.370

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

RULE-SEQ I: IBFI, D: DOME, O: OFFSET, 2: 2BEG, 2D: 2BEG-DOME, M: MBFI, MD: MB_DOME
FC: FCFA, AL: ALTER, NB: NEW_BEG, RB: RET_BEG, NBE: NEW_BEG_END, RBE: RET_BEG_END

Table XIII. Rankings of AS by IDLE/OVER - Part I[1] (Cont'ed)

ENV	# 5	ENV	# 6	ENV	# 7	ENV	# 8
N= 10	Unp= 0	N= 10	Unp= -15	N= 10	Unp= 0	N= 10	Unp= -15
P_N= 0.15	P_W= 0	P_N= 0.15	P_W= 0	P_N= 0.15	P_W= 0.15	P_N= 0.15	P_W= 0.15
2-NB	5.980 [a]	2-NB	5.472 [a]	2D-NB	5.880 [a]	2-NB	5.315 [a]
2D-NB	6.047 [a]	2D-NB	5.503 [a]	2-NB	5.912 [a]	2D-NB	5.328 [a]
MD-NB	6.428 [b]	MD-NB	5.630 [a]	MD-NB	6.297 [b]	MD-NB	5.503 [b]
M-NB	6.470 [b]	M-NB	5.640 [a]	M-NB	6.421 [b]	M-NB	5.533 [b]
2-RBE	6.949 [c]	2-RBE	5.838 [b]	2D-RBE	6.973 [c]	2D-RBE	5.824 [c]
2D-RBE	6.954 [c]	2D-RBE	5.839 [b]	2-RBE	7.070 [c]	2-RBE	5.851 [c]
2-AL	7.474	2-AL	6.139 [c]	2-AL	7.234 [d]	2-AL	6.015 [d]
I-NB	7.637 [d]	I-NB	6.225 [cd]	2D-AL	7.298 [de]	D-NB	6.083 [de]
D-NB	7.675 [d]	D-NB	6.236 [cd]	D-NB	7.382 [ef]	2D-AL	6.090 [de]
2D-AL	7.675 [d]	2D-AL	6.253 [de]	2-NBE	7.426 [efg]	I-NB	6.118 [de]
2-FC	7.697 [d]	2-NBE	6.352 [def]	2-FC	7.459 [fg]	2-NBE	6.169 [e]
2-NBE	7.886 [e]	M-RBE	6.381 [def]	I-NB	7.478 [fg]	2-FC	6.308 [f]
2D-FC	7.945 [ef]	MD-RBE	6.411 [ef]	2D-FC	7.545 [g]	2D-FC	6.406 [fg]
M-RBE	8.085 [fg]	2-FC	6.481 [fg]	2D-NBE	7.744	2D-NBE	6.410 [fg]
MD-RBE	8.126 [g]	2D-FC	6.626 [gh]	O-NB	7.896	MD-RBE	6.460 [g]
2D-NBE	8.464 [h]	M-AL	6.678 [hi]	MD-RBE	8.069 [h]	M-RBE	6.472 [g]
M-AL	8.520 [h]	2D-NBE	6.694 [hi]	M-RBE	8.133 [hi]	O-NB	6.482 [g]
O-NB	8.581 [h]	MD-AL	6.832 [ij]	M-AL	8.143 [hi]	M-AL	6.557 [gh]
MD-AL	8.756 [i]	O-NB	6.892 [j]	MD-AL	8.227 [i]	MD-AL	6.656 [h]
M-FC	8.829 [i]	M-FC	7.081 [k]	M-FC	8.436 [j]	M-NBE	6.835 [i]
MD-FC	8.958 [j]	M-NBE	7.166 [kl]	MD-FC	8.452 [j]	M-FC	6.895 [i]
M-NBE	9.282	MD-FC	7.171 [kl]	M-NBE	8.474 [j]	MD-NBE	6.921 [i]
MD-NBE	9.465	MD-NBE	7.289 1	MD-NBE	8.545 [j]	MD-FC	6.943 [i]
2-RB	9.887 [k]	2-RB	7.540 [m]	2-RB	9.351	2-RB	7.403
I-RBE	9.940 [k]	I-RBE	7.568 [mn]	I-AL	9.697 [k]	I-RBE	7.643 [jk]
D-RBE	10.179	D-RBE	7.708 [n]	I-RBE	9.770 [kl]	I-AL	7.704 [jk]
I-AL	10.546 [l]	2D-RB	8.093 [o]	2D-RB	9.821 [klmn]	D-RBE	7.709 [jk]
2D-RB	10.678 [lm]	I-AL	8.125 [p]	D-RBE	9.858 [lmno]	2D-RB	7.790 [jk]
I-FC	10.681 [lm]	O-RBE	8.240 [op]	D-AL	9.886 [lmno]	D-AL	7.866 [kl]
O-RBE	10.817 [mn]	I-FC	8.324 [p]	I-FC	9.939 [mno]	I-FC	7.954 [lm]
D-AL	10.927 [no]	D-AL	8.378 [p]	I-NBE	9.978 [op]	I-NBE	7.962 [lmn]
D-FC	11.038 [o]	D-FC	8.569 [q]	D-FC	10.097 [pq]	O-RBE	8.024 [mn]
I-NBE	11.269	I-NBE	8.661 [q]	D-NBE	10.141 [q]	D-FC	8.101 [mn]
D-NBE	11.609	D-NBE	8.895 [r]	O-AL	10.512 [q]	D-NBE	8.110 [n]
M-RB	11.928 [p]	M-RB	8.998 [r]	O-FC	10.689	O-AL	8.482 [o]
O-AL	12.027 [p]	O-AL	9.422 [s]	M-RB	10.939	M-RB	8.614 [op]
O-FC	12.065 [p]	O-FC	9.480 [s]	O-NBE	11.176	O-FC	8.649 [p]
MD-RB	12.569	MD-RB	9.512 [s]	MD-RB	11.339	MD-RB	8.975 [q]
O-NBE	13.334	O-NBE	10.491	I-RB	12.786	O-NBE	9.086 [q]
I-RB	14.329	I-RB	11.031	D-RB	13.406	I-RB	10.224
D-RB	15.286	D-RB	11.830	O-RB	14.141	D-RB	10.775
O-RB	16.497	O-RB	13.048	O-RBE	10.206	O-RB	11.521

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

RULE-SEQ I: IBFI, D: DOME, O: OFFSET, 2: 2BEG, 2D: 2BEG-DOME, M: MBFI, MD: MB_DOME FC: FCFA, AL: ALTER, NB: NEW_BEG, RB: RET_BEG, NBE: NEW_BEG_END, RBE: RET_BEG_END

Table XIII. Rankings of AS by IDLE/OVER - Part I[1] (Cont'ed)

ENV	# 9	ENV	# 10	ENV	# 11	ENV	# 12
N= 20	Unp= 0	N= 20	Unp= -15	N= 20	Unp= 0	N= 20	Unp= -15
P_N= 0	P_W= 0	P_N= 0	P_W= 0	P_N= 0	P_W= 0.15	P_N= 0	P_W= 0.15
2-NB	1.699 [a]	2-NB	1.382 [a]	2D-NB	2.580 [a]	2-NB	2.393 [a]
2D-NB	1.769 [a]	2D-NB	1.423 [ab]	2-NB	2.617 [a]	2D-NB	2.406 [a]
M-NB	1.877 [b]	M-NB	1.439 [ab]	MD-NB	2.679	M-NB	2.427 [a]
MD-NB	1.932 [b]	MD-NB	1.476 [bc]	M-NB	2.743	MD-NB	2.434 [ab]
I-NB	2.168 [c]	I-NB	1.547 [cd]	D-NB	2.852	D-NB	2.487 [bc]
D-NB	2.191 [c]	D-NB	1.579 [de]	O-NB	2.936 [b]	I-NB	2.495 [c]
O-NB	2.419	2D-RBE	1.636 [ef]	I-NB	2.961 [b]	O-NB	2.543 [cd]
2-AL	2.523 [d]	2-RBE	1.649 [efg]	2-AL	3.133 [c]	2-AL	2.566 [de]
2D-RBE	2.544 [de]	2-AL	1.679 [fg]	2D-AL	3.164 [c]	2D-RBE	2.601 [ef]
2-RBE	2.611 [e]	O-NB	1.727 [g]	2-NBE	3.173 [c]	2-NBE	2.621 [f]
2-FC	2.698	2D-AL	1.832 [h]	2D-RBE	3.268 [d]	2D-AL	2.622 [f]
2D-AL	2.788 [f]	M-AL	1.848 [h]	2-FC	3.285 [d]	2-RBE	2.647 [fg]
2-NBE	2.811 [f]	2-NBE	1.852 [h]	2D-FC	3.290 [d]	M-AL	2.684 [g]
2D-FC	2.887 [g]	MD-RBE	1.876 [h]	2D-NBE	3.363 [e]	2-FC	2.698 [gh]
M-AL	2.904 [g]	M-RBE	1.894 [h]	M-AL	3.401 [ef]	2D-FC	2.745 [hi]
MD-RBE	3.034 [h]	2-FC	1.898 [h]	2-RBE	3.430 [f]	MD-AL	2.749 [hi]
M-RBE	3.078 [h]	2D-FC	2.022 [i]	MD-AL	3.435 [f]	M-NBE	2.753 [hi]
M-FC	3.087 [h]	MD-AL	2.042 [i]	M-NBE	3.436 [f]	2D-NBE	2.763 [i]
MD-AL	3.189 [i]	M-FC	2.089 [ij]	M-FC	3.568 [g]	MD-RBE	2.785 [ij]
M-NBE	3.244 [ij]	M-NBE	2.103 [ij]	MD-FC	3.569 [g]	M-FC	2.830 [jk]
MD-FC	3.288 [j]	2D-NBE	2.154 [jk]	MD-NBE	3.616 [gh]	M-RBE	2.846 [k]
2D-NBE	3.292 [j]	I-AL	2.187 [k]	MD-RBE	3.643 [h]	I-AL	2.881 [kl]
I-AL	3.422	D-RBE	2.226 [k]	I-AL	3.749 [i]	MD-FC	2.883 [kl]
I-FC	3.568 [k]	MD-FC	2.231 [k]	I-NBE	3.768 [i]	MD-NBE	2.907 [lm]
D-RBE	3.601 [k]	I-RBE	2.234 [k]	D-AL	3.776 [i]	I-NBE	2.943 [m]
I-RBE	3.609 [k]	O-RBE	2.338 [l]	M-RBE	3.795 [i]	D-AL	2.945 [m]
D-AL	3.691 [l]	I-FC	2.380 [lm]	O-AL	3.898 [j]	I-FC	3.036 [n]
MD-NBE	3.716 [lm]	D-AL	2.385 [lm]	D-NBE	3.915 [j]	D-RBE	3.049 [n]
O-RBE	3.717 [lm]	MD-NBE	2.431 [m]	D-FC	3.929 [j]	O-AL	3.053 [n]
I-NBE	3.748 [lm]	I-NBE	2.453 [m]	I-FC	3.932 [j]	D-FC	3.083 [no]
D-FC	3.779 [m]	D-FC	2.540	O-FC	4.035 [k]	O-RBE	3.089 [no]
O-AL	3.977 [n]	O-AL	2.645	D-RBE	4.076 [kl]	D-NBE	3.093 [no]
O-FC	4.021 [n]	O-FC	2.754 [n]	O-RBE	4.116 [lm]	I-RBE	3.117 [o]
D-NBE	4.168	D-NBE	2.769 [n]	O-NBE	4.141 [m]	O-FC	3.176
2-RB	4.443	2-RB	2.863	I-RBE	4.209	O-NBE	3.287
O-NBE	4.625	O-NBE	3.190	2-RB	4.493	2-RB	3.370
2D-RB	5.000 [o]	2D-RB	3.340 [o]	2D-RB	4.741	2D-RB	3.607
M-RB	5.045 [o]	M-RB	3.372 [o]	M-RB	4.931	M-RB	3.718
MD-RB	5.646 [p]	MD-RB	3.914 [p]	MD-RB	5.222	MD-RB	4.001
I-RB	5.662 [p]	I-RB	3.937 [p]	I-RB	5.390	I-RB	4.115
D-RB	6.293	D-RB	4.521	D-RB	5.710	D-RB	4.429
O-RB	6.529	O-RB	4.774	O-RB	5.830	O-RB	4.555

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

RULE-SEQ I: IBFI, D: DOME, O: OFFSET, 2: 2BEG, 2D: 2BEG-DOME, M: MBFI, MD: MB_DOME
FC: FCFA, AL: ALTER, NB: NEW_BEG, RB: RET_BEG, NBE: NEW_BEG_END, RBE: RET_BEG_END

Table XIII. Rankings of AS by IDLE/OVER - Part I[1] (Cont'ed)

ENV	# 13	ENV	# 14	ENV	# 15	ENV	# 16
N= 20	Unp= 0	N= 20	Unp= -15	N= 20	Unp= 0	N= 20	Unp= -15
P_N= 0.15	P_W= 0	P_N= 0.15	P_W= 0	P_N= 0.15	P_W= 0.15	P_N= 0.15	P_W= 0.15
2-NB	2.778	2-NB	2.419 ^{a}	2-NB	2.397 ^{a}	2-NB	2.045 ^{a}
2D-NB	2.934 ^{a}	2D-NB	2.485 ^{ab}	2D-NB	2.439 ^{a}	2D-NB	2.087 ^{ab}
M-NB	2.966 ^{a}	M-NB	2.493 ^{bc}	M-NB	2.575 ^{b}	M-NB	2.117 ^{b}
MD-NB	3.124	MD-NB	2.559 ^{cd}	MD-NB	2.601 ^{b}	MD-NB	2.155 ^{b}
I-NB	3.254	2-RBE	2.627 ^{de}	I-NB	2.842 ^{c}	I-NB	2.240 ^{c}
2-RBE	3.387 ^{b}	I-NB	2.627 ^{de}	D-NB	2.845 ^{c}	D-NB	2.267 ^{c}
D-NB	3.400 ^{b}	2D-RBE	2.671 ^{e}	O-NB	3.010	O-NB	2.387 ^{d}
2D-RBE	3.483	D-NB	2.691 ^{e}	2-AL	3.185	2D-RBE	2.398 ^{d}
2-AL	3.674 ^{c}	2-AL	2.807 ^{f}	2D-RBE	3.200 ^{de}	2-RBE	2.401 ^{d}
2-FC	3.684 ^{c}	M-RBE	2.821 ^{fg}	2-RBE	3.234 ^{de}	2-AL	2.422 ^{d}
O-NB	3.703 ^{cd}	2-FC	2.874 ^{fg}	2-FC	3.267 ^{e}	2-FC	2.530 ^{e}
M-RBE	3.766 ^{d}	MD-RBE	2.875 ^{fg}	2D-AL	3.356 ^{f}	2D-AL	2.552 ^{e}
MD-RBE	3.889	O-NB	2.895 ^{g}	2-NBE	3.359 ^{f}	2-NBE	2.555 ^{e}
2D-FC	4.003 ^{e}	M-AL	2.978 ^{h}	2D-FC	3.402 ^{f}	M-AL	2.598 ^{ef}
M-AL	4.021 ^{ef}	2D-AL	3.009 ^{hi}	M-AL	3.500	MD-RBE	2.631 ^{f}
2D-AL	4.043 ^{ef}	2-NBE	3.047 ^{hij}	MD-RBE	3.592 ^{g}	M-RBE	2.632 ^{f}
M-FC	4.068 ^{ef}	2D-FC	3.052 ^{hij}	M-FC	3.597 ^{g}	2D-FC	2.642 ^{f}
2-NBE	4.092 ^{f}	M-FC	3.080 ^{ij}	M-RBE	3.606 ^{g}	M-FC	2.723 ^{g}
I-RBE	4.225	I-RBE	3.098 ^{j}	MD-AL	3.686 ^{h}	MD-AL	2.749 ^{gh}
D-RBE	4.391 ^{g}	D-RBE	3.173 ^{k}	2D-NBE	3.699 ^{h}	M-NBE	2.779 ^{ghi}
MD-FC	4.404 ^{g}	MD-AL	3.222 ^{kl}	M-NBE	3.709 ^{h}	2D-NBE	2.802 ^{hi}
MD-AL	4.427 ^{g}	MD-FC	3.281 ^{lm}	MD-FC	3.739	MD-FC	2.847 ^{ij}
I-FC	4.541 ^{h}	M-NBE	3.335 ^{mn}	I-AL	3.916	I-AL	2.894 ^{jk}
M-NBE	4.553 ^{h}	O-RBE	3.343 ^{mn}	I-FC	3.993 ^{i}	I-RBE	2.926 ^{kl}
I-AL	4.564 ^{h}	I-AL	3.351 ^{mn}	I-RBE	4.026 ^{ij}	D-RBE	2.937 ^{kl}
O-RBE	4.598 ^{hi}	I-FC	3.382 ^{n}	MD-NBE	4.028 ^{ij}	I-FC	2.988 ^{lm}
2D-NBE	4.652 ^{i}	2D-NBE	3.394 ^{n}	D-RBE	4.044 ^{ijk}	O-RBE	3.029 ^{mn}
D-FC	4.893 ^{j}	D-AL	3.586 ^{o}	D-AL	4.091 ^{jkl}	MD-NBE	3.030 ^{mn}
D-AL	4.938 ^{j}	D-FC	3.602 ^{o}	I-NBE	4.110 ^{kl}	D-AL	3.036 ^{mn}
I-NBE	5.080 ^{k}	MD-NBE	3.691 ^{p}	D-FC	4.145 ^{l}	I-NBE	3.067 ^{no}
MD-NBE	5.084 ^{k}	I-NBE	3.721 ^{p}	O-RBE	4.145 ^{l}	D-FC	3.116 ^{o}
O-FC	5.233	2-RB	3.831 ^{q}	O-AL	4.303 ^{m}	O-AL	3.230 ^{p}
O-AL	5.323 ^{l}	O-FC	3.891 ^{qr}	O-FC	4.329 ^{mn}	O-FC	3.280 ^{p}
2-RB	5.335 ^{l}	O-AL	3.920 ^{r}	D-NBE	4.388 ^{n}	D-NBE	3.300 ^{p}
D-NBE	5.552	D-NBE	4.055	2-RB	4.671 ^{o}	2-RB	3.434
M-RB	5.940	M-RB	4.297 ^{s}	O-NBE	4.721 ^{o}	O-NBE	3.613
2D-RB	6.014	2D-RB	4.347 ^{s}	2D-RB	5.077	2D-RB	3.784 ^{q}
O-NBE	6.105	O-NBE	4.561	M-RB	5.147	M-RB	3.825 ^{q}
I-RB	6.583 ^{m}	I-RB	4.840 ^{t}	MD-RB	5.589 ^{p}	MD-RB	4.215
MD-RB	6.652 ^{m}	MD-RB	4.869 ^{t}	I-RB	5.649 ^{p}	I-RB	4.268
D-RB	7.318	D-RB	5.456	D-RB	6.112	D-RB	4.686
O-RB	7.673	O-RB	5.818	O-RB	6.315	O-RB	4.897

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

RULE-SEQ I: IBFI, D: DOME, O: OFFSET, 2: 2BEG, 2D: 2BEG-DOME, M: MBFI, MD: MB_DOME
FC: FCFA, AL: ALTER, NB: NEW_BEG, RB: RET_BEG, NBE: NEW_BEG_END, RBE: RET_BEG_END

Table XIV. Rankings of AS by WAIT - Part I[1]

ENV	# 1	ENV	# 2	ENV	# 3	ENV	# 4
N= 10	Unp= 0	N= 10	Unp= -15	N= 10	Unp= 0	N= 10	Unp= -15
P_N= 0	P_W= 0	P_N= 0	P_W= 0	P_N= 0	P_W= 0.15	P_N= 0	P_W= 0.15
O-RB	8.877	O-RB	6.641	O-RB	16.222	O-RB	14.324
I-RB	9.735	I-RB	7.123	D-RB	17.591 [a]	I-RB	15.654 [a]
D-RB	10.030 [a]	D-RB	7.846	I-RB	17.977 [a]	D-RB	15.785 [a]
O-NBE	10.077 [a]	M-RB	8.807 [a]	O-NBE	18.754 [b]	M-RB	17.700
O-AL	10.235 [a]	O-AL	8.834 [a]	M-RB	19.004 [bc]	O-NBE	18.390 [b]
M-RB	10.573 [b]	O-NBE	9.436 [b]	MD-RB	19.223 [c]	MD-RB	18.559 [b]
D-NBE	10.809 [bc]	I-NBE	9.511 [bc]	O-AL	19.758 [d]	O-AL	18.695 [b]
I-NBE	10.909 [c]	I-AL	9.706 [bcd]	2D-RB	19.853 [de]	2-RB	19.450 [c]
D-AL	11.222 [d]	D-AL	9.795 [cd]	D-NBE	19.900 [de]	I-NBE	19.451 [c]
2-RB	11.251 [d]	2-RB	9.933 [de]	2-RB	20.213 [e]	D-NBE	19.613 [cd]
MD-RB	11.394 [d]	D-NBE	10.191 [ef]	I-NBE	20.613 [f]	2D-RB	19.921 [de]
2D-RB	11.515 [d]	MD-RB	10.220 [ef]	D-AL	20.983 [f]	D-AL	19.986 [de]
I-AL	11.867 [e]	O-FC	10.282 [f]	O-FC	21.646	I-AL	20.315 [e]
O-FC	11.989 [e]	O-RBE	10.872 [g]	I-AL	22.143	O-FC	20.335 [e]
D-FC	13.097	2D-RB	10.995 [g]	D-FC	22.952	D-FC	21.744 [f]
M-NBE	13.534	D-FC	11.441 [h]	M-NBE	23.437 [g]	O-RBE	21.875 [f]
O-RBE	13.915 [f]	I-FC	11.670 [h]	MD-NBE	23.728 [g]	I-FC	22.349
I-FC	14.025 [fg]	D-RBE	12.421	I-FC	24.326 [h]	D-RBE	23.481
M-AL	14.242 [gh]	I-RBE	13.419	O-RBE	24.328 [h]	M-NBE	24.164
MD-NBE	14.343 [h]	M-AL	13.888 [i]	MD-AL	24.394 [h]	M-AL	24.679 [g]
MD-AL	14.355 [h]	M-NBE	14.062 [i]	M-AL	24.716 [h]	I-RBE	24.687 [g]
D-RBE	15.416	MD-AL	14.818	D-RBE	25.823 [i]	MD-AL	25.222 [h]
MD-FC	15.905 [i]	M-FC	15.373 [j]	MD-FC	26.006 [i]	MD-NBE	25.239 [h]
M-FC	15.980 [i]	MD-NBE	15.579 [jk]	M-FC	26.444	M-FC	26.160 [i]
O-NB	16.748 [j]	MD-RBE	15.829 [kl]	2-NBE	27.136 [j]	MD-FC	26.571 [i]
MD-RBE	16.920 [jk]	M-RBE	15.854 [kl]	2D-NBE	27.200 [jk]	MD-RBE	27.168 [j]
I-RBE	16.934 [jk]	MD-FC	16.130 [l]	2D-AL	27.375 [jk]	M-RBE	27.357 [j]
2-NBE	16.969 [jk]	O-NB	16.847	I-RBE	27.616 [kl]	2-NBE	28.721 [k]
2D-AL	17.076 [k]	2-AL	17.911 [m]	MD-RBE	27.624 [kl]	2-AL	28.830 [kl]
2-AL	17.172 [k]	D-NB	17.994 [m]	2-AL	27.869 [l]	O-NB	29.103 [kl]
2D-NBE	17.650 [l]	2-NBE	18.452 [n]	M-RBE	28.675 [m]	2D-AL	29.267 [lm]
M-RBE	17.768 [l]	I-NB	18.631 [no]	2D-FC	28.798 [m]	2D-NBE	29.592 [m]
D-NB	17.785 [l]	2D-AL	18.711 [no]	O-NB	28.838 [m]	2-FC	30.179 [n]
2D-FC	18.475 [m]	2D-RBE	18.794 [op]	2-FC	29.430 [n]	2D-RBE	30.400 [no]
2D-RBE	18.530 [m]	2-RBE	19.063 [pq]	2D-RBE	29.620 [n]	2D-FC	30.425 [no]
2-FC	18.757 [m]	2-FC	19.264 [q]	D-NB	30.092	D-NB	30.496 [no]
I-NB	19.511	2D-FC	19.884 [r]	2-RBE	31.000	2-RBE	30.738 [o]
2-RBE	19.826	2D-NBE	19.886 [r]	I-NB	31.999	I-NB	31.294
MD-NB	23.136	M-NB	25.086	MD-NB	35.328	M-NB	37.309
M-NB	23.459	MD-NB	25.760	M-NB	35.799	MD-NB	37.803
2D-NB	28.494	2-NB	31.619	2D-NB	40.296	2-NB	43.266 [p]
2-NB	28.801	2D-NB	32.169	2-NB	40.776	2D-NB	43.625 [p]

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

<u>RULE-SEQ</u> I: IBFI, D: DOME, O: OFFSET, 2: 2BEG, 2D: 2BEG-DOME, M: MBFI, MD: MB_DOME
FC: FCFA, AL: ALTER, NB: NEW_BEG, RB: RET_BEG, NBE: NEW_BEG_END, RBE: RET_BEG_END

Table XIV. Rankings of AS by WAIT - Part I[1] (Cont'ed)

ENV	# 5	ENV	# 6	ENV	# 7	ENV	# 8
N= 10	Unp= 0	N= 10	Unp= -15	N= 10	Unp= 0	N= 10	Unp= -15
P_N= 0.15	P_W= 0	P_N= 0.15	P_W= 0	P_N= 0.15	P_W= 0.15	P_N= 0.15	P_W= 0.15
O-RB	6.865	O-RB	5.119 [a]	O-RB	12.954	O-RB	11.378
I-RB	7.282 [a]	I-RB	5.235 [a]	D-RB	14.035 [a]	I-RB	12.210 [a]
O-NBE	7.459 [a]	D-RB	5.997	I-RB	14.137 [a]	D-RB	12.500 [a]
O-AL	7.474 [a]	O-AL	6.286 [b]	O-NBE	14.276 [a]	M-RB	13.631 [b]
I-NBE	7.715 [b]	M-RB	6.424 [b]	M-RB	14.878 [b]	O-NBE	13.664 [b]
D-RB	7.726 [b]	I-NBE	6.453 [b]	O-AL	14.988 [bc]	O-AL	13.895 [bc]
M-RB	7.894 [b]	I-AL	6.471 [b]	D-NBE	15.117 [bcd]	I-NBE	14.181 [c]
D-NBE	7.948 [bc]	O-NBE	6.791 [c]	MD-RB	15.301 [cde]	D-NBE	14.551 [d]
D-AL	8.143 [cd]	D-AL	6.892 [cd]	I-NBE	15.402 [de]	MD-RB	14.572 [d]
2-RB	8.296 [d]	2-RB	7.069 [de]	2D-RB	15.583 [ef]	2-RB	14.686 [d]
I-AL	8.305 [d]	O-FC	7.074 [de]	2-RB	15.633 [ef]	I-AL	14.806 [d]
O-FC	8.579	D-NBE	7.275 [ef]	D-AL	15.894 [f]	D-AL	14.809 [d]
2D-RB	8.825 [e]	O-RBE	7.377 [f]	O-FC	16.266 [g]	O-FC	14.937 [d]
MD-RB	8.839 [e]	I-FC	7.660 [g]	I-AL	16.532 [g]	2D-RB	15.330
D-FC	9.342 [f]	D-FC	7.829 [g]	D-FC	17.236 [h]	D-FC	15.953 [e]
M-NBE	9.469 [f]	MD-RB	7.846 [g]	M-NBE	17.253 [h]	O-RBE	16.046 [e]
I-FC	9.721 [g]	2D-RB	8.253 [h]	MD-NBE	17.731 [i]	I-FC	16.168 [e]
O-RBE	9.783 [g]	D-RBE	8.379 [h]	I-FC	18.047 [ij]	D-RBE	17.193 [f]
M-AL	9.913 [g]	I-RBE	8.819	O-RBE	18.181 [j]	M-NBE	17.296 [f]
MD-AL	10.378 [h]	M-AL	9.173	M-AL	18.240 [j]	M-AL	17.664 [g]
MD-NBE	10.439 [h]	M-NBE	9.446	MD-AL	18.258 [j]	I-RBE	17.898 [g]
D-RBE	10.829 [i]	M-FC	10.052	D-RBE	19.306 [k]	MD-AL	18.401 [h]
M-FC	11.004 [i]	M-RBE	10.292 [i]	MD-FC	19.347 [k]	MD-NBE	18.441 [h]
O-NB	11.237 [j]	MD-AL	10.315 [i]	M-FC	19.438 [k]	M-FC	18.668 [h]
MD-FC	11.311 [j]	MD-RBE	10.692 [j]	2-NBE	19.656 [kl]	MD-FC	19.266 [i]
2-NBE	11.652 [k]	O-NB	10.751 [j]	2D-NBE	19.983 [lm]	M-RBE	19.521 [ij]
I-RBE	11.678 [k]	MD-FC	11.023 [k]	2D-AL	20.089 [m]	MD-RBE	19.655 [j]
2-AL	11.692 [k]	MD-NBE	11.032 [k]	2-AL	20.234 [mn]	O-NB	20.158 [k]
D-NB	11.820 [kl]	D-NB	11.337 [l]	I-RBE	20.461 [no]	2-AL	20.242 [k]
MD-RBE	11.975 [l]	I-NB	11.466 [lm]	MD-RBE	20.565 [no]	2-NBE	20.288 [k]
2D-AL	12.021 [lm]	2-AL	11.597 [m]	O-NB	20.622 [o]	2D-AL	20.916 [l]
M-RBE	12.223 [m]	2-RBE	12.105 [n]	2D-FC	21.045 [p]	D-NB	21.038 [lm]
2D-NBE	12.602 [n]	2D-RBE	12.261 [no]	M-RBE	21.102 [pq]	2-FC	21.241 [lmn]
2-FC	12.730 [no]	2-NBE	12.266 [no]	2-FC	21.341 [pqr]	2D-NBE	21.344 [mno]
I-NB	12.764 [no]	2-FC	12.453 [o]	D-NB	21.461 [qr]	I-NB	21.462 [no]
2D-RBE	12.800 [no]	2D-AL	12.709	2D-RBE	21.679 [r]	2D-RBE	21.532 [no]
2D-FC	12.873 [o]	2D-FC	13.373	2-RBE	22.577 [s]	2-RBE	21.595 [no]
2-RBE	13.453	2D-NBE	13.916	I-NB	22.728 [s]	2D-FC	21.714 [o]
M-NB	15.298 [p]	M-NB	15.695	MD-NB	24.970 [t]	M-NB	25.523
MD-NB	15.378 [p]	MD-NB	16.61	M-NB	25.177 [t]	MD-NB	26.147
2-NB	18.790 [q]	2-NB	20.095	2D-NB	28.301 [u]	2-NB	29.666
2D-NB	18.930 [q]	2D-NB	21.07	2-NB	28.518 [u]	2D-NB	30.255

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

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FC: FCFA, AL: ALTER, NB: NEW_BEG, RB: RET_BEG, NBE: NEW_BEG_END, RBE: RET_BEG_END

Table XIV. Rankings of AS by WAIT - Part I[1] (Cont'ed)

ENV	# 9	ENV	# 10	ENV	# 11	ENV	# 12
N= 20 P_N= 0	Unp= 0 P_W= 0	N= 20 P_N= 0	Unp= -15 P_W= 0	N= 20 P_N= 0	Unp= 0 P_W= 0.15	N= 20 P_N= 0	Unp= -15 P_W= 0.15
O-RB	8.28	O-RB	5.789 [a]	O-RB	13.889	O-RB	11.985
I-RB	8.774 [a]	I-RB	5.887 [a]	D-RB	14.59	D-RB	12.806 [a]
O-AL	8.788 [a]	M-RB	6.309 [b]	MD-RB	15.026 [a]	I-RB	13.052 [a]
D-RB	8.840 [a]	D-RB	6.418 [b]	2D-RB	15.329 [ab]	MD-RB	13.815 [b]
M-RB	8.858 [a]	2-RB	6.566 [b]	I-RB	15.412 [bc]	M-RB	13.837 [b]
2-RB	8.881 [ab]	MD-RB	7.078	M-RB	15.727 [c]	2-RB	14.593 [c]
2D-RB	8.969 [ab]	2D-RB	7.419 [c]	2-RB	16.103	2D-RB	14.631 [c]
MD-RB	9.013 [ab]	O-AL	7.593 [cd]	O-NBE	16.908	O-AL	17.109
I-NBE	9.028 [ab]	I-AL	7.840 [de]	D-NBE	17.362 [d]	O-NBE	17.554 [d]
O-NBE	9.087 [ab]	D-AL	8.021 [e]	O-AL	17.391 [d]	D-AL	17.863 [de]
D-AL	9.222 [b]	I-NBE	8.040 [e]	D-AL	18.076 [e]	I-NBE	17.895 [def]
D-NBE	9.232 [b]	O-FC	8.436	I-NBE	18.134 [e]	D-NBE	18.177 [efg]
O-FC	9.955 [c]	O-NBE	8.950 [f]	O-FC	18.929	O-FC	18.273 [fg]
I-AL	10.059 [c]	D-FC	8.971 [f]	MD-NBE	19.359 [f]	I-AL	18.450 [g]
M-NBE	10.087 [c]	O-RBE	9.086 [f]	M-NBE	19.577 [fg]	D-FC	19.051
MD-AL	10.407 [d]	D-NBE	9.199 [f]	D-FC	19.590 [fg]	O-RBE	19.844 [h]
D-FC	10.432 [d]	I-FC	9.275 [f]	MD-AL	19.690 [fg]	I-FC	19.979 [h]
MD-NBE	10.853 [e]	M-AL	9.728 [g]	I-AL	19.774 [g]	M-NBE	20.511 [i]
M-AL	10.887 [e]	D-RBE	9.856 [g]	MD-FC	20.959 [h]	MD-AL	20.592 [i]
MD-FC	11.438 [f]	M-NBE	10.246 [h]	M-AL	20.973 [h]	D-RBE	20.744 [ij]
2-NBE	11.514 [fg]	MD-AL	10.305 [h]	2D-AL	21.427 [i]	M-AL	20.821 [ij]
2D-AL	11.630 [fg]	M-FC	10.955 i	2-NBE	21.460 [i]	MD-NBE	21.125 [j]
I-FC	11.678 [fg]	MD-FC	11.115 [i]	2D-NBE	21.501 [i]	MD-FC	21.566
2-AL	11.848 [g]	MD-RBE	11.233 [j]	I-FC	21.576 [i]	M-FC	22.009
M-FC	12.290 [h]	I-RBE	11.625 [j]	O-RBE	22.119 [j]	MD-RBE	22.577 [k]
O-RBE	12.376 [h]	2-AL	11.665 [j]	2-AL	22.391 [jk]	I-RBE	22.758 [k]
2D-NBE	12.551 [h]	MD-NBE	11.824 [j]	M-FC	22.497 [jk]	2-AL	23.152 [l]
2D-FC	12.624 [h]	2-NBE	12.501 [k]	2D-FC	22.593 [kl]	2-NBE	23.161 [l]
D-RBE	13.143 [i]	2D-AL	12.505 [k]	D-RBE	22.922 [l]	2D-AL	23.242 [l]
2-FC	13.249 [ij]	M-RBE	12.613 [k]	MD-RBE	23.652 [m]	2D-NBE	23.918 [m]
MD-RBE	13.541 [j]	2D-RBE	12.620 [k]	2-FC	23.831 [m]	2D-FC	24.062 [m]
2D-RBE	13.872	2-FC	12.788 [k]	2D-RBE	24.486	M-RBE	24.137 [mn]
I-RBE	15.626 [k]	2D-FC	13.256	I-RBE	25.732	2-FC	24.194 [mn]
O-NB	15.632 [k]	2-RBE	13.691	M-RBE	26.220	2D-RBE	24.473 [n]
M-RBE	15.852 [kl]	2D-NBE	14.254	2-RBE	26.890	2-RBE	25.656
D-NB	16.031 [l]	O-NB	17.093	O-NB	28.061	O-NB	29.957
2-RBE	16.140 [l]	D-NB	17.633	D-NB	28.709	D-NB	30.758
I-NB	17.786	I-NB	17.968	I-NB	30.791	I-NB	31.442
MD-NB	18.799	M-NB	21.524 1	MD-NB	31.591	MD-NB	34.690 [o]
M-NB	19.720	MD-NB	21.687 1	M-NB	32.861	M-NB	34.890 [o]
2D-NB	21.924	2-NB	25.165	2D-NB	34.758	2-NB	38.333 [p]
2-NB	22.339	2D-NB	25.628	2-NB	35.505	2D-NB	38.462 [p]

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

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FC: FCFA, AL: ALTER, NB: NEW_BEG, RB: RET_BEG, NBE: NEW_BEG_END, RBE: RET_BEG_END

Table XIV. Rankings of AS by WAIT - Part I[1] (Cont'ed)

ENV	# 13	ENV	# 14	ENV	# 15	ENV	# 16
N= 20	Unp= 0	N= 20	Unp= -15	N= 20	Unp= 0	N= 20	Unp= -15
P_N= 0.15	P_W= 0	P_N= 0.15	P_W= 0	P_N= 0.15	P_W= 0.15	P_N= 0.15	P_W= 0.15
I-NBE	5.928 [a]	I-RB	3.992 [a]	O-RB	10.567	O-RB	8.945
O-AL	6.078 [ab]	O-RB	4.205 [ab]	D-RB	11.082 [a]	I-RB	9.467 [a]
O-RB	6.162 [ab]	M-RB	4.302 [b]	MD-RB	11.382 [ab]	D-RB	9.535 [a]
I-RB	6.204 [bc]	2-RB	4.401 [bc]	I-RB	11.407 [ab]	M-RB	9.955 [b]
2-RB	6.244 [bcd]	I-AL	4.581 [cd]	2D-RB	11.498 [bc]	MD-RB	10.234 [bc]
M-RB	6.278 [bcd]	D-RB	4.603 [cd]	M-RB	11.617 [bcd]	2-RB	10.338 [c]
D-AL	6.288 [bcd]	I-NBE	4.815 [de]	O-NBE	11.696 [bcde]	2D-RB	10.674
O-NBE	6.329 [bcd]	O-AL	4.887 [e]	2-RB	11.807 [cde]	O-AL	11.246 [d]
D-NBE	6.368 [bcde]	D-AL	5.081 [ef]	D-NBE	11.962 [def]	I-NBE	11.445 [de]
I-AL	6.479 [cde]	MD-RB	5.161 [fg]	O-AL	12.038 [ef]	O-NBE	11.615 [ef]
D-RB	6.520 [def]	O-FC	5.243 [fgh]	I-NBE	12.226 [fg]	D-AL	11.700 [efg]
M-NBE	6.532 [def]	I-FC	5.340 [fghi]	D-AL	12.474 [g]	I-AL	11.850 [fg]
2D-RB	6.630 [ef]	2D-RB	5.372 [ghi]	O-FC	13.025 [h]	D-NBE	11.976 [g]
MD-RB	6.696 [fg]	O-RBE	5.492 [hi]	M-NBE	13.053 [h]	O-FC	11.979 [g]
O-FC	6.700 [fg]	D-FC	5.510 [hi]	MD-NBE	13.219 [hi]	D-FC	12.475
D-FC	6.959 [gh]	M-AL	5.617 [ij]	I-AL	13.389 [i]	I-FC	12.913 [h]
M-AL	6.965 [gh]	O-NBE	5.833 [jk]	MD-AL	13.451 [i]	M-NBE	13.048 [h]
MD-AL	7.058 [hi]	D-RBE	5.892 [kl]	D-FC	13.470 [i]	O-RBE	13.095 [hi]
2-NBE	7.306 [ij]	D-NBE	5.941 [kl]	M-AL	14.107 [j]	M-AL	13.231 [hi]
2-AL	7.398 [jk]	M-NBE	6.117 [lm]	2-NBE	14.113 [j]	MD-AL	13.406 [ij]
I-FC	7.435 [jk]	M-FC	6.245 [m]	MD-FC	14.300 [jk]	D-RBE	13.691 [jk]
MD-NBE	7.436 [jk]	MD-AL	6.506 [n]	2D-AL	14.390 [jkl]	MD-NBE	13.940 [kl]
MD-FC	7.606 [kl]	2-AL	6.559 [no]	2D-NBE	14.501 [kl]	MD-FC	14.060 [l]
2D-AL	7.714 [l]	I-RBE	6.724 [no]	I-FC	14.648 [lm]	M-FC	14.100 [l]
M-FC	7.781 [lm]	MD-RBE	6.737 [no]	2-AL	14.850 [m]	2-AL	14.519 [m]
O-RBE	7.994 [mn]	MD-FC	6.835 [o]	M-FC	15.170 [n]	2-NBE	14.643 [mn]
2D-FC	8.236 [no]	2-FC	7.167 [p]	2D-FC	15.209 [n]	MD-RBE	14.803 [mno]
2-FC	8.240 [no]	M-RBE	7.239 [p]	O-RBE	15.264 [n]	2D-AL	14.951 [no]
D-RBE	8.455 [o]	2D-RBE	7.355 [p]	D-RBE	15.838 [o]	I-RBE	14.999 [o]
2D-NBE	8.462 [o]	2-NBE	7.394 [p]	2-FC	15.912 [o]	2-FC	15.355 [p]
MD-RBE	8.771 [p]	2-RBE	7.651 [q]	MD-RBE	16.282	2D-FC	15.557 [pq]
2D-RBE	8.891 [p]	MD-NBE	7.711 [q]	2D-RBE	16.665	2D-NBE	15.729 [q]
O-NB	9.405 [q]	2D-AL	7.743 [q]	I-RBE	17.722 [p]	M-RBE	15.778 [q]
D-NB	9.535 [q]	2D-FC	8.033	O-NB	17.993 [p]	2D-RBE	15.796 [q]
I-RBE	9.852 [r]	2D-NBE	9.277 [r]	M-RBE	18.001 [p]	2-RBE	16.556
M-RBE	10.009 [r]	I-NB	9.509 [rs]	2-RBE	18.331 [q]	O-NB	18.564
2-RBE	10.095 [r]	O-NB	9.585 [s]	D-NB	18.352 [q]	D-NB	19.003
I-NB	10.358	D-NB	9.760 [s]	I-NB	19.787	I-NB	19.321
MD-NB	11.204 [s]	M-NB	11.605	MD-NB	20.175	M-NB	21.589 [r]
M-NB	11.384 [s]	MD-NB	12.413	M-NB	21.008	MD-NB	21.760 [r]
2-NB	12.891 [t]	2-NB	13.878	2D-NB	22.273	2-NB	23.999
2D-NB	13.091 [t]	2D-NB	15.027	2-NB	22.706	2D-NB	24.477

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

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FC: FCFA, AL: ALTER, NB: NEW_BEG, RB: RET_BEG, NBE: NEW_BEG_END, RBE: RET_BEG_END

5.1.6. Efficient Frontiers

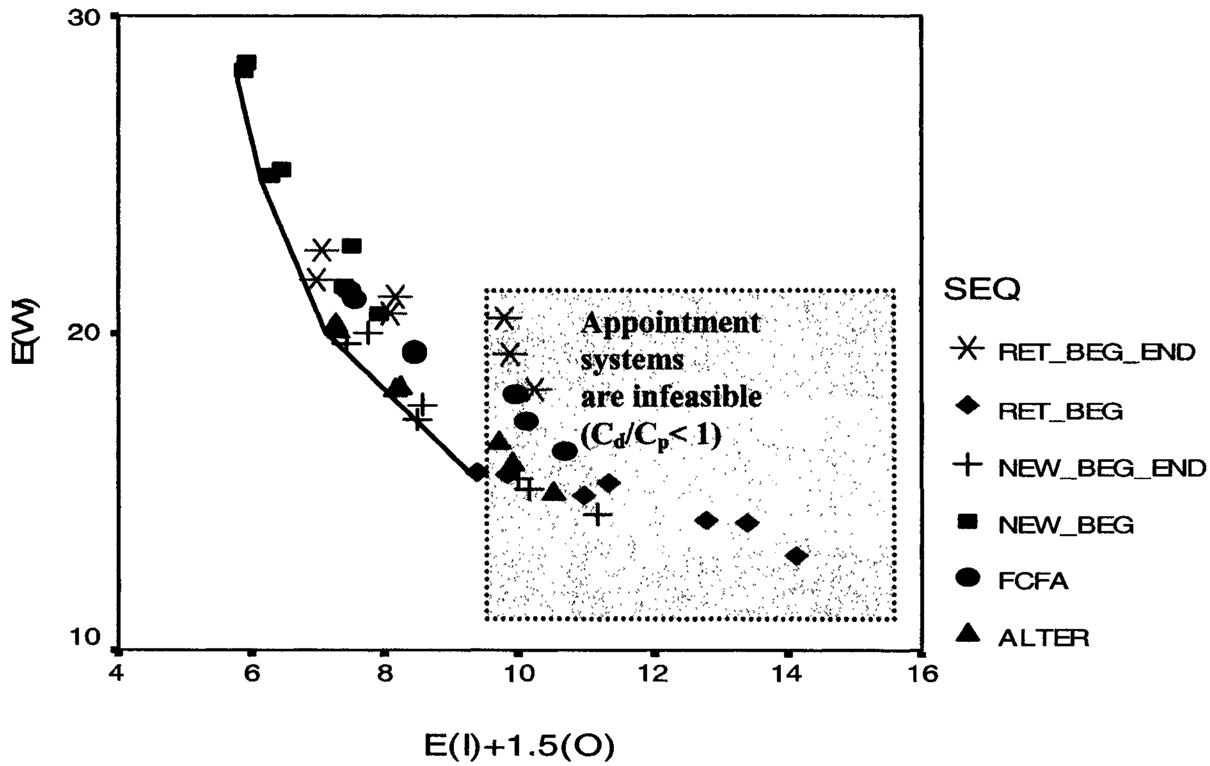
Next, efficient frontiers were plotted for each environment, for the mean performance measurements of IDLE/OVER and WAIT listed in Tables XIII and XIV, respectively. Unlike previous studies, we included overtime explicitly when plotting the efficient frontiers. Figure IX presents the most adverse environment with high walk in rates, high no-show rates, and higher patient lateness for N= 10. The only discernible difference caused by a larger clinic session size is that both doctors' idle/overtime and patients' waiting time shrink, causing a parallel, downward shift in costs for all AS. Also, recall that almost all interaction effects between environmental factors and decision factors were found to be infatuating effects (and not cross effects), this environment truly portrays generalized findings.

Note also that, in the efficient frontiers, groupings by sequencing rules are more clustered, compared to groupings by appointment rules. This confirms our ANOVA findings, which indicated that the choice of sequencing rule matters more than the choice of appointment rule.

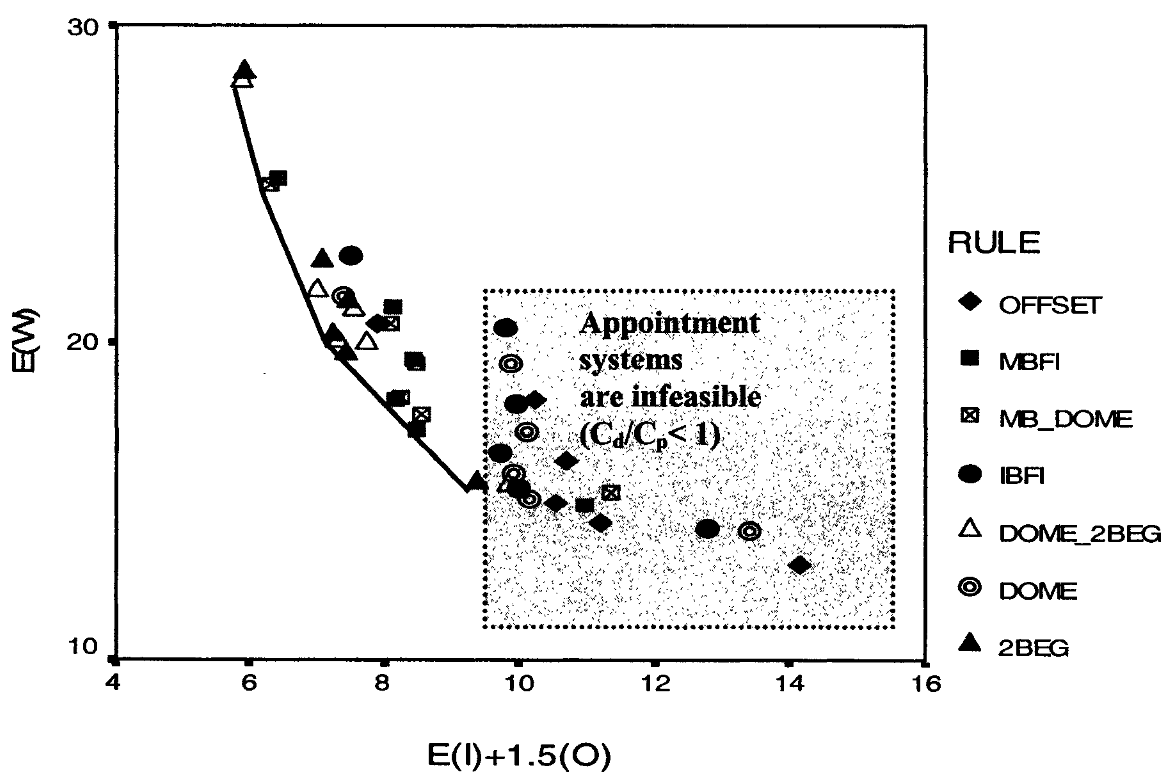
There is a general pattern observed in the efficient frontiers. In terms of sequencing rules, upper-left frontiers are consistently dominated by the NEW_BEG rule, and the preference shifts to ALTER and then to RET_BEG, as the relative value of doctor's time compared to patients' time decreases (i.e. the C_d/C_p ratio decreases). Similarly, in terms of appointment rules, the preference shifts from 2BEG to multiple-block rule, and then to individual-block rules as the C_d/C_p ratio decreases.

Figure IX. Efficient Frontier for Env #7: N= 10, P_N= 0.15, P_W= 0.15, Unp= 0 min.

(a) Grouping by Sequencing Rules



(b) Grouping by Appointment Rules



Even though basically the same AS tend to appear as best performers in all environments, the exact C_d/C_p valuation at which each AS becomes the best choice, varies widely from one environment to another. Table XV lists the best AS for the sixteen environments that we investigated, and the approximate C_d/C_p values at which each should be chosen are displayed. For example, 2BEG/RET_BEG is the best choice in environment #1, if it is assumed that patient's time is as valuable as doctor's time (C_d/C_p= 1). In environment #2, the same AS becomes preferable for C_d/C_p values in between [1-5]. Note that sometimes an AS is preferable only when the C_d/C_p ratio is less than 1. Since it is unlikely that in practice doctor's time will be valued less than patients' time, those AS are considered infeasible, and they are excluded from the list of best AS. As also noted by Yang et al. (1998), it is usually assumed that C_d> C_p. This is because C_d includes not only the cost of the idle doctor but also the cost of the idle facility.

After our detailed analysis of efficient frontiers, and specific C_d/C_p valuations calculated for the best AS under each environment (Table XV), we summarize our most important findings.

(a) *Sequencing Rules*:

- Under all environments, scheduling patients on a first-call, first-appointment basis (FCFA) performs badly. This confirms that the use of patient classification in sequencing patients throughout the day improves both patient waiting times and doctors' idle and overtime, without any trade-offs.
- Scheduling long-consultation patients in the beginning of the session (i.e. NEW_BEG) performs best when applied to appointment rules 2BEG and MBFI that utilize multiple blocks. However, in clinic environments with early arrivals and low

Table XV. Best Appointment Systems and their Corresponding C_d/C_p Ratios - Part I

#	Environment	O-RB	O-AL	I-RB	I-AL*	2-RB	M-AL*	2-AL	2-RBE*	M-NB*	2-NB*
1	N= 10, P_N= 0, P_W= 0, Unp= 0	**<1**	**<1**			1	2	3-5	6	7-15	>15
2	N= 10, P_N= 0, P_W= 0, Unp= -15	**<1**		**<1**		1-5	6-7		7-32	33-56	>56
3	N= 10, P_N= 0, P_W= 0.15, Unp= 0	**<1**	1			2-3	3-4	5-11		12-16	>16
4	N= 10, P_N= 0, P_W= 0.15, Unp= -15	1				2-7	8-10	11-23	24-33	34-61	>61
5	N= 10, P_N= 0.15, P_W= 0, Unp= 0	**<1**				1	1.5	2	2-5	5-7	>7
6	N= 10, P_N= 0.15, P_W= 0, Unp= -15	**<1**		**<1**		1-2	3		4-18	19-26	>26
7	N= 10, P_N= 0.15, P_W= 0.15, Unp =0	**<1**	**<1**			1	2	3-5		6-7	>7
8	N= 10, P_N= 0.15, P_W= 0.15, Unp= -15	**<1**				1-3	4	5-6	7-13	14-19	>19
9	N= 20, P_N= 0, P_W= 0, Unp= 0	**<1**	1		1.5		**2**	3-11		12-18	>18
10	N= 20, P_N= 0, P_W= 0, Unp= -15	**<1**			2-4	1	5-11	12-22	23-45	46-64	>64
11	N= 20, P_N= 0, P_W= 0.15, Unp =0	1	3-4			2	5-6		7-20	21-32	>32
12	N= 20, P_N= 0, P_W= 0.15, Unp= -15	1-2			8-12	2-7	13-19	20-84		85-102	>103
13	N= 20, P_N= 0.15, P_W= 0, Unp= 0				1			1-5		6-7	>7
14	N= 20, P_N= 0.15, P_W= 0, Unp= -15			**<1**	1-2		3-5		6-29	30	>31
15	N= 20, P_N= 0.15, P_W= 0.15, Unp =0	**<1**			1-2		3	4-9		10-15	>15
16	N= 20, P_N= 0.15, P_W= 0.15, Unp= -15	**<1**		1	3-4	2	5-7	8-23		24-33	>33

<u>RULE-SEQ</u> I: IBFI, D: DOME, O: OFFSET, 2: 2BEG, 2D: 2BEG_ DOME, M: MBFI, MD: MB_DOME
FC: FCFA, AL: ALTER, NB: NEW_BEG, RB: RET_BEG, NBE: NEW_BEG_END, RBE: RET_BEG_END

* D-AL is not significantly different from I-AL at alpha 0.05, and thus results are combined. Similarly, M-NBE is combined with M-AL, 2D-RBE with 2-RBE, MD-NB with M-NB, and 2D-NB with 2-NB.

no-show rates, these AS result in exaggerated patient waiting times with only minor improvements in doctors' idle/overtime Thus they should be avoided unless doctors' time is deemed substantially more valuable than patients' waiting time. This was true in environments #2, 4, 10, and 12.

- Combining the approach of scheduling short-consultation patients in the beginning of the session (i.e. RET_BEG) with the 2BEG rule, appears on the efficient frontiers as one of the best-performing AS under most environments. On the other hand, RET_BEG sequencing rule should not be used with individual-block rules of IBFI and OFFSET, as the resulting AS are generally infeasible ($C_d < C_p$). Few exceptions include environments characterized by high walk-ins, low no-shows, and/or early patients, such as environments #4, 11, 12, and 16.
- The NEW_BEG_END rule usually performs badly, or at best similar to the ALTER rule.
- The RET_BEG_END rule performs best only in combination with 2BEG (or 2BEG_DOME) rule, and less so in larger clinics with $N = 20$.

(b) <u>*Appointment Rules*</u>:

- Among the appointment rules tested, 2BEG has the strongest existence on the efficient frontiers, appearing as the best choice over a wide range of C_d/C_p valuations [1-100]. The rule performs best in combination with all sequencing approaches tested. MBFI performs best in combination with ALTER and NEW_BEG, whereas the individual-block rules, IBFI and OFFSET, both perform best with ALTER and RET_BEG.

- The individual-block rules are more suited to clinics/specialties with shorter consultation times (*N*= 20), especially when patients are usually early, walk-ins are high, and no-shows are low - for example, in environment #12. On the other hand, in clinics with longer mean consultation times (*N*= 10), individual-block rules appear as the best choice only if walk-ins are high and no-shows are low, and only if patient's time is assumed as valuable as doctor's time.
- The OFFSET rule results in highest idle/overtime and lowest patient wait time, which makes it infeasible for the majority of the environments. It is the best choice in few environments with high walk-ins and low no-shows, yet only under the assumption that patient's time is highly valuable - usually as high as doctor's time. The fixed-interval IBFI rule appears on efficient frontiers more often and under a wider range of C_d/C_p values.
- The DOME rule appears as the best choice only in one of the sixteen environments (Env# 12), and is not significantly different than IBFI. Similarly, Tukey's test results show that the 2BEG_DOME and MB_DOME rules are usually not significantly different from their fixed-interval counterparts at α= 0.05, even though these rules occasionally appear as best-performers. Thus, for simplicity, the results are combined under the IBFI, 2BEG and MBFI rules in Table XV.
- MBFI, which calls patients two-at-a-time, was identified as a poor performer in Ho and Lau's (1992) simulation study. However, the results of our study show that MBFI performs among the best appointment rules under a wide range of environments. This is most likely because the consequences of multiple-blocks are not as severe when the assumption of punctual patients is relaxed.

5.1.7. Summary of Part I

The results from the first part of our analysis show that using patient classification for sequencing purposes promises improvements in clinic performance, measured in terms of patients' waiting times, doctor's idle time and doctor's overtime. In general, sequencing decisions have a more pronounced impact on performance than the choice of an appointment rule.

Among the six environmental factors we investigated, no-shows, walk-ins, clinic size, and patient unpunctuality, emerged as the major factors affecting choice of AS. Service-time variability of patients proved to be less important, even though statistically significant. Limiting environments to these four factors, forty-two appointment systems (combinations of six sequencing rules and seven appointment rules) were compared on the basis of mean performance measures plotted on efficient frontiers. The results of our analysis indicated that, placing new patients in the beginning of the session is preferred when doctor's idle time is assumed to be highly valuable compared to patients' time. At the other extreme, placing return patients in the beginning of the session is preferred when patients' time is highly valued. For each environment, alternating new and return patients performed the best in between these two extremes. In short, the simpler NEW_BEG, ALTER, and RET_BEG rules generally performed the best among the sequencing rules tested.

In terms of appointment rules, 2BEG, MBFI and IBFI, dominated the efficient frontiers. Even though OFFSET was preferred in environments with low no-shows and high walk-ins, usually under the restrictive assumption that patient's time is valued as high as doctor's time. One of the goals of this study was to test the performance of variable-block rules with "dome-shaped" intervals. These rules performed either inferior to or insignificantly different than their fixed-interval counterparts. Furthermore, our findings indicated that the individual-block rules are mostly suited to specialties with short consultation times. In fact, these rules should be avoided in clinics with long consultation times, unless walk-ins are high, no-shows are low, and patient's time is assumed to be equally valuable as doctor's time. On the other hand, rules that utilize multiple-blocks, 2BEG and MBFI, appear among the best performers in *all* the sixteen environments and for a wide range of C_d/C_p values. Confirming our previous findings that indicated sequencing approaches are more important than appointment rules, the best choice among these appointment rules, depends on the combination with a particular sequencing rule.

5.2. ANALYSIS PART II

The first part of the analysis focused on the first two decision factors in AS design: "appointment rules", and "sequencing rules". Patient classification was used for sequencing *only*, without adjusting the appointment intervals for patient class. Thus, all appointment intervals were fixed, regardless of differences in consultation times of new/return patients assigned to slots.

The next step of our analysis includes the third decision factor: "interval-adjustment for patient class". It is hypothesized that the use of patient classification for *both* sequencing and interval adjustment may further improve clinic performance. Illustrated for the new/return classification, this means the scheduler assigns longer slots for new patients and shorter ones for return patients, determined by the consultation time characteristics of each patient type.

The investigation is carried on with the best performing AS identified in Part I. These include three sequencing rules (NEW_BEG, ALTER, and RET_BEG), and three appointment rules (IBFI, 2BEG, and MBFI). The nine combinations of appointment systems are tested with or without interval-adjustment, resulting in eighteen AS. The formulations of these appointment systems can be found in Appendix D.

In Part II, we retain the most critical environmental factors identified in Part I, including the clinic size, the presence of walk-ins, the presence of no-shows and the patients' unpunctuality. Service-time variability of patients, which proved to be less important in analysis Part II, is fixed at one level for both new and return patients ($CV_{Ret}= CV_{New}= 0.35$). Two additional factors are hypothesized to be important in AS design when patient classification is used: the percentage of new patients, and the ratio of the mean consultation time of new patients to the mean consultation time of return patients. Table XVI summarizes the experimental factors and their factor settings investigated in Part II of our analysis. Similar to in Part I, each setting is measured using the five performance criteria; IDLE, OVER, WAIT, LESS30, and FAIR.

Table XVI. Summary of Factors Explored in Part II

Decision Factor	**Symbol**	**Levels**	**Settings**
Appointment rule	RULE	3	IBFI, 2BEG, MBFI
Scheduling rule	SEQ	3	ALTER, NEW_BEG, RET_BEG
Interval-adjustment for patient class	ADJ	2	No Adj (0), With Adj (1)
		18 Total	

Environmental Factor	**Symbol**	**Levels**	**Settings**
Number of patients per clinic session	N	2	10, 20
Coefficient of variation for return patients	CV_{Ret}	1	0.35
Coefficient of variation for new patients	CV_{New}	1	0.35
Probability of walk-ins	P_W	2	0, 0.15
Probability of no-shows	P_N	2	0, 0.15
Mean unpunctuality of patients	*Unp*	2	-15, 0 min.
Percentage of new patients	*%New*	2	0.20, 0.40
Ratio of the mean consultation times of new patients to the mean consultation times of return patients	μ_{New}/μ_{Ret}	2	1.33, 2
		64 Total	

Results of the ANOVA procedure are shown in Table XVII for the entire set of dependent variables. We discuss the results only for the main effects of decision factors and environmental factors, and the two-way interactions with decision factors. In order to avoid repetition with Part I, the discussion mostly focuses on the new factors added in the second stage of our analysis, namely the decision factor, ADJ, and the environmental factors *%New*, and μ_{New}/μ_{Ret}.

5.2.1. Effects of Decision Factors

All decision factors, RULE, SEQ, and ADJ are significant at alpha 0.05 for the five performance measures tested (Table XVII). Among the three, the main effect of ADJ is the weakest, as indicated by the smaller F-values in ANOVA tables. Contrary to ANOVA results in Part I, the main effect of SEQ is smaller than that of RULE for all dependent variables. However, note that the inclusion of the third decision factor, ADJ, has resulted in a very powerful new interaction: SEQ*ADJ. When the main and interaction effects are evaluated combined, then the results support those seen in Part I of our analysis. Decisions regarding sequencing rules still explain a larger portion of variability in clinic performance than decisions regarding appointment rules.

Table XVII. ANOVA on Performance Measures - Part II

IDLE	DF	F-value	Sign.
Corrected Model	211	29436	0.000
Intercept	1	1694071	0.000
PN	1	3099040	0.000
PW	1	1319527	0.000
UNP	1	454206	0.000
µN/µR	1	176637	0.000
RULE	2	111635	0.000
N	1	92976	0.000
SEQ	2	70863	0.000
%NEW	1	65683	0.000
ADJ	1	15068	0.000
SEQ * ADJ	2	83746	0.000
SEQ * µN/µR	2	21709	0.000
SEQ * UNP	2	5282	0.000
SEQ * %NEW	2	3360	0.000
SEQ * RULE	4	1907	0.000
SEQ * PW	2	515	0.000
SEQ * N	2	137	0.000
SEQ * PN	2	87	0.000
RULE * UNP	2	9686	0.000
RULE * N	2	9538	0.000
RULE * µN/µR	2	1316	0.000
RULE * %NEW	2	727	0.000
RULE * PW	2	443	0.000
RULE * PN	2	97	0.000
RULE * ADJ	2	41	0.000
ADJ * µN/µR	1	9256	0.000
ADJ * %NEW	1	3453	0.000
ADJ * PW	1	544	0.000
ADJ * N	1	129	0.000
ADJ * UNP	1	28	0.000
ADJ * PN	1	9	0.000
PN * PW	1	155670	0.000
µN/µR * PN	1	20971	0.000
%NEW * µN/µR	1	20355	0.000
N * PW	1	9968	0.000
%NEW * PN	1	8298	0.000
µN/µR * PW	1	5940	0.000
%NEW * PW	1	2699	0.000
PW * UNP	1	1287	0.000
PN * UNP	1	688	0.000
N * PN	1	603	0.000
µN/µR * N	1	438	0.000
N * UNP	1	339	0.000
%NEW * UNP	1	334	0.000
µN/µR * UNP	1	333	0.000
%NEW * N	1	277	0.000
RULE * SEQ * ADJ	4	1271	0.000
R-SQUARE		0.982	

OVER	DF	F-value	Sign.
Corrected Model	211	22798	0.000
Intercept	1	1455869	0.000
PW	1	2350316	0.000
PN	1	911691	0.000
UNP	1	396622	0.000
µN/µR	1	135901	0.000
RULE	2	97482	0.000
N	1	74699	0.000
SEQ	2	63854	0.000
%NEW	1	52616	0.000
ADJ	1	13158	0.000
SEQ * ADJ	2	73129	0.000
SEQ * µN/µR	2	19187	0.000
SEQ * UNP	2	4612	0.000
SEQ * %NEW	2	2955	0.000
SEQ * RULE	4	1665	0.000
SEQ * PW	2	450	0.000
SEQ * N	2	100	0.000
SEQ * PN	2	19	0.000
RULE * UNP	2	8458	0.000
RULE * N	2	8329	0.000
RULE * µN/µR	2	1149	0.000
RULE * %NEW	2	635	0.000
RULE * PW	2	387	0.000
RULE * PN	2	85	0.000
RULE * ADJ	2	36	0.000
ADJ * µN/µR	1	8083	0.000
ADJ * %NEW	1	3015	0.000
ADJ * PW	1	475	0.000
ADJ * N	1	113	0.000
ADJ * UNP	1	24	0.000
ADJ * PN	1	8	0.005
PN * PW	1	135934	0.000
µN/µR * PW	1	20126	0.000
%NEW * µN/µR	1	16164	0.000
N * PW	1	11634	0.000
%NEW * PW	1	9241	0.000
µN/µR * PN	1	6563	0.000
%NEW * PN	1	3789	0.000
PW * UNP	1	1124	0.000
PN * UNP	1	601	0.000
N * PN	1	572	0.000
%NEW * N	1	371	0.000
N * UNP	1	296	0.000
%NEW * UNP	1	292	0.000
µN/µR * UNP	1	291	0.000
µN/µR * N	1	0	0.730*
RULE * SEQ * ADJ	4	1110	0.000
R-SQUARE		0.977	

* Insignificant at alpha 0.05.

Environmental Factors: N: number of patients per session; PN: probability of no-shows; PW: probability of walk-ins; UNP: unpunctuality of patients; %NEW: percentage of new patients; µN/µR: ratio of the mean consultation time of new patients to the mean consultation time of return patients

Decision Factors: SEQ: sequencing rule; RULE: appointment rule, ADJ: interval-adjustment

Table XVII. ANOVA on Performance Measures - Part II (Cont'ed)

WAIT	DF	F-value	Sign.
Corrected Model	211	24035	0.000
Intercept	1	16923	0.000
PW	1	20106	0.000
PN	1	75356	0.000
N	1	51836	0.000
μN/μR	1	28723	0.000
SEQ	2	18738	0.000
RULE	2	12588	0.000
%NEW	1	77036	0.000
ADJ	1	19861	0.000
UNP	1	8473	0.000
SEQ * ADJ	2	92322	0.000
SEQ * μN/μR	2	52545	0.000
SEQ * PN	2	18412	0.000
SEQ * %NEW	2	14385	0.000
SEQ * PW	2	9214	0.000
SEQ * UNP	2	2253	0.000
SEQ * RULE	4	2158	0.000
SEQ * N	2	1723	0.000
RULE * N	2	20558	0.000
RULE * UNP	2	10121	0.000
RULE * PN	2	8577	0.000
RULE * μN/μR	2	1582	0.000
RULE * PW	2	820	0.000
RULE * ADJ	2	325	0.000
RULE * %NEW	2	275	0.000
ADJ * μN/μR	1	12786	0.000
ADJ * %NEW	1	1225	0.000
ADJ * UNP	1	1131	0.000
ADJ * PN	1	953	0.000
ADJ * PW	1	451	0.000
ADJ * N	1	17	0.000
PN * PW	1	53300	0.000
%NEW * μN/μR	1	22898	0.000
μN/μR * PW	1	15315	0.000
μN/μR * PN	1	10161	0.000
%NEW * PW	1	6536	0.000
N * PW	1	3569	0.000
%NEW * PN	1	3277	0.000
PW * UNP	1	3179	0.000
μN/μR * N	1	1795	0.000
PN * UNP	1	1726	0.000
N * PN	1	1056	0.000
%NEW * UNP	1	319	0.000
N * UNP	1	255	0.000
%NEW * N	1	238	0.000
μN/μR * UNP	1	11	0.001
RULE * SEQ * ADJ	4	3528	0.000
R-SQUARE		0.978	

LESS30	DF	F-value	Sign.
Corrected Model	211	12819	0.000
Intercept	1	2852372	0.000
PW	1	554271	0.000
PN	1	377397	0.000
N	1	295149	0.000
μN/μR	1	269720	0.000
SEQ	2	138041	0.000
%NEW	1	62192	0.000
RULE	2	56512	0.000
ADJ	1	25996	0.000
UNP	1	12842	0.000
SEQ * ADJ	2	58140	0.000
SEQ * μN/μR	2	50030	0.000
SEQ * PN	2	17494	0.000
SEQ * %NEW	2	13604	0.000
SEQ * PW	2	11650	0.000
SEQ * N	2	6338	0.000
SEQ * RULE	4	4096	0.000
SEQ * UNP	2	1772	0.000
RULE * N	2	16075	0.000
RULE * PN	2	6440	0.000
RULE * μN/μR	2	4147	0.000
RULE * UNP	2	3787	0.000
RULE * PW	2	1196	0.000
RULE * ADJ	2	829	0.000
RULE * %NEW	2	349	0.000
ADJ * μN/μR	1	19012	0.000
ADJ * %NEW	1	2440	0.000
ADJ * PN	1	1946	0.000
ADJ * UNP	1	1009	0.000
ADJ * PW	1	168	0.000
ADJ * N	1	82	0.000
PN * PW	1	61261	0.000
%NEW * μN/μR	1	19558	0.000
μN/μR * PN	1	15599	0.000
μN/μR * PW	1	6747	0.000
μN/μR * N	1	6006	0.000
%NEW * PN	1	4606	0.000
N * PW	1	3400	0.000
N * PN	1	3295	0.000
%NEW * PW	1	1921	0.000
PW * UNP	1	919	0.000
%NEW * UNP	1	340	0.000
N * UNP	1	112	0.000
%NEW * N	1	83	0.000
PN * UNP	1	9	0.003
μN/μR * UNP	1	0	0.636*
RULE * SEQ * ADJ	4	3733	0.000
R-SQUARE		0.959	

* Insignificant at alpha 0.05.

Environmental Factors: N: number of patients per session; PN: probability of no-shows; PW: probability of walk-ins; UNP: unpunctuality of patients; %NEW: percentage of new patients; μN/μR: ratio of the mean consultation time of new patients to the mean consultation time of return patients

Decision Factors: SEQ: sequencing rule; RULE: appointment rule, ADJ: interval-adjustment

Table XVII. ANOVA on Performance Measures - Part II (Cont'ed)

FAIR	DF	F-value	Sign.
Corrected Model	211	9887	0.000
Intercept	1	61941	0.000
PW	1	60595	0.000
PN	1	47308	0.000
μN/μR	1	20665	0.000
N	1	17380	0.000
%NEW	1	85481	0.000
RULE	2	24875	0.000
ADJ	1	11185	0.000
SEQ	2	9096	0.000
UNP	1	7902	0.000
SEQ * ADJ	2	27070	0.000
SEQ * %NEW	2	9998	0.000
SEQ * UNP	2	6095	0.000
SEQ * μN/μR	2	5586	0.000
SEQ * N	2	2897	0.000
SEQ * PW	2	2191	0.000
SEQ * RULE	4	154	0.000
SEQ * PN	2	90	0.000
RULE * UNP	2	6978	0.000
RULE * N	2	6432	0.000
RULE * PW	2	1216	0.000
RULE * μN/μR	2	1116	0.000
RULE * PN	2	806	0.000
RULE * %NEW	2	39	0.000
RULE * ADJ	2	10	0.000
ADJ * μN/μR	1	13544	0.000
ADJ * %NEW	1	10547	0.000
ADJ * PW	1	8167	0.000
ADJ * N	1	839	0.000
ADJ * UNP	1	414	0.000
ADJ * PN	1	249	0.000
PN * PW	1	99068	0.000
%NEW * μN/μR	1	29520	0.000
%NEW * PN	1	5980	0.000
%NEW * PW	1	4410	0.000
μN/μR * PN	1	4225	0.000
PW * UNP	1	3918	0.000
N * UNP	1	2572	0.000
μN/μR * N	1	1754	0.000
μN/μR * PW	1	459	0.000
%NEW * UNP	1	407	0.000
%NEW * N	1	246	0.000
N * PW	1	231	0.000
N * PN	1	147	0.000
μN/μR * UNP	1	15	0.000
PN * UNP	1	4	0.044
RULE * SEQ * ADJ	4	4767	0.000
R-SQUARE		0.948	

* Insignificant at alpha 0.05.

Environmental Factors: N: number of patients per session; PN: probability of no-shows; PW: probability of walk-ins; UNP: unpunctuality of patients; %NEW: percentage of new patients; μN/μR: ratio of the mean consultation time of new patients to the mean consultation time of return patients

Decision Factors: SEQ: sequencing rule; RULE: appointment rule, ADJ: interval-adjustment

5.2.2. Interactions Between Decision Factors

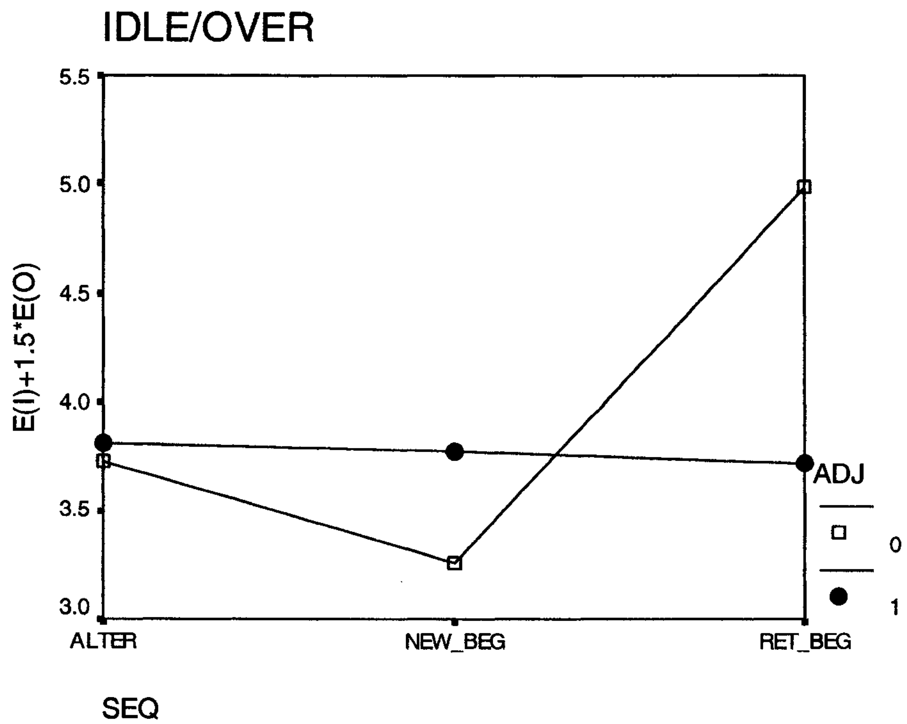
As can be seen from Table XVII, the SEQ*ADJ interaction is much more powerful compared to SEQ*RULE or RULE*ADJ, even though all three are significant at alpha 0.05. Next, we investigate interaction plots of SEQ*ADJ and RULE*ADJ.

(a) *SEQ*ADJ Interaction*

The cross effects observed in interaction plots of SEQ*ADJ, suggest that the effect of interval-adjustment is not uniform; but rather depends on the underlying sequencing rule (See Figure X). Some of the interesting results are discussed below:

- Among the three sequencing rules, the effect of interval-adjustment is the weakest on ALTER, which alternates new and return patients. This is also tested statistically by multiple t-tests, which show that the overall performance of ALTER-1 (with adjustment) is not significantly different than ALTER-0 (no adjustment) at alpha 0.05 for all dependent variables tested.
- When interval-adjustment is performed on RET_BEG, doctor's idle/overtime improves, and patients tend to wait longer. This is not surprising, as for the RET_BEG rule, interval-adjustment corresponds to shorter appointment slots in the beginning of the session, and as a result, congestion increases earlier in the session. The effect of interval-adjustment is exactly the opposite for the NEW_BEG rule. Longer appointment slots assigned in the beginning of the session, increases the risk of doctor's idle/overtime, yet decreases average patient waiting time.

Figure X. Two-Way Interactions Between Decision Factors: SEQ*ADJ



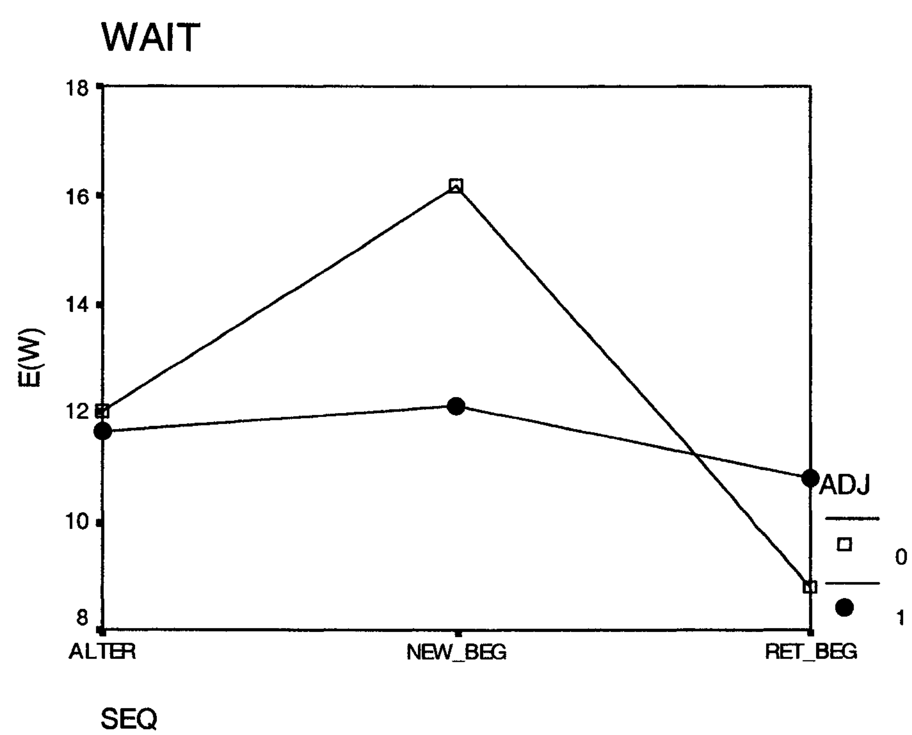
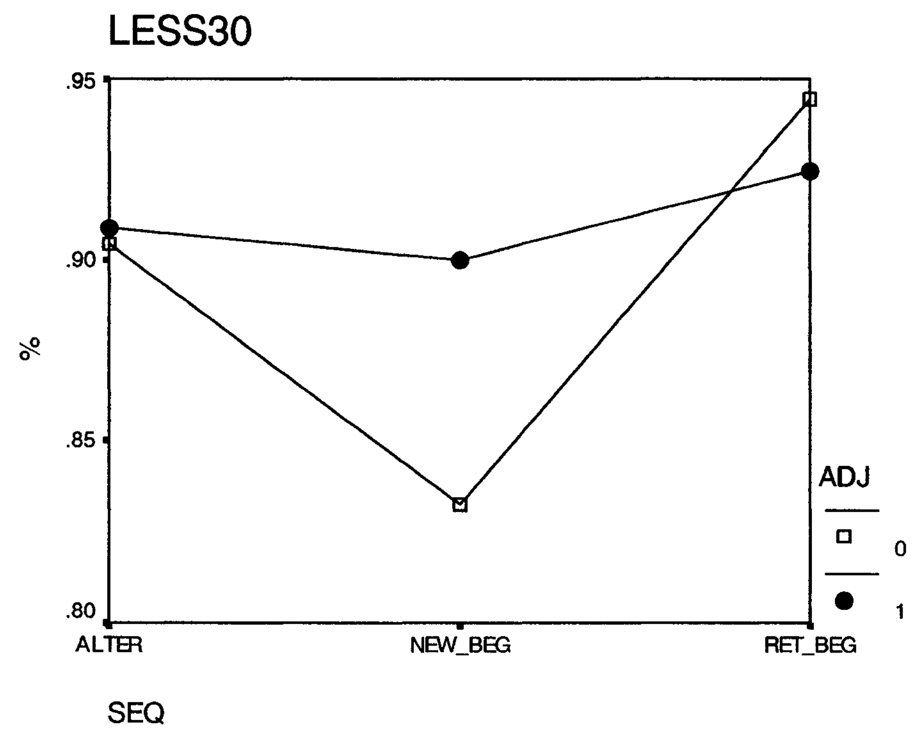
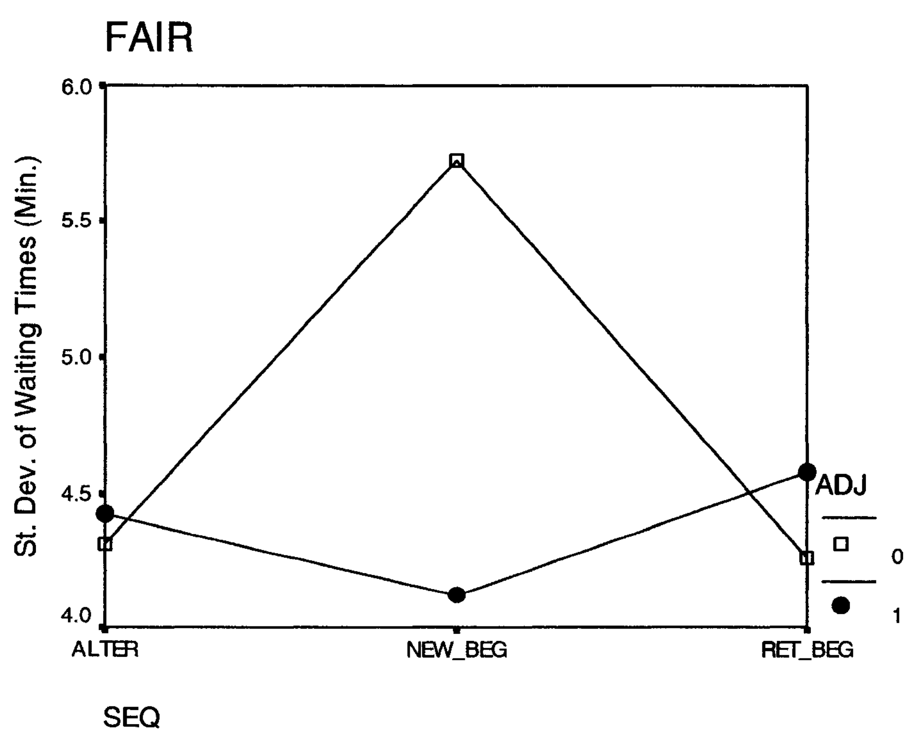


Figure X. Two-Way Interactions Between Decision Factors: SEQ*ADJ (Cont'ed)



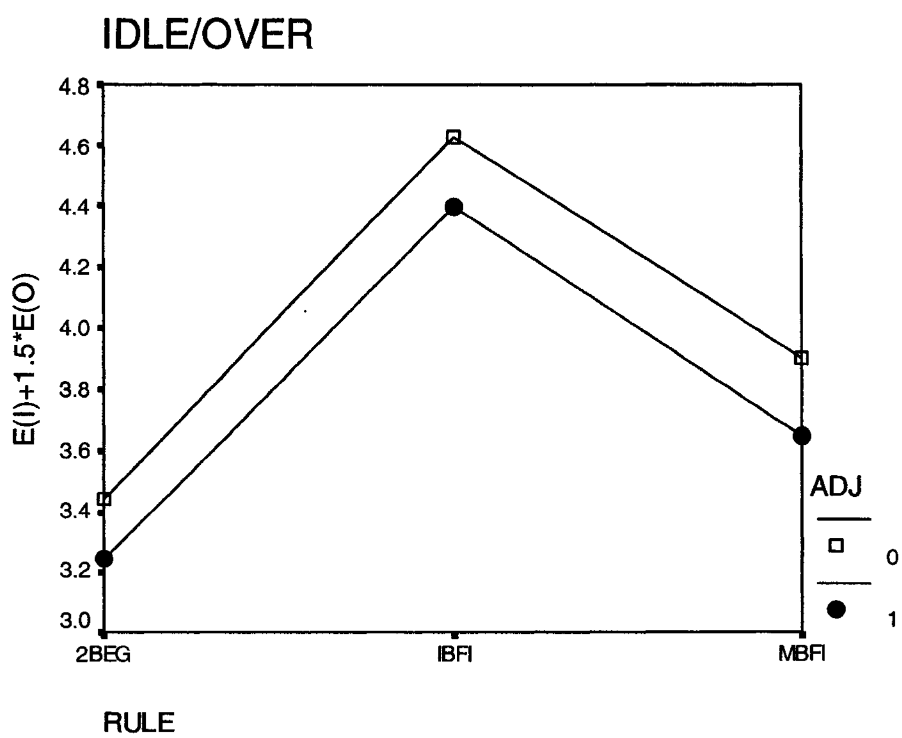


- All combinations of AS result in the percentage of patients seen within 30 minutes of their appointment times (LESS30) above threshold value 75 percent.
- NEW_BEG-1 is the most "fair" AS, leading to more uniform waiting times for patients. On the other hand, the same rule without interval-adjustment, NEW_BEG-0, performs the worst in terms of fairness. Interval-adjustment deteriorates FAIRness for the other sequencing rules, ALTER and RET_BEG.
- Overall, sequencing rules perform more uniformly when interval-adjustment is made for patient class (i.e. flatter plots for ADJ= 1, compared to ADJ= 0).

(b) *RULE*ADJ interaction*

ANOVA results indicated that the RULE*ADJ interaction was much weaker, compared to SEQ*ADJ, even though significant at alpha 0.05. An investigation of interaction plots reveals that the RULE*ADJ interaction is only an infatuating effect, and there are no cross effects. These results suggest that decisions regarding interval-adjustment can be made regardless of appointment rules. As illustrated in Figure XI, the effect of interval-adjustment is equally positive on all appointment rules for all performance measures.

Figure XI. Two-Way Interactions Between Decision Factors: RULE*ADJ



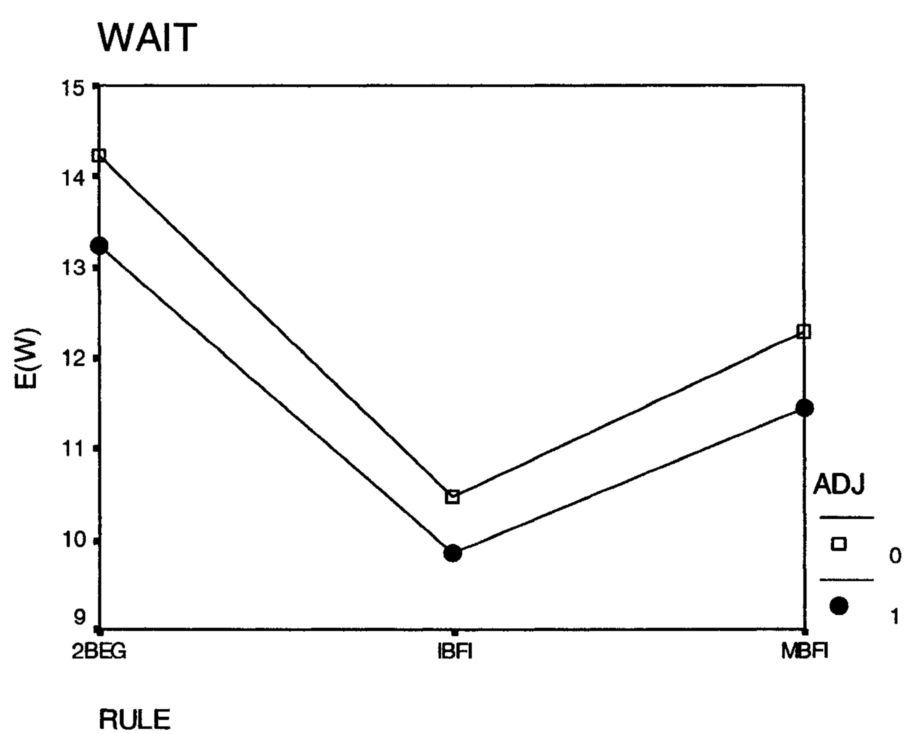
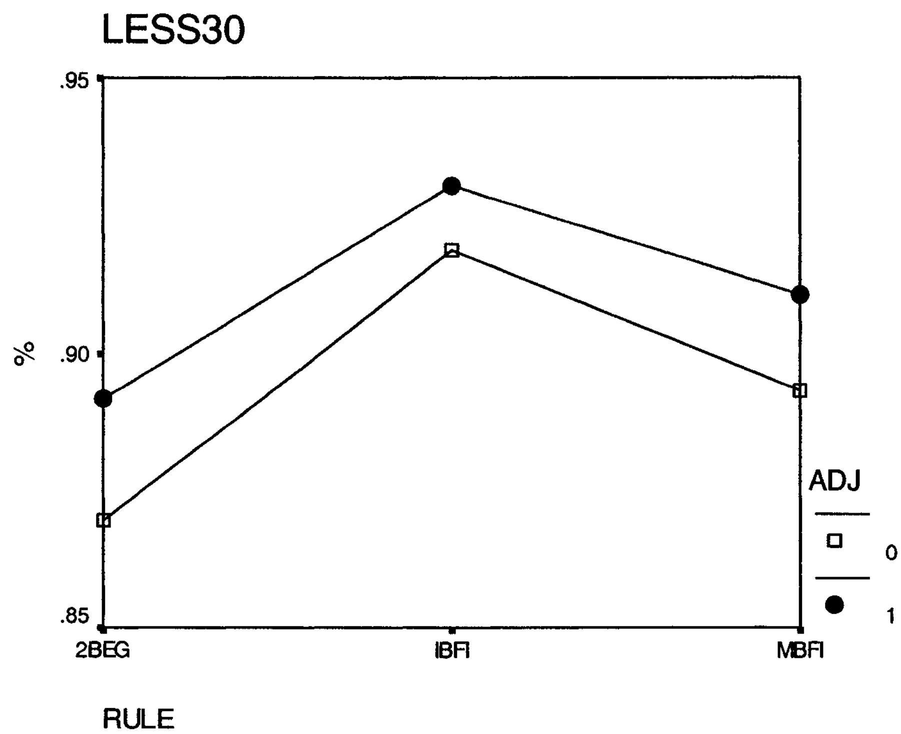
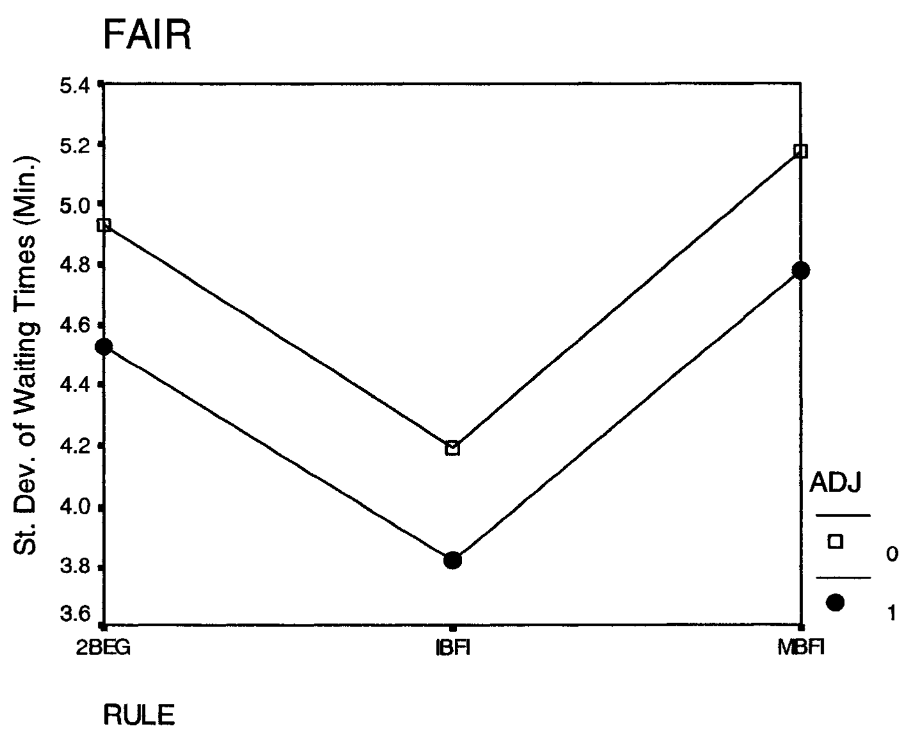


Figure XI. Two-Way Interactions Between Decision Factors: RULE*ADJ (Cont'ed)





5.2.3. Environmental Factor Effects

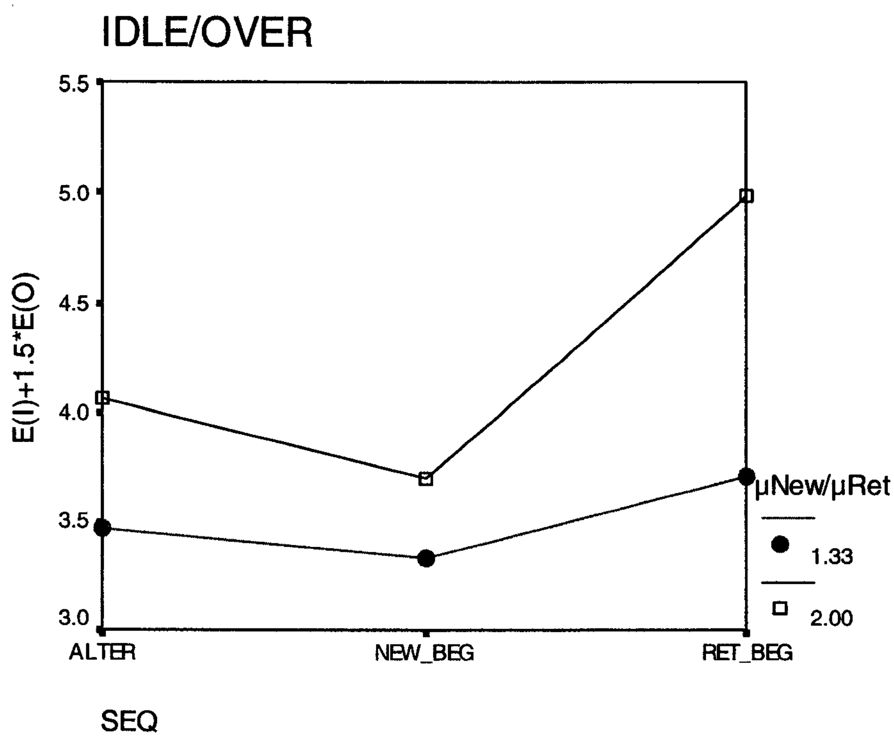
As can be observed from ANOVA results in Table XVII, the two new environmental factors μ_{New}/μ_{Ret} and *%New*, are both significant at alpha 0.05. Furthermore, for the particular factor levels tested, the change in the μ_{New}/μ_{Ret} ratio explains a larger proportion of variability in performance measures compared to the change in the percentage of new patients.

As μ_{New}/μ_{Ret} increases, doctor's idle/overtime increases, as well as the mean and the standard deviation of patients' waiting times. Same effect is observed when *%New* increases from 20 to 40 percent. Note that the underlying effect of increasing both factors is to increase service time variability. Therefore, it is no surprise that similar to high *CV,* high μ_{New}/μ_{Ret} ratio and high *%New* deteriorate clinic performance on all measures.

5.2.4. Interactions Between Environmental Factors and Decision Factors

As mentioned earlier, we focus our discussion on the interaction effects of the new environmental factors, *%New*, and μ_{New}/μ_{Ret}, and the new decision factor, ADJ. The F-values in ANOVA table, show very powerful two-way interaction effects for SEQ and ADJ with μ_{New}/μ_{Ret} and *%New*, in order of decreasing importance (See Table XVII). These results confirm our hypothesis that when patient classification is used (either for sequencing alone, or for both sequencing and interval adjustment), these environmental factors will have significant effects on ambulatory care performance. The interactions of μ_{New}/μ_{Ret} and *%New* with RULE are much weaker, even though significant at $\alpha = 0.05$. When we investigate the interaction plots in Figures XII-XIII, we see that all interactions are infatuating effects, and not cross effects. An important observation is that the dispersion among different approaches to patient classification becomes more pronounced as the μ_{New}/μ_{Ret} ratio and *%New* increase. This implies that there is more value to using patient classification in AS design, when the percentage of new patients is high, and/or when there is a greater difference between the consultation times of different classes of patients.

Figure XII. Two-Way Interactions of SEQ with μ_{New}/μ_{Ret}



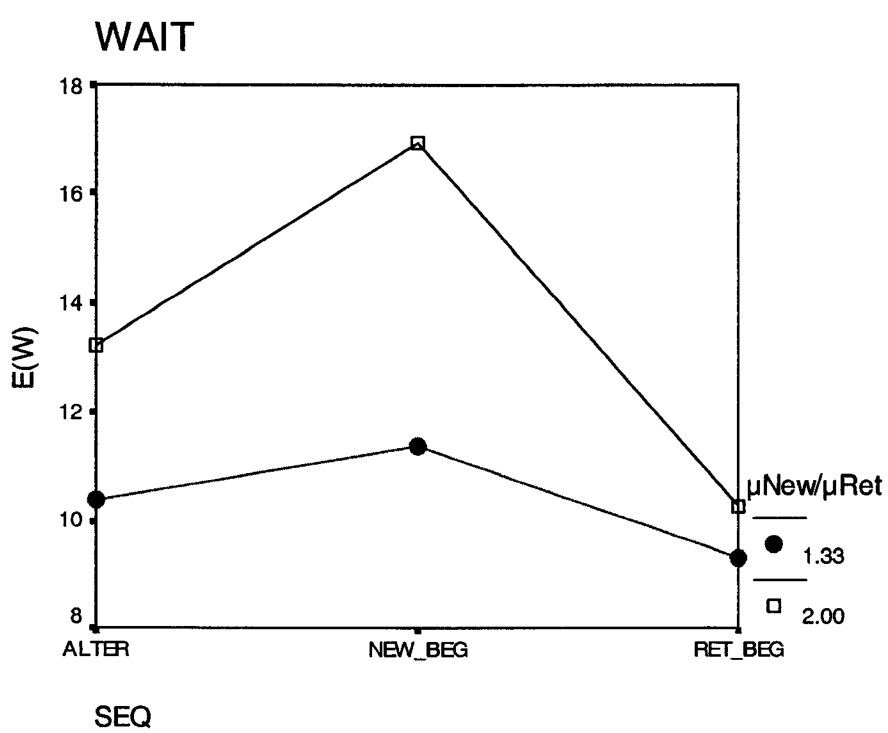
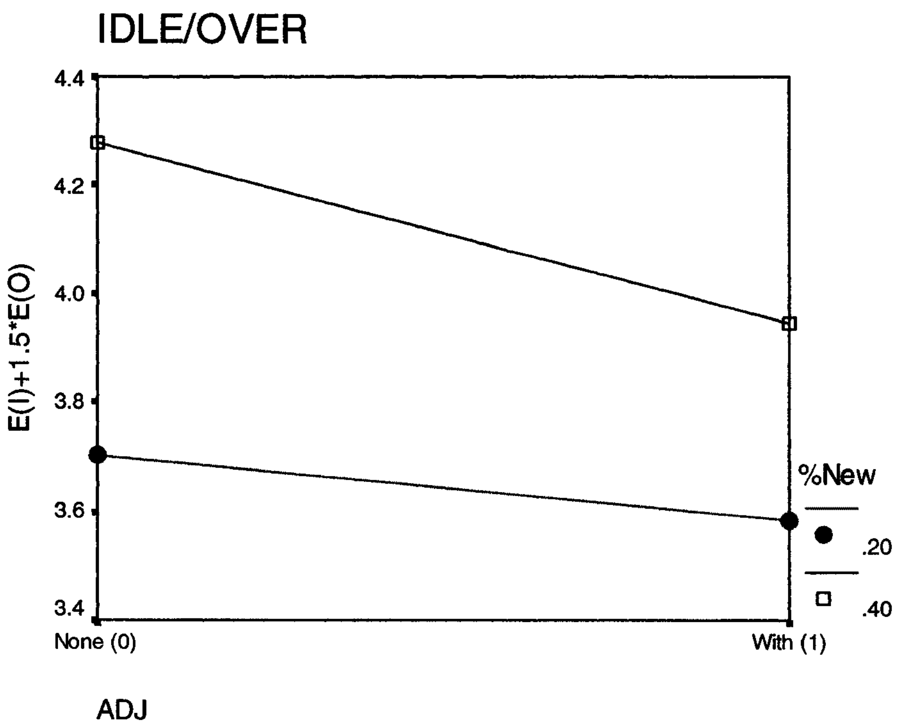
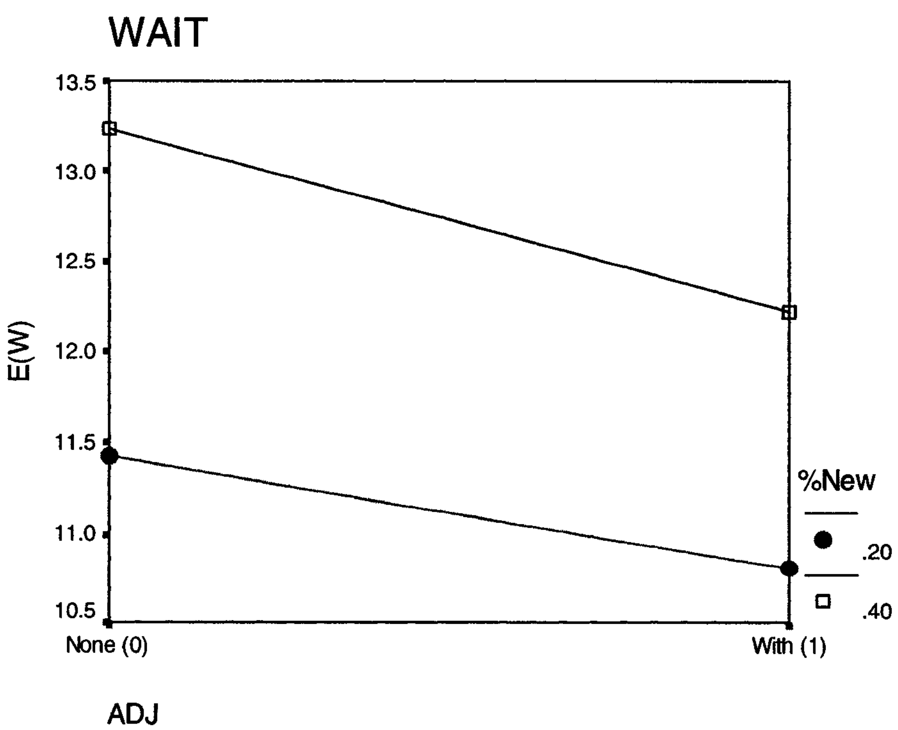


Figure XIII. Two-Way Interactions of ADJ with *%New*





5.2.5. Comparison of Appointment Systems

We continue our analysis by retaining the most prominent environmental factors in terms of their effects on patient classification (i.e. decision factors SEQ and ADJ). These include μ_{New}/μ_{Ret}, *%New*, *Unp* and P_N, based on comparison of F-values in Table XVII. As a result, the total number of environments is reduced to sixteen (2 μ_{New}/μ_{Ret} x 2 *%New* x 2 *Unp* x 2 P_N).

Tukey's honestly significant difference test is conducted for pairwise comparisons of appointment systems in each environment to detect significant differences at 95 percent confidence level. Tables XVIII and XIX provide rankings of AS for primary measures of IDLE/OVER and WAIT, respectively. The total number of AS is eighteen, resulting from combinations of three appointment rules, three sequencing rules, and two approaches to interval-adjustment. Homogeneous AS that are not significantly different at alpha 0.05 are joined by the same superscript. In Section 5.2.2, interaction plots revealed that among the three sequencing rules, the effect of interval-adjustment was the weakest on ALTER. This is also supported by Tukey's test results in Tables XVIII-XIX. In the majority of the environments, the performances of appointment systems that use ALTER sequencing without interval-adjustment (ALTER-0) are similar to those with interval-adjustment (ALTER-1). On the other hand, results show that interval-adjustment is effective for sequencing rules NEW_BEG and RET_BEG, leading to significant differences at alpha 0.05.

Table XVIII. Rankings of AS by IDLE/OVER - Part II [1]

ENV	# 1	ENV	# 2	ENV	# 3	ENV	# 4
μ_{New}/μ_{Ret}= 2	P_N= 0	μ_{New}/μ_{Ret}= 2	P_N= 0	μ_{New}/μ_{Ret}= 2	P_N= 0.15	μ_{New}/μ_{Ret}= 2	P_N= 0.15
%New= 0.40	Unp= 0	%New= 0.40	Unp= -15	%New= 0.40	Unp= 0	%New= 0.40	Unp= -15
2-NB-0	2.909 [a]	2-NB-0	2.566 [a]	2-NB-0	3.890 [a]	2-NB-0	3.480 [a]
M-NB-0	3.164 [ab]	M-NB-0	2.632 [a]	M-NB-0	4.205 [ab]	M-NB-0	3.589 [ab]
2-RB-1	3.430 [bc]	2-RB-1	2.668 [ab]	2-RB-1	4.530 [bc]	2-RB-1	3.692 [abc]
2-NB-1	3.562 [bc]	2-NB-1	2.763 [abc]	2-NB-1	4.726 [cd]	2-NB-1	3.807 [abcd]
2-AL-0	3.748 [cd]	2-AL-1	2.824 [abc]	I-NB-0	4.885 [cde]	2-AL-1	3.918
2-AL-1	3.774 [cd]	2-AL-0	2.837 [abc]	2-AL-1	4.950 [cdef]	I-NB-0	3.922
I-NB-0	3.810 [cde]	I-NB-0	2.885 [abc]	2-AL-0	5.000 [cdef]	2-AL-0	3.961 [bcde]
M-RB-1	4.067 [def]	M-RB-1	2.905 [abc]	M-RB-1	5.232 [defg]	M-RB-1	4.031 [bcde]
M-NB-1	4.208 [ef]	M-NB-1	3.027 [bc]	M-NB-1	5.379 [efg]	M-NB-1	4.127 [cde]
M-AL-1	4.327 [f]	M-AL-1	3.054 [c]	M-AL-1	5.503 [fg]	M-AL-1	4.196 [de]
M-AL-0	4.385 [f]	M-AL-0	3.104 [c]	M-AL-0	5.663 [g]	M-AL-0	4.297 [e]
I-RB-1	5.262 [g]	I-RB-1	3.595 [d]	I-NB-1	6.452 [h]	I-NB-1	4.772 [f]
I-AL-1	5.329 [g]	I-AL-1	3.640 [d]	I-AL-1	6.513 [h]	I-AL-1	4.842 [f]
I-NB-1	5.386 [g]	I-NB-1	3.679 [d]	I-RB-1	6.568 [hi]	I-RB-1	4.892 [f]
I-AL-0	5.483 [g]	I-AL-0	3.808 [de]	I-AL-0	6.852 [hi]	I-AL-0	5.140 [f]
2-RB-0	5.906	2-RB-0	4.027 [e]	2-RB-0	7.043 [i]	2-RB-0	5.195 [f]
M-RB-0	7.159	M-RB-0	4.988	M-RB-0	8.292	M-RB-0	6.123
I-RB-0	8.503	I-RB-0	6.203	I-RB-0	9.707	I-RB-0	7.352

ENV	# 5	ENV	# 6	ENV	# 7	ENV	# 8
μ_{New}/μ_{Ret}= 1.33	P_N= 0	μ_{New}/μ_{Ret}= 1.33	P_N= 0	μ_{New}/μ_{Ret}= 1.33	P_N= 0.15	μ_{New}/μ_{Ret}= 1.33	P_N= 0.15
%New= 0.40	Unp= 0	%New= 0.40	Unp= -15	%New= 0.40	Unp= 0	%New= 0.40	Unp= -15
2-NB-0	2.689	2-NB-0	2.140 [a]	2-NB-0	3.570 [a]	2-NB-0	2.898 [a]
2-RB-1	3.001 [a]	2-RB-1	2.203 [ab]	2-RB-1	3.900 [ab]	2-RB-1	3.004 [ab]
2-NB-1	3.051 [a]	2-NB-1	2.244 [ab]	2-NB-1	3.982 [b]	2-NB-1	3.056 [ab]
2-AL-0	3.084 [a]	2-AL-1	2.248 [ab]	M-NB-0	4.017 [b]	2-AL-1	3.073 [ab]
M-NB-0	3.088 [a]	2-AL-0	2.253 [ab]	2-AL-1	4.021 [b]	M-NB-0	3.080 [ab]
2-AL-1	3.095 [a]	M-NB-0	2.261 [ab]	2-AL-0	4.035 [b]	2-AL-0	3.086 [ab]
M-RB-1	3.564 [b]	M-RB-1	2.407 [abc]	M-RB-1	4.507 [c]	M-RB-1	3.277 [bc]
2-RB-0	3.612 [b]	2-RB-0	2.432 [bc]	M-NB-1	4.554 [c]	M-AL-1	3.315 [bc]
M-NB-1	3.613 [b]	M-AL-1	2.440 [bc]	M-AL-1	4.563 [c]	2-RB-0	3.316 [bc]
M-AL-1	3.618 [b]	M-AL-0	2.452 [bc]	2-RB-0	4.570 [c]	M-NB-1	3.326 [bc]
M-AL-0	3.627 [b]	M-NB-1	2.454 [bc]	M-AL-0	4.606 [c]	M-AL-0	3.344 [bc]
I-NB-0	3.799 [b]	I-NB-0	2.566 [cd]	I-NB-0	4.753 [c]	I-NB-0	3.469 [cd]
M-RB-0	4.358 [c]	M-RB-0	2.799 [de]	M-RB-0	5.338 [d]	M-RB-0	3.739 [de]
I-RB-1	4.445 [c]	I-RB-1	2.882 [e]	I-NB-1	5.399 [d]	I-NB-1	3.815 [e]
I-AL-1	4.468 [c]	I-AL-1	2.890 [e]	I-AL-1	5.429 [d]	I-AL-1	3.835 [e]
I-NB-1	4.475 [c]	I-NB-1	2.897 [e]	I-RB-1	5.443 [d]	I-RB-1	3.854 [e]
I-AL-0	4.486 [c]	I-AL-0	2.926 [e]	I-AL-0	5.503 [d]	I-AL-0	3.908 [e]
I-RB-0	5.336 [c]	I-RB-0	3.443	I-RB-0	6.334 [d]	I-RB-0	4.434

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

RULE-SEQ-ADJ I: IBFI, 2: 2BEG, M: MBFI AL: ALTER, NB: NEW_BEG, RB: RET_BEG
0: Without Interval-Adjustment, 1: With Interval-Adjustment

Table XVIII. Rankings of AS by IDLE/OVER - Part II[1] (Cont'ed)

ENV	# 9	ENV	# 10	ENV	# 11	ENV	# 12
μ_{New}/μ_{Ret}= 2 %New= 0.20	P_N= 0 Unp= 0	μ_{New}/μ_{Ret}= 2 %New= 0.20	P_N= 0 Unp= -15	μ_{New}/μ_{Ret}= 2 %New= 0.20	P_N= 0.15 Unp= 0	μ_{New}/μ_{Ret}= 2 %New= 0.20	P_N= 0.15 Unp= -15
2-NB-0	2.672 [a]	2-NB-0	2.241 [a]	2-NB-0	3.603 [a]	2-NB-0	3.064 [a]
M-NB-0	2.966 [ab]	2-AL-0	2.293 [ab]	2-AL-0	3.915 [ab]	2-AL-0	3.157 [ab]
2-AL-0	2.967 [ab]	2-RB-1	2.311 [abc]	M-NB-0	3.967 [abc]	M-NB-0	3.202 [abc]
2-RB-1	3.096 [bc]	M-NB-0	2.329 [abc]	2-RB-1	4.067 [bc]	2-RB-1	3.202 [abc]
2-NB-1	3.233 [bc]	2-NB-1	2.400 [abcd]	2-NB-1	4.222 [bcd]	2-NB-1	3.294 [abcd]
2-AL-1	3.311 [bce]	2-AL-1	2.412 [abcd]	2-AL-1	4.300 [bcd]	2-AL-1	3.323 [abcd]
M-AL-0	3.401 [ce]	M-AL-0	2.439 [abcd]	M-AL-0	4.376 [cde]	M-AL-0	3.349 [abcd]
I-NB-0	3.590 [ef]	M-RB-1	2.496 [abcd]	M-RB-1	4.606 [def]	M-RB-1	3.447 [bcd]
M-RB-1	3.621 [ef]	I-NB-0	2.588 [bcde]	I-NB-0	4.642 [def]	I-NB-0	3.546 [cde]
M-NB-1	3.769 [f]	M-NB-1	2.615 [cde]	M-NB-1	4.778 [ef]	M-NB-1	3.556 [cde]
M-AL-1	3.849 [f]	M-AL-1	2.640 [de]	M-AL-1	4.875 [fg]	M-AL-1	3.606 [de]
I-AL-0	4.197	I-AL-0	2.816 [ef]	I-AL-0	5.213 [g]	I-AL-0	3.811 [ef]
2-RB-0	4.625 [g]	2-RB-0	3.070 [fg]	I-NB-1	5.681 [h]	I-NB-1	4.080 [fg]
I-RB-1	4.661 [g]	I-RB-1	3.076 [fg]	I-AL-1	5.738 [h]	I-AL-1	4.126 [fg]
I-AL-1	4.726 [g]	I-AL-1	3.116 [g]	I-RB-1	5.779 [h]	I-RB-1	4.182 [g]
I-NB-1	4.747 [g]	I-NB-1	3.135 [g]	2-RB-0	5.860 [h]	2-RB-0	4.218 [g]
M-RB-0	5.538	M-RB-0	3.662	M-RB-0	6.805	M-RB-0	4.862
I-RB-0	6.632	I-RB-0	4.555	I-RB-0	7.936	I-RB-0	5.814

ENV	# 13	ENV	# 14	ENV	# 15	ENV	# 16
μ_{New}/μ_{Ret}= 1.33 %New= 0.20	P_N= 0 Unp= 0	μ_{New}/μ_{Ret}= 1.33 %New= 0.20	P_N= 0 Unp= -15	μ_{New}/μ_{Ret}= 1.33 %New= 0.20	P_N= 0.15 Unp= 0	μ_{New}/μ_{Ret}= 1.33 %New= 0.20	P_N= 0.15 Unp= -15
2-NB-0	2.670 [a]	2-NB-0	2.044 [a]	2-NB-0	3.546 [a]	2-NB-0	2.791 [a]
2-AL-0	2.812 [ab]	2-AL-0	2.070 [a]	2-AL-0	3.680 [ab]	2-AL-0	2.831 [ab]
2-RB-1	2.895 [ab]	2-RB-1	2.089 [a]	2-RB-1	3.762 [ab]	2-RB-1	2.856 [ab]
2-NB-1	2.938 [ab]	2-AL-1	2.111 [a]	2-NB-1	3.816 [abc]	2-NB-1	2.889 [ab]
2-AL-1	2.941 [ab]	2-NB-1	2.116 [a]	2-AL-1	3.822 [bc]	2-AL-1	2.891 [ab]
M-NB-0	3.088 [bc]	M-NB-0	2.181 [a]	M-NB-0	4.013 [bcd]	M-NB-0	2.985 [ab]
M-AL-0	3.287 [cd]	M-AL-0	2.233 [a]	M-AL-0	4.183 [cd]	M-AL-0	3.049 [ab]
2-RB-0	3.300 [cd]	2-RB-0	2.257 [ab]	2-RB-0	4.263 [d]	M-RB-1	3.092 [abc]
M-RB-1	3.408 [d]	M-RB-1	2.268 [ab]	M-RB-1	4.296 [d]	2-RB-0	3.107 [abc]
M-AL-1	3.458 [d]	M-AL-1	2.306 [ab]	M-NB-1	4.360 [d]	M-NB-1	3.136 [bc]
M-NB-1	3.460 [d]	M-NB-1	2.310 [ab]	M-AL-1	4.371 [d]	M-AL-1	3.143 [bc]
I-NB-0	3.792 [e]	I-NB-0	2.499 [bcd]	I-NB-0	4.745 [e]	I-NB-0	3.382 [cd]
M-RB-0	3.934 [e]	M-RB-0	2.539 [cd]	M-RB-0	4.922 [ef]	M-RB-0	3.452 [d]
I-AL-0	4.047 [ef]	I-AL-0	2.602 [d]	I-AL-0	4.967 [ef]	I-AL-0	3.490 [d]
I-RB-1	4.239 [f]	I-AL-1	2.711 [d]	I-NB-1	5.151 [f]	I-NB-1	3.595 [d]
I-AL-1	4.249 [f]	I-RB-1	2.712 [d]	I-AL-1	5.165 [f]	I-AL-1	3.607 [d]
I-NB-1	4.261 [f]	I-NB-1	2.720 [d]	I-RB-1	5.177 [f]	I-RB-1	3.630 [d]
I-RB-0	4.810	I-RB-0	3.074	I-RB-0	5.819	I-RB-0	4.054

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

<u>RULE-SEQ-ADJ</u> I: IBFI, 2: 2BEG, M: MBFI AL: ALTER, NB: NEW_BEG, RB: RET_BEG
0: Without Interval-Adjustment, 1: With Interval-Adjustment

Table XIX. Rankings of AS by WAIT - Part II[1]

ENV	# 1	ENV	# 2	ENV	# 3	ENV	# 4
μ_{New}/μ_{Ret}= 2	P_N= 0	μ_{New}/μ_{Ret}= 2	P_N= 0	μ_{New}/μ_{Ret}= 2	P_N= 0.15	μ_{New}/μ_{Ret}= 2	P_N= 0.15
%New= 0.40	Unp= 0	%New= 0.40	Unp= -15	%New= 0.40	Unp= 0	%New= 0.40	Unp= -15
I-RB-0	12.025 [a]	I-RB-0	9.433 [a]	I-RB-0	8.972 [a]	I-RB-0	6.943 [a]
M-RB-0	12.574 [a]	M-RB-0	10.630 [ab]	I-RB-1	9.218 [ab]	I-RB-1	7.551 [ab]
I-RB-1	12.951 [a]	I-RB-1	11.121 [b]	M-RB-0	9.381 [ab]	M-RB-0	7.778 [ab]
2-RB-0	13.057 [a]	2-RB-0	11.505 [bc]	2-RB-0	9.651 [abc]	2-RB-0	8.252 [bc]
I-AL-0	14.552 [b]	I-AL-0	12.595 [cd]	I-AL-0	10.036 [bc]	I-AL-0	8.276 [bc]
M-RB-1	15.229 [bc]	I-AL-1	13.086 [d]	I-AL-1	10.548 [cd]	I-AL-1	8.550 [bc]
I-AL-1	15.392 [bc]	M-RB-1	14.778 [e]	M-RB-1	10.664	I-NB-1	9.296 [cd]
M-AL-0	16.405 [cd]	I-NB-1	14.875 [e]	M-AL-0	11.221 [def]	M-RB-1	9.685 [de]
M-AL-1	16.967 [de]	M-AL-0	16.082 [ef]	M-AL-1	11.591 [efg]	M-AL-0	10.378 [ef]
2-RB-1	17.531 [def]	M-AL-1	16.320 [f]	I-NB-1	11.681 [fgh]	M-AL-1	10.521 [efg]
I-NB-1	17.697 [defg]	M-NB-1	17.650 [g]	M-NB-1	11.899 [fgh]	M-NB-1	10.943 [fg]
M-NB-1	18.123 [efg]	2-RB-1	18.146 [gh]	2-RB-1	12.030 [fgh]	2-RB-1	11.512 [gh]
2-AL-0	18.698 [fg]	2-AL-1	19.328 [hi]	2-AL-0	12.507 [ghi]	2-AL-1	12.128 [hi]
2-AL-1	18.944 [g]	2-AL-0	19.550 [i]	2-AL-1	12.688 [hi]	2-AL-0	12.298 [hi]
2-NB-1	20.445	2-NB-1	21.360	2-NB-1	13.173 [i]	2-NB-1	12.992 [i]
I-NB-0	24.274	I-NB-0	24.425	I-NB-0	15.430	I-NB-0	14.605
M-NB-0	27.577	M-NB-0	29.812	M-NB-0	17.422	M-NB-0	18.048
2-NB-0	31.913	2-NB-0	35.164	2-NB-0	20.164	2-NB-0	21.635

ENV	# 5	ENV	# 6	ENV	# 7	ENV	# 8
μ_{New}/μ_{Ret}= 1.33	P_N= 0	μ_{New}/μ_{Ret}= 1.33	P_N= 0	μ_{New}/μ_{Ret}= 1.33	P_N= 0.15	μ_{New}/μ_{Ret}= 1.33	P_N= 0.15
%New= 0.40	Unp= 0	%New= 0.40	Unp= -15	%New= 0.40	Unp= 0	%New= 0.40	Unp= -15
I-RB-0	10.299 [a]	I-RB-0	8.119	I-RB-0	7.304 [a]	I-RB-0	5.567 [a]
M-RB-0	11.012 [ab]	I-RB-1	9.473 [a]	I-RB-1	7.674 [ab]	I-RB-1	6.186 [ab]
I-RB-1	11.088 [ab]	I-AL-0	9.872 [a]	M-RB-0	7.747 [ab]	I-AL-0	6.324 [ab]
I-AL-0	11.549 [bc]	M-RB-0	9.938 [a]	I-AL-0	7.862 [abc]	I-AL-1	6.411 [ab]
I-AL-1	11.823 [bcd]	I-AL-1	10.040 [a]	I-AL-1	8.021 [abcd]	M-RB-0	6.630 [b]
2-RB-0	12.039 [bcde]	I-NB-1	10.603 [a]	2-RB-0	8.318 [bcde]	I-NB-1	6.666 [b]
M-RB-1	12.474 [cdef]	2-RB-0	11.791 [b]	I-NB-1	8.448 [bcde]	2-RB-0	7.610 [c]
I-NB-1	12.611 [cdef]	M-RB-1	12.224 [bc]	M-RB-1	8.517 [bcde]	M-RB-1	7.759 [c]
M-AL-0	12.774 [defg]	M-AL-0	12.605 [bc]	M-AL-0	8.603 [cde]	I-NB-0	7.831 [c]
M-AL-1	12.965 [efg]	M-AL-1	12.689 [bc]	M-AL-1	8.724 [defg]	M-AL-0	7.903 [c]
M-NB-1	13.442 [fgh]	I-NB-0	12.947 [bc]	M-NB-1	8.927 [efg]	M-AL-1	7.949 [c]
I-NB-0	13.817 [ghi]	M-NB-1	13.132 [c]	I-NB-0	9.041 [efgh]	M-NB-1	8.126 [c]
2-RB-1	14.157 [hij]	2-RB-1	14.962 [d]	2-RB-1	9.472 [ghi]	2-RB-1	9.235 [d]
2-AL-0	14.476 [hij]	2-AL-1	15.313 [d]	2-AL-0	9.542 [ghi]	2-AL-1	9.356 [d]
2-AL-1	14.553 [ijk]	2-AL-0	15.397 [de]	2-AL-1	9.592 [ghi]	2-AL-0	9.423 [d]
2-NB-1	15.065 [jk]	2-NB-1	15.965 [de]	2-NB-1	9.808 [hi]	2-NB-1	9.676 [d]
M-NB-0	15.545 [k]	M-NB-0	16.481 [e]	M-NB-0	10.036 [i]	M-NB-0	9.905 [d]
2-NB-0	17.989	2-NB-0	20.120	2-NB-0	11.450	2-NB-0	12.036

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

RULE-SEQ-ADJ I: IBFI, 2: 2BEG, M: MBFI AL: ALTER, NB: NEW_BEG, RB: RET_BEG
0: Without Interval-Adjustment, 1: With Interval-Adjustment

Table XIX. Rankings of AS by WAIT - Part II[1] (Cont'ed)

ENV	# 9	ENV	# 10	ENV	# 11	ENV	# 12
μ_{New}/μ_{Ret}= 2 %New= 0.20	P_N= 0 Unp= 0	μ_{New}/μ_{Ret}= 2 %New= 0.20	P_N= 0 Unp= -15	μ_{New}/μ_{Ret}= 2 %New= 0.20	P_N= 0.15 Unp= 0	μ_{New}/μ_{Ret}= 2 %New= 0.20	P_N= 0.15 Unp= -15
I-RB-0	9.120 ^{a}	I-RB-0	7.047	I-RB-0	6.770 ^{a}	I-RB-0	5.182
M-RB-0	9.740 ^{ab}	M-RB-0	8.525	M-RB-0	7.182 ^{ab}	M-RB-0	6.109 ^{a}
2-RB-0	10.526 ^{bc}	I-RB-1	9.723 ^{a}	2-RB-0	7.637 ^{b}	I-RB-1	6.522 ^{ab}
I-RB-1	11.353 ^{c}	2-RB-0	9.881 ^{a}	I-RB-1	8.009 ^{bc}	2-RB-0	6.856 ^{abc}
M-RB-1	13.131 ^{d}	I-AL-1	11.387 ^{b}	M-RB-1	9.170 ^{c}	I-AL-1	7.346 ^{bcd}
I-AL-1	13.486 ^{de}	I-NB-1	12.055 ^{bc}	I-AL-1	9.183 ^{c}	I-NB-1	7.547 ^{cde}
I-AL-0	14.236 ^{ef}	M-RB-1	12.812 ^{c}	I-NB-1	9.529 ^{c}	I-AL-0	8.238 ^{def}
I-NB-1	14.366 ^{ef}	I-AL-0	12.921 ^{c}	I-AL-0	9.662 ^{c}	M-RB-1	8.357 ^{ef}
M-AL-1	14.566 ^{ef}	M-AL-1	14.099 ^{d}	M-NB-1	9.822 ^{c}	M-AL-1	9.035 ^{fg}
2-RB-1	14.674 ^{f}	M-NB-1	14.530 ^{de}	M-AL-1	9.905 ^{c}	M-NB-1	9.080 ^{fg}
M-NB-1	14.812 ^{f}	2-RB-1	15.356 ^{ef}	2-RB-1	10.048 ^{cd}	2-RB-1	9.737 ^{ghi}
M-AL-0	16.123 ^{h}	M-AL-0	16.432 ^{fg}	M-AL-0	10.826 ^{de}	M-AL-0	10.338 ^{hi}
2-AL-1	16.536 ^{h}	2-AL-1	17.043 ^{g}	2-NB-1	10.872 ^{de}	I-NB-0	10.612 ^{hi}
2-NB-1	16.642 ^{h}	I-NB-0	17.466 ^{g}	I-NB-0	10.999 ^{e}	2-AL-1	10.649 ^{hi}
I-NB-0	17.036 ^{h}	2-NB-1	17.538 ^{g}	2-AL-1	11.041 ^{e}	2-NB-1	10.798 ^{i}
2-AL-0	18.375	2-AL-0	19.848	2-AL-0	12.143 ^{f}	2-AL-0	12.311
M-NB-0	19.722	M-NB-0	21.942	M-NB-0	12.632 ^{f}	M-NB-0	13.444
2-NB-0	23.067	2-NB-0	26.250	2-NB-0	14.699	2-NB-0	16.220

ENV	# 13	ENV	# 14	ENV	# 15	ENV	# 16
μ_{New}/μ_{Ret}= 1.33 %New= 0.20	P_N= 0 Unp= 0	μ_{New}/μ_{Ret}= 1.33 %New= 0.20	P_N= 0 Unp= -15	μ_{New}/μ_{Ret}= 1.33 %New= 0.20	P_N= 0.15 Unp= 0	μ_{New}/μ_{Ret}= 1.33 %New= 0.20	P_N= 0.15 Unp= -15
I-RB-0	9.643 ^{a}	I-RB-0	7.779	I-RB-0	6.767 ^{a}	I-RB-0	5.236 ^{a}
M-RB-0	10.422 ^{ab}	I-RB-1	9.007 ^{a}	M-RB-0	7.230 ^{ab}	I-RB-1	5.844 ^{ab}
I-RB-1	10.549 ^{abc}	I-AL-1	9.467 ^{a}	I-RB-1	7.262 ^{ab}	I-AL-1	6.031 ^{bc}
I-AL-1	11.194 ^{bcd}	I-NB-1	9.674 ^{a}	I-AL-1	7.591 ^{bc}	I-NB-1	6.085 ^{bc}
I-AL-0	11.365 ^{bcde}	M-RB-0	9.762 ^{a}	I-AL-0	7.691 ^{bcd}	I-AL-0	6.275 ^{bc}
I-NB-1	11.483 ^{cde}	I-AL-0	9.914 ^{a}	I-NB-1	7.707 ^{bcd}	M-RB-0	6.388 ^{bc}
2-RB-0	11.595 ^{def}	I-NB-0	10.949 ^{b}	I-NB-0	7.829 ^{bcd}	I-NB-0	6.733 ^{cd}
M-RB-1	11.745 ^{def}	M-RB-1	11.568 ^{bc}	2-RB-0	7.889 ^{bcd}	M-RB-1	7.316 ^{de}
I-NB-0	11.793 ^{def}	2-RB-0	11.822 ^{bc}	M-RB-1	7.990 ^{bcde}	M-AL-1	7.473 ^{de}
M-AL-1	12.173 ^{def}	M-AL-1	11.938 ^{bc}	M-AL-1	8.195 ^{cdef}	M-NB-1	7.489 ^{de}
M-NB-1	12.316 ^{efg}	M-NB-1	12.077 ^{c}	M-NB-1	8.215 ^{cdef}	2-RB-0	7.491 ^{de}
M-AL-0	12.627 ^{fg}	M-AL-0	12.669 ^{c}	M-AL-0	8.452 ^{defg}	M-AL-0	7.873 ^{ef}
2-RB-1	13.196 ^{gh}	2-RB-1	14.046 ^{d}	M-NB-0	8.720 ^{efgh}	M-NB-0	8.584 ^{fg}
M-NB-0	13.299 ^{gh}	M-NB-0	14.102 ^{d}	2-RB-1	8.808 ^{fgh}	2-RB-1	8.652 ^{gh}
2-AL-1	13.755 ^{hi}	2-AL-1	14.541 ^{de}	2-NB-1	9.027 ^{gh}	2-AL-1	8.870 ^{gh}
2-NB-1	13.805 ^{hi}	2-NB-1	14.677 ^{de}	2-AL-1	9.063 ^{gh}	2-NB-1	8.918 ^{gh}
2-AL-0	14.323 ^{i}	2-AL-0	15.465 ^{e}	2-AL-0	9.403 ^{hi}	2-AL-0	9.416 ^{h}
2-NB-0	15.408	2-NB-0	17.312	2-NB-0	9.919 ^{i}	2-NB-0	10.446

[1] AS joined by the same superscript are not significantly different at alpha 0.05.

RULE-SEQ-ADJ I: IBFI, 2: 2BEG, M: MBFI AL: ALTER, NB: NEW_BEG, RB: RET_BEG
0: Without Interval-Adjustment, 1: With Interval-Adjustment

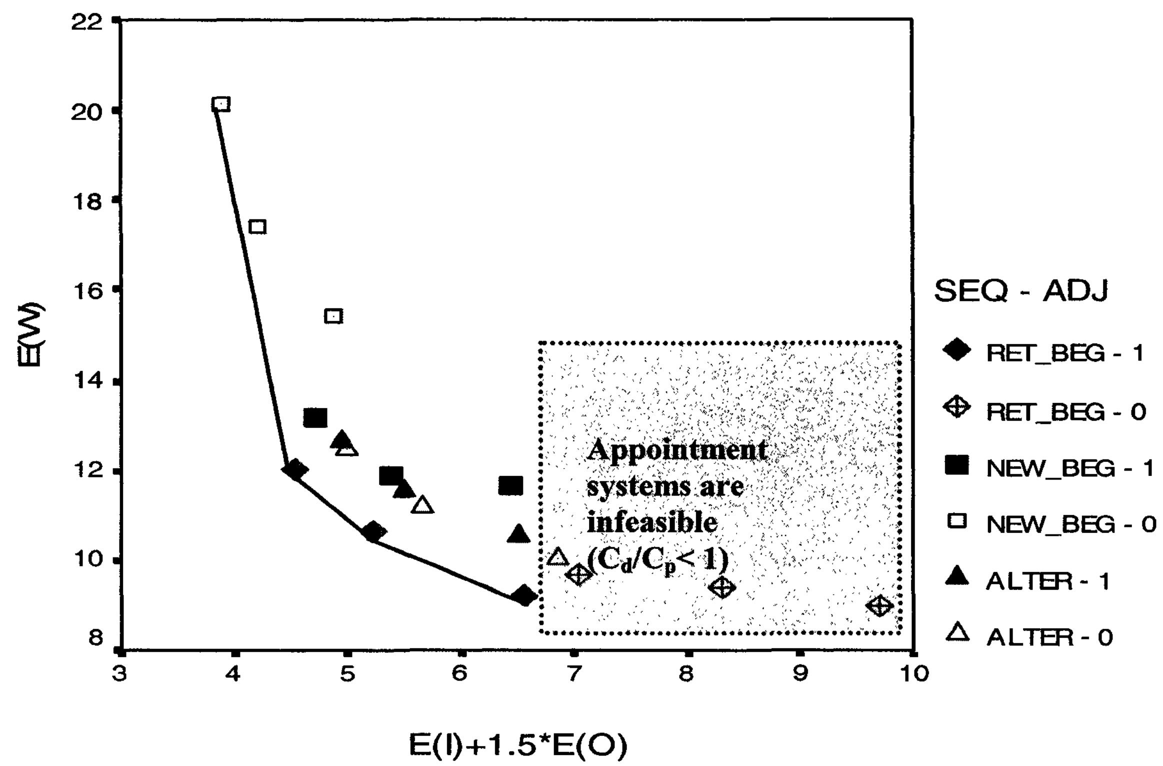
5.2.6. Efficient Frontiers

Efficient frontiers are plotted for all the sixteen environments. In Section 5.2.4, recall that all interaction effects between environmental and decision factors were infatuating effects, and not cross effects. As a result, the general shape of the efficient frontiers remains the same in all environments, with basically the same AS appearing as best performers.

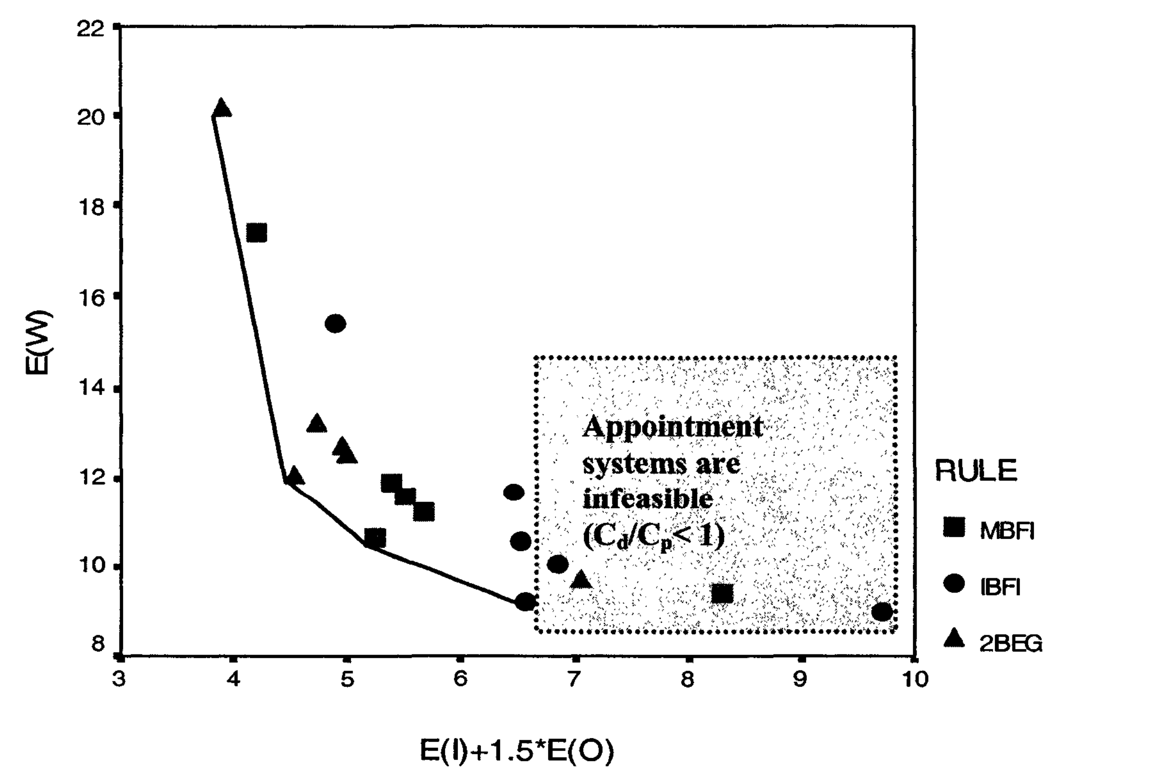
Figure XIV presents the efficient frontier for environment #3, which has high percentage of new patients, high no-show probability, high μ_{New}/μ_{Ret} ratio, and mean unpunctuality 0 minutes. The best AS are 2BEG/NEW_BEG-0, 2BEG/RET_BEG-1, MBFI/RET_BEG-1, IBFI/RET_BEG-1, and IBFI/RET_BEG-0, from left to right as they appear on the efficient frontier. The order is important, determining the shift in preference as the value assigned to C_d/C_p ratio declines. 2BEG/NEW_BEG-0 results in highest waiting time for patients and lowest idle/overtime for doctors, and thus it is preferred when doctor's time is highly valuable compared to patient's time. On the other extreme, IBFI/RET_BEG-0 leads to lowest patients' waiting time and highest doctor's idle/overtime, so it is appropriate for low C_d/C_p values. In the majority of the environments, including environment #3 illustrated in Figure XIV, IBFI/RET_BEG-0 becomes preferable when C_d/C_p value is less than 1. In practice, doctor's time is always valued higher than patients' time. For this reason, AS with C_d/C_p values less than 1, are considered infeasible, and they are excluded from the efficient frontiers.

Figure XIV. Efficient Frontier for Env #3: μ_{New}/μ_{Ref}=2, *%New*=0.4, P_N=0.15, *Unp*=0 min.

(a) Grouping by Patient Classification (Sequencing & Interval-Adjustment)



(b) Grouping by Appointment Rules



Similar to Part I, even though the same AS appear as best performers in all environments, the exact C_d/C_p values at which they should be chosen, varies widely from one environment to another. The best performing AS for each environment and their calculated C_d/C_p values are listed in Table XX.

Table XX. Best Appointment Systems and their Corresponding C_d/C_p Ratios - Part II

#	Environment	I-RB-0	I-RB-1	M-RB-1	2-RB-1	2-NB-0
1	μ_{New}/μ_{Ret}= 2, *%New*= 0.4, P_N= 0, *Unp*= 0	**<1**	1-2	2-3	4-27	>27
2	μ_{New}/μ_{Ret}= 2, *%New*= 0.4, P_N= 0, *Unp*= -15	**<1**	1-5	6-14	15-166	>166
3	μ_{New}/μ_{Ret}= 2, *%New*= 0.4, P_N= 0.15, *Unp*= 0	**<1**	1	1.1-2	3-12	>12
4	μ_{New}/μ_{Ret}= 2, *%New*= 0.4, P_N= 0.15, *Unp*= -15	**<1**	1-2	3-5	6-47	>47
5	μ_{New}/μ_{Ret}= 1.33, *%New*= 0.4, P_N= 0, *Unp*= 0	**<1**	1[c]	2-3[a]	4-12	>12
6	μ_{New}/μ_{Ret}= 1.33, *%New*= 0.4, P_N= 0, *Unp*= -15	1-2	3-5	6-13[a]	14-82	>82
7	μ_{New}/μ_{Ret}= 1.33, *%New*= 0.4, P_N= 0.15, *Unp*= 0	**<1**	**<1**	1[a]	2-5	>5
8	μ_{New}/μ_{Ret}= 1.33, *%New*= 0.4, P_N= 0.15, *Unp*= -15	1	2	3-5	6-26	>26
9	μ_{New}/μ_{Ret}= 2, *%New*= 0.2, P_N= 0, *Unp*= 0	**<1**	1-2[b]	3	4-19	>19
10	μ_{New}/μ_{Ret}= 2, *%New*= 0.2, P_N= 0, *Unp*= -15	1	2-5[c]	6-13	14-155	>155
11	μ_{New}/μ_{Ret}= 2, *%New*= 0.2, P_N= 0.15, *Unp*= 0	**<1**	1[b]	2	3-10	>10
12	μ_{New}/μ_{Ret}= 2, *%New*= 0.2, P_N= 0.15, *Unp*= -15	**<1**	1-2	3-5	6-46	>46
13	μ_{New}/μ_{Ret}= 1.33, *%New*= 0.2, P_N= 0, *Unp*= 0	**<1**	1[c]	2-3[a]	4-9	>9
14	μ_{New}/μ_{Ret}= 1.33, *%New*= 0.2, P_N= 0, *Unp*= -15	1-3	4-6[c]	7-13	14-72	>72
15	μ_{New}/μ_{Ret}= 1.33, *%New*= 0.2, P_N= 0.15, *Unp*= 0	**<1**	1[c]	1.5[a]	2-5	>5
16	μ_{New}/μ_{Ret}= 1.33, *%New*= 0.2, P_N= 0.15, *Unp*= -15	1	2	3-5	6-27	>27

RULE-SEQ-ADJ I: IBFI, 2: 2BEG, M: MBFI AL:ALTER, NB: NEW_BEG, RB: RET_BEG
0: Without Interval-Adjustment, 1: With Interval-Adjustment

[a] 2-RB-0 is not significantly different from M-RB-1 at alpha 0.05, and results are combined. Similarly, [b] 2-RB-0 is combined with I-RB-1, and [c] M-RB-0 is combined with I-RB-1.

In an effort to develop practical guidelines for managers who are responsible for designing appointment systems, we limit the C_d/C_p values to approximately 1, 10, and 100, corresponding to "low", "moderate", and "high" valuations of doctor's time relative to patient's time. This narrows down the range of alternatives in each environment, and makes it possible to summarize results a decision tree format (see Figure XV). In this evaluation, patient arrival pattern faced by the clinic is considered to represent an "easy" case, if patients almost always show up, and they usually arrive before their appointment times, corresponding to our simulated values (P_N= 0, *Unp*= -15 min.). A "difficult" patient arrival pattern is when no-shows are high, and patients are *relatively* more likely to be late (P_N= 0.15, *Unp*= 0 min.). Note that this study did not model *Unp*-values greater than zero, which would imply patients are usually late, based on empirical evidence that shows patients are early more often than late. "Moderate" cases correspond to the other two combinations of (*Unp* x P_N), where low no-show probability offsets the risk of idle time created by late patients, or vice versa, where early arrivals offset the risk of idle time created by high no-shows.

Figure XV. Decision Tree for Choosing the Best Appointment System

C_d/C_p Ratio	μ_{New}/μ_{Ret}	Patient Arrival Pattern	AS
Low	*High*	*Difficult*	I-RB-1
		Moderate	I-RB-1
		Easy	I-RB-1
	Low	*Difficult*	I-RB-1
		Moderate	I-RB-0
		Easy	I-RB-0
Moderate	*High*	*Difficult*	2-RB-1
		Moderate	2-RB-1
		Easy	M-RB-1
	Low	*Difficult*	2-NB-0
		Moderate	2-RB-1
		Easy	M-RB-1
High	*High*	*Difficult*	2-NB-0
		Moderate	2-NB-0
		Easy	2-RB-1
	Low	*Difficult*	2-NB-0
		Moderate	2-NB-0
		Easy	2-NB-0

Based on detailed investigation of efficient frontiers, Table XX, and Figure XV, some of the important findings are summarized below:

- Using interval-adjustment in AS design was successful in shifting the efficient frontiers down, improving patients' waiting times and doctor's idle plus overtime simultaneously.
- Only the RET_BEG sequencing rule remains on the efficient frontiers, when combined with interval-adjustment. NEW_BEG performs best without interval-adjustment, and the ALTER rule, with or without interval-adjustment, is completely eliminated from the efficient frontiers.
- When the C_d/C_p value is low, the best AS are the individual-block/fixed-interval rule combined with RET_BEG sequencing with or without interval-adjustment (I-RB-1 and I-RB-0). The latter, which is the extreme AS with the lowest idle/overtime, and highest patient waiting time, is only preferred when there is a smaller dispersion between the mean consultation times of new/return patients (low μ_{New}/μ_{Ret} ratio), and if the clinic does not face a difficult arrival pattern.
- When the C_d/C_p value is high, the combination of 2BEG rule with NEW_BEG sequencing without interval-adjustment, shortly referred to as 2-NB-0, is usually the best AS. However, 2-NB-0 should be avoided in clinics with high μ_{New}/μ_{Ret} ratio, if patient arrival pattern suggests early patients and low no-shows. This is probably because, congestion created by assigning long-consultation patients at the beginning of the session becomes "excessive" for high μ_{New}/μ_{Ret} ratios, especially when the arrival pattern itself already creates congestion. Under these circumstances, 2-RB-1 should be preferred, instead.

- In between these two extremes, for moderate C_d/C_p values, there are three best AS. The dominant choice is 2BEG combined with RET_BEG sequencing with interval-adjustment (2-RB-1). In clinics that face an "easy" arrival pattern with low no-shows and early patients, the same sequencing approach could be applied to "two-at-a-time" rule, which causes relatively less congestion (i.e. M-RB-1). Lastly, the combination of 2BEG with NEW_BEG-0, emerges as the best choice when the clinic faces a difficult arrival pattern with high no-shows and late patients, when the μ_{New}/μ_{Ret} ratio is small.

5.2.7. Summary of Part II

The results from the second part of our analysis indicated that a more comprehensive approach to patient classification, which combines sequencing and interval-adjustment, provides opportunities to improve ambulatory care performance. Some of the resulting new appointment systems were successful in reducing doctor's idle/overtime and patients' waiting times *simultaneously*.

The ANOVA results showed that the effect of interval-adjustment is different for different sequencing rules. For example, when interval-adjustment is performed on the RET_BEG, which puts short-consultation (return) patients earlier in the session, doctor's idle/overtime improves, and patients tend to wait longer. However, the opposite effect is observed when interval-adjustment is performed on the NEW_BEG sequencing rule. As for the ALTER rule, which alternates new and return patients, there is no significant benefit obtained from interval-adjustment. An investigation of the interactions between appointment rules and interval-adjustment, revealed extremely weak and purely infatuating effects. This suggests that decisions on interval-adjustment can be made regardless of appointment rules.

The two new factors added in the second part of our analysis - the percentage of new patients, and the ratio of the mean consultation times of new patients to the mean consultation times of return patients - both emerged as very powerful factors when patient classification was used in AS design. The effect of patient classification is amplified when there is a greater difference between the mean consultation times of different classes of patients, and/or when the percentage of new patients is high. In addition to these factors, the unpunctuality of patients and the probability of no-shows emerged as the most important factors affecting the relative performance of AS when patient classification was used.

Next, we compared eighteen appointment systems (combinations of three appointment rules, three sequencing rules, and two approaches to interval-adjustment) under sixteen environments, retaining the above-mentioned most critical environmental factors. The comparison of AS was done by plotting the efficient frontiers. An important finding was the disappearance of the ALTER sequencing rule (with or without interval-adjustment) *completely* from the efficient frontiers. Of the eighteen AS tested, only five remained as the best alternatives: 2BEG/NEW_BEG-0, 2BEG/RET_BEG-1, MBFI/RET_BEG-1, IBFI/RET_BEG-1, and IBFI/RET_BEG-0. In terms of patient classification, that leaves only three best choices: assigning new patients in the beginning of the session without interval-adjustment, and assigning return patients in the beginning with or without adjustment. Notice that RET_BEG was the only sequencing rule combined with interval-adjustment. And this combination (RET_BEG-1) had a very strong existence on the efficient frontiers, as it was the only approach combined with all three appointment rules.

On the efficient frontiers, even though the same patient-classification approaches were the best choices in all the environments, the final decision depended on the value decision-makers placed on patient's time relative to doctor's time, as well as the specific environment. As we move from NEW_BEG-0 to RET_BEG-1, and to RET_BEG-0, the appointment system increasingly favors patients' waiting times at the expense of doctors' idle/overtime. The same is also true as we move from 2BEG to multiple-block rule, and to individual-block rules. Therefore, when doctor's time is valued significantly higher than patient's time, the AS that combines 2BEG rule with NEW-BEG-0 provides maximum protection against the risk of doctor's staying idle or running overtime. However, this AS is not suited to clinics that face low no-shows and early patients when the μ_{New}/μ_{Ret} ratio is high (i.e. high variability in service times due to greater differences in consultation times of new/ret patients). When patient's time is assumed to be approximately as high as doctor's time, the individual-block rule combined with RET_BEG with or without interval-adjustment should be preferred. IBFI/RET_BEG-0 results in highest idle/overtime for patients, and thus should be avoided unless the risk is offset by early patients, low no-shows, and small μ_{New}/μ_{Ret} ratio. In between these two extremes, for moderate values given to doctor's time relative to patient's time, the two multiple-block approaches (2BEG and MBFI) combined with RET_BEG sequencing with interval adjustment, generally perform the best. For the majority of the environments, 2BEG/RB-1 should be chosen. MBFI/RB-1 is a better choice, when the clinic represents an environment with low no-shows and early patients. And, finally, when the clinic faces high no-shows and late patients, and has a small μ_{New}/μ_{Ret} ratio, 2BEG/NEW-BEG-0 is the best option for a moderated solution.

CHAPTER VI

CONCLUSIONS

6.1. SUMMARY OF FINDINGS AND PRACTICAL CONSIDERATIONS

This study addresses two approaches to using patient classification in appointment system design. The underlying assumption is that the patient population can be distinctly classified into groups based on consultation time length, such as new/return, or type of procedure. In the first approach, the scheduler uses extra information on patient class *only* for sequencing purposes. Various sequencing approaches were compared to the commonly-used approach of scheduling patients on a first-call-first-appointment basis (i.e. no patient classification used). In the second approach, the appointment intervals are matched to the consultation time characteristics of different patient classes, based on the underlying sequencing rule. Our results indicated that both approaches to using patient classification, either for sequencing alone or for sequencing and interval-adjustment, promise improvements in ambulatory care performance on the basis of patients' waiting times, doctor's idle time, and doctor's overtime. A number of secondary performance measures were used, including the percentage of patients seen within 30 minutes of their appointment times, and "fairness" measured by the uniformity of waiting times.

The results of ANOVA analysis of the main effects of the three decision factors in appointment system design showed that sequencing rules and interval-adjustment explain much of the variability in clinic performance. This means decisions that pertain to patient classification are far more important than the set of rules for determining the template for appointment slots. Given the fact that most of the research in the area, as well as most of the efforts in practice, have focused on finding the best appointment rules, these results suggest great opportunities to improve appointment systems by incorporating patient classification.

A major contribution of this study was to model the unpunctuality of patients and the presence of walk-ins, which helped us characterize a more realistic arrival pattern for patients compared to prior research. Among the eight environmental factors investigated, service-time variability of new and return patients proved to be least important, although statistically significant. Presence of walk-ins, no-shows, and unpunctual patients, clinic size, the ratio of the mean consultation times of new patients to the mean consultation times of return patients, and the percentage of new patients, all emerged as important factors affecting ambulatory care performance, in the order of decreasing significance. As one would expect, an increase in walk-ins reduces doctor's idle time, increases doctor's overtime, increases patients' waiting time, and reduces uniformity of patients' waiting times (fairness). The opposite effect is observed for no-shows; doctor's overtime, patients' waiting times and fairness improve, yet at the cost of higher idle time for the doctor. Environmental factor effects that deteriorate clinic performance on *all* performance measures *simultaneously*, include an increase in service time variability, an increase in the ratio of the mean consultation times of new patients to the mean consultation times of return patients, an increase in the percentage of new patients, increase in average lateness of patients, and a decrease in clinic size (a smaller clinic size implies longer mean consultation times, given that duration of clinic session is fixed).

Therefore, designing effective appointment systems becomes even more crucial under these circumstances.

Analysis showed that the interaction between sequencing rules and interval-adjustment for patient class is most important. The effect of interval-adjustment is different for different sequencing rules. When interval-adjustment is performed on the sequencing approach that puts short-consultation (return) patients earlier in the session, doctor's idle/overtime declines, and patients' waiting time increases. The opposite effect is observed when interval-adjustment is performed on the sequencing approach that puts long-consultation (new) patients earlier in the session. As for the sequencing rule that alternates new and return patients, the results showed no significant improvement obtained from interval-adjustment. Interaction plots showed only infatuating effects; the effect of sequencing was the same on all appointment rules, and the effect of appointment rules was the same on all sequencing approaches. Only the extent of improvement changed. Lastly, the interaction between appointment rules and interval-adjustment emerged as *extremely* weak, even though statistically significant, and interaction plots revealed purely infatuating effects. This result suggests that decisions on interval-adjustment can be made regardless of appointment rules.

Interactions between the decision factors and the environmental factors, provided some interesting insights which also have practical relevance. Clinic size (i.e. mean consultation time) was the most important environmental factor affecting the choice of appointment rules, followed by no-shows, walk-ins, and patient unpunctuality. Our results indicated that individual-block rules are more suited to clinics with shorter consultation times. Uncertainty increases with longer consultations, so it is not surprising that there is a higher pressure to reduce the risk of doctor's idle time through employing multiple-blocks in clinics/specialties with longer mean consultation times. This is especially true for environments where no-shows are high, walk-ins are low, and/or patients are late. Regarding decision factors that relate to patient classification (sequencing rules and interval-adjustment), the ratio of the mean consultation times of new patients to the mean consultation times of return patients, and the percentage of new patients resulted in the strongest two-way interaction effects, in the decreasing order of significance. Patient classification is more effective when there is a substantial difference between the mean consultation times of different classes, and/or when the percentage of new patients is high. The choice of sequencing approach is also largely affected by the arrival pattern of patients (e.g. unpunctuality of patients, no-shows and walk-ins). Sequencing rules which assign long-consultation (new) patients in the beginning of the session are more suited to clinic environments with low walk-ins, high no-shows, and/or late patients. Sequencing rules which assign short-consultation (return) patients in the beginning of the session are more preferable in exactly opposite environments. On the other hand, decisions related to patient classification can be made regardless of clinic size.

Limiting the environments to these most significant factors, various appointment systems (combinations of appointment rules, sequencing rules, and different approaches to interval-adjustment) were evaluated on the basis of mean doctor idle/overtime and mean patient waiting time. The final selection among the best appointment systems, requires that a decision is made in terms of trade-offs between the respective values placed on patient and physician time.

In the first part of our analysis, forty-two appointment systems (seven appointment rules and six sequencing rules) were compared. Among the appointment rules tested, the fixed-interval rules dominated the efficient frontiers. Specifically, these included the individual-block rule, multiple-block rule that calls patients two-at-a-time, and Bailey's rule that calls two patients at the beginning of the session, and the rest individually. Note that the "two-at-a-time" rule was regarded as a poor performer in earlier simulation studies. This difference in results is most likely due to the fact that those studies assumed patients were strictly punctual, and thus calling two patients to the same block created more severe consequences than would be the case when that assumption is relaxed. OFFSET rule, which increases appointment intervals toward the end of the session, was infeasible for the majority of the environments tested, resulting in highest doctor idle/overtime and lowest patient waiting time. This rule was preferred in few environments characterized by low no-shows and high walk-ins, yet only under the restrictive assumption that patient's time is almost as valuable as doctor's time. One of the goals of this study was to test the performance of rules with "dome-shaped" intervals. Our results indicated that these rules do not offer any significant improvements over their fixed-interval counterparts. In terms of sequencing rules, we were able to narrow down the range of options from six to three; assigning long-consultation (new) patients in the beginning of the session, assigning short-consultation (return) patients in the beginning of the session, and sequencing patients in alternating pattern. First-come-first-appointment approach, which is the base case that corresponds to 'no sequencing', performed strictly inferior in all the environments investigated. The other two sequencing approaches that assigned new (or return) patients in the beginning and in the end of the session generally performed worse. As a result, these best performing appointment rules and sequencing rules were retained for the second part of our analysis.

The results from the second part of our analysis indicated that, using interval-adjustment for patient class offers opportunities to further improve appointment systems. Some of the resulting new appointment systems *simultaneously* improved all the primary measures. Out of the eighteen appointment systems tested, the best alternatives were narrowed down to the following five, as they appear on the efficient frontiers from left to right. The order of appearance determines the shift in preference as the decision-maker increasingly favors patient time relative to doctor time. Interestingly, the alternating sequencing rule completely disappeared from the efficient frontiers.

1) Bailey's rule/long consultations in the beginning of the session/without interval-adjustment,
2) Bailey's rule/short consultations in the beginning of the session/with interval-adjustment,
3) Two-at-a time/short consultations in the beginning of the session/with interval-adjustment,
4) Individual-block/short consultations in the beginning of the session/with interval-adjustment, and
5) Individual-block/short consultations in the beginning of the session/without interval-adjustment.

An overall assessment of the performance of appointment systems under the environments addressed in the first and second part of our analysis leads to some general guidelines that will help practitioners choose the best appointment system depending on the specific objectives of the practice and the characteristics of the patient population. The choice of a specific appointment system presents three broad philosophies, which depend on the value placed on competing and conflicting objectives of minimizing patients' waiting times, and doctors' idle/overtime: (1) When doctor's time is valued significantly higher than patient's time, the most appealing appointment system is one that combines Bailey's rule with a sequencing approach that assigns long-consultation time patients in the beginning of the session without interval-adjustment for patient class. This suggestion becomes more compelling if and when the specific practice involves a patient population with late arrivals, high no-shows and/or low walk-ins, and smaller differences in consultation times of different patient classes, (2) When patient's time commands a high premium, the individual-block rule combined with a sequencing approach that places short-consultation patients in the beginning of the session is preferred, especially when the clinic faces early arrivals, low no-shows, and high walk-ins. Furthermore, the effect will be amplified if this sequencing approach is performed without interval-adjustment for patient class. However, these appointment systems are mostly recommended for clinics/specialties with short mean consultation times (large clinic size), and with small differences in consultation times of different patient classes, (3) When the objective is to strike a balance between the two conflicting objectives, a moderated solution may generally be achieved by combining Bailey's rule with the sequencing approach that assigns short-consultations in the beginning of the session with interval adjustment. If the arrival pattern presents a case with low no-shows, high walk-ins and early patients, then "two-at-time" rule with the same sequencing approach should be preferred. Lastly, a third option for a moderated solution is to combine Bailey's rule with the sequencing approach that assigns long-consultations in the beginning of the session without interval adjustment, when the clinic faces late patients, high no-shows and/or low walk-ins, and small difference in consultation times of different patient classes.

The results from this study provide guidance to managers responsible for designing a wide variety of ambulatory care delivery systems. Decision-makers responsible for group practices, radiology centers, and hospital clinics will be able to make explicit choices of appointment rules and patient classification approaches in light of readily observable characteristics of their patient populations. In other words, different clinics could have different appointment systems within the same organization. They will also be able to make the all-important trade-off between the respective value of patient time and physician time.

6.2. LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

There are various limitations of this study, which can be addressed by future research:

- Our study modeled single-server, single-phase systems. Although most practices indicate that doctors usually have their own list of patients, it is likely that some clinics use a common queue for multiple-doctors. Multi-phase models that depict the interaction of clinics with various supporting facilities (e.g. lab, x-ray, etc.) are more realistic than the commonly used single-level analysis of individual services. Another limitation of the model is the assumption of independence of clinic sessions. This may not always be true since some patients from a morning clinic may spill over to the afternoon session. We assumed that service times are i.i.d., yet in practice doctors may increase their service rates when they observe congestion in their waiting areas. In our simulation model, all walk-ins were admitted to the clinic, without any respect to the current congestion level in the clinic. In real life, the clerk may ask a non-urgent walk-in to return the next day, if the clinic is already congested. Lastly, we postulated that the doctor starts the session on time, and there are no gap times between two consecutive consultations. Future studies may model more realistic queuing environments by relaxing these modeling assumptions made in this study.

- Sensitivity analysis may be performed on all the parameters used in our simulation model, including those used for formulating appointment rules - such as multipliers, and early/delay parameters for "dome-shaped" rules. We assumed lognormal distribution for service times and normal distribution for the unpunctuality of patients. An analysis may be performed to test the sensitivity of results to different distributions, as well as to different mean and variances.

- One suggested research area is to address the restrictive nature of appointment systems that use patient classification, which emerged as best performers in this study. These appointment systems are less flexible than those that assign patients on a FCFA basis, as they limit the number of alternative appointment times that can be offered to patients. For example, in real application, there may be occasions when a type-X patient insists on a slot that is reserved for a type-Y patient. Furthermore, even if the ratios of different types of patients may be known over the long term, daily ratios may fluctuate such that the predetermined AS may fail to meet the demand or fulfill the quota of a particular day. In that case, the scheduler may assign a certain type of patient to a non-matching slot, defeating the goal of sequencing. Another option for the scheduler is to postpone that patient to another day. In the latter case, some near-future slots may be left vacant, and delays between the time of request and the appointment may increase. Future research may investigate if the best appointment systems identified in this study still perform well under these more realistic assumptions. Additional performance measures, such as delays between requests and appointments, and the percentage of patients that received the slots they requested, could be used to assess appointment systems.

- There is also a lack of rigorous research that investigates different approaches to refining an appointment system to accommodate walk-ins and no-shows. Literature suggests two general approaches. One is to overbook when no-shows exceed walk-ins, or to leave some slots open for the opposite case. A sub-decision is to choose which blocks to overbook or leave open. A second approach is to decrease/increase appointment intervals proportionally to the expected number of no-shows and walk-ins. These approaches may be tested on traditional rules to see if further improvements are possible through such explicit adjustments for no-shows/walk-ins. Studying the impact of walk-in seasonality (regular and emergency) may also be an interesting research area, which has a practical bearing on certain practices such as radiology (summer fractures and winter colds), pulmonary specialties (seasonal asthma and allergy agents), etc.

- Future research should continue to reveal the dynamics of environmental factors on appointment systems. For example, the presence of emergencies (pre-emptive or non-preemptive) is one environmental factor that is not rigorously investigated.

- The assumption of homogeneous waiting costs for all patients may be questionable, since late patients and walk-ins are more likely to tolerate long waits compared to scheduled patients. Thus, it may be more realistic to use different waiting costs for heterogeneous patients. Also, the common assumption of linearity between waiting cost and waiting time may not really capture the complexity of different patients' attitudes toward waiting.

- There are still appointment rules that have not been fully explored, such as variable-block, variable-interval rules. The biggest challenge for future research will be to find new appointment systems that will improve ambulatory care performance over a wide range of measures with minimum trade-offs.

- Despite many published work, the impact on outpatient clinics has been very limited. Findings of theoretical work should be developed into easy-to-use heuristics that can be used by practitioners who are responsible for designing appointment systems. Empirical research has a potential to contribute to appointment scheduling literature.

Appointment systems identified as best performers may be tested in real clinic environments. It may also be interesting to determine what are the most commonly used appointment systems in practice. The main goal of future research should be to close this gap between theory and practice.

Today, health care industry is facing an increasingly competitive marketplace. Patients' expectations are changing and surveys indicate that patients choose among providers by their ability to honor their appointment times as well as medical proficiency. Therefore, healthcare administrators cannot ignore the consequences of poorly designed appointment systems.

APPENDICES

```
* Clock-Minutes
*
***********************************************************************************************
*                               OUTPATIENT CLINIC MODEL-GPSS/H                                *
***********************************************************************************************
     SIMULATE
***********************************************************************************************
*                          Compiler Directives & Control Statements                           *
***********************************************************************************************
       UNLIST
*      UNLIST    CSECHO                                  do not print source code listing
       NOXREF                                            no listings of symbols and constants
       INTEGER   &I,&J,&K,&L,&M                          index
*
       INTEGER   &CVR,&CVN,&MPUN,&PWAL,&PNSHW            set environmental factor levels CV_Ret, CV_New, Unp, P_W, P_N
NEW    SYN       1                                       1= new patient
RET    SYN       0                                       0= return patient
EARLY  SYN       1                                       1= early patient
LATE   SYN       2                                       2= late patient
WALKIN SYN       3                                       3= walk-in patient
*
***********************************************************************************************
*      Ampervariables & Functions                                                             *
***********************************************************************************************
* Define Environmental Factors:
*------------------------------
       INTEGER        &N
       LET            &N=10                              [input] no of patients scheduled per session, N
*
       REAL           &PNEW,&MNEW,&MRET,&MSERV,&SL,&INITIAL
       LET            &PNEW=0.40                         [input] % of new patients, %New
       LET            &MNEW=30                           [input] mean service time for new patients, μ_New
       LET            &MRET=15                           [input] mean service time for return patients, μ_Ret
       LET            &MSERV=(&PNEW*&MNEW)+((1-&PNEW)*(&MRET))  calculate overall mean service time, μ
       LET            &SL=&MSERV*&N                      calculate official session length, T
       LET            &INITIAL=120                       initial period when doctor is unavailable is 120 min.
*
* Define Functions:
*------------------
NOSHOW FUNCTION       &PNSHW*0.15,S2,Z
0,LOW/0.15,HIGH                                          Low no-show probability: P_N= 0, High: P_N= 0.15
*
LOW    FUNCTION       RN2,D2                             If Low, patients are transferred to block "NSHOW" w/ P_N=0
0.0,NSHOW/1.0,SHOWUP                                     and to block "SHOWUP" with 100% probability
*
```

```
HIGH   FUNCTION       RN3,D2                            If High, patients are transferred to block "NSHOW" with
PN= 0.15
0.15,NSHOW/1.0,SHOWUP                                   and to block "SHOWUP" with 85% probability

NEWRET FUNCTION       RN4,D2                            assign new/return to walk-ins based on %New
0.400,NEW/1.0,RET
*
SERVICE FUNCTION      PF(NEW),E2                        lognormal service times (variance= CV*μ)^2
*                                                       - If return patient (PF=0), use relevant mean and CV
*                                                       - If new patient (PF=1), use relevant mean and CV
0,RVLNOR(5,&MRET,(&CVR*0.35*&CVR*0.35*&MRET*&MRET))/1,RVLNOR(6,&MNEW,(&CVN*0.35*&CVN*0.35*&MNEW*&MNEW))
*
CALWT  FUNCTION       PF(TYPE),E3                       calculate waiting times based on patient type
EARLY,PL(APT)/LATE,PL(ARR)/WALKIN,PL(ARR)               - If early patient: wait from time of appointment
*                                                       - late/walk-in: wait from time of arrival
* Define Appointment System:
*--------------------------
       CHAR*20        &AS                               label appointment system
ASR    MATRIX         ML,&N,2                           matrix savevalue contains the appt system simulated
*
* Appointment systems are read from four different files, when various CV-values are simulated for new and return
patients.
* This is because, appointment formula use standard deviation of service times, which change as CV-values change.
* Appointment times are read from row 1 in files, and sequencing rules are read from row 2 (1 for new, 0 for return
patients.
*
FILE11 FILEDEF        'ARule11seqAdj.txt'               read appt systems from FILE11, if CVRet=0.35, CVNew=0.35
FILE21 FILEDEF        'ARule21seqAdj.txt'               "  " from FILE21, CVRet=0.70, CVNew=0.35
FILE12 FILEDEF        'ARule12seqAdj.txt'               "  " from FILE12 , CVRet=0.35, CVNew=0.70
FILE22 FILEDEF        'ARule22seqAdj.txt'               "  " from FILE22 , CVRet=0.70, CVNew=0.70
*
CV11   BVARIABLE      &CVR'E'1*&CVN'E'1
CV21   BVARIABLE      &CVR'E'2*&CVN'E'1
CV12   BVARIABLE      &CVR'E'1*&CVN'E'2
CV22   BVARIABLE      &CVR'E'2*&CVN'E'2
*
* Define Matrix Savevalues:
*--------------------------
WAITNO MATRIX         ML,1,(&N*2)                       collect information on waiting times by appt no 1st,..etc.
*
CHECK  MATRIX         ML,11,(&N*2)                      collect various info to check patient flow in clinic
*
* Define Variables:
*------------------
NXTPAT    BVARIABLE   PL(ARR)'LE'XL(WLKARR)             either walk-in or earlier patient (if any)
```

```
PENALTY  FVARIABLE    (PL(ARR)-PL(APT))/&MSERV              penalize a late patient if lateness > μ
*
LESS30   BVARIABLE    (NOT(PF(TYPE)=3))*(PL(WAIT)'LE'30)    count scheduled patients (not walk-ins) who waited ≤30
min.
*
* Define Tables:
*---------------
WAIT   FUNCTION      PF(TYPE),S3,T                          tabulate mean waiting times by patient type
1,EARLY/2,LATE/3,WALKIN
*
EARLY  TABLE         PL(WAIT),0,10,&SL
LATE   TABLE         PL(WAIT),0,10,&SL
WALKIN TABLE         PL(WAIT),0,10,&SL
WAITA  TABLE         PL(WAIT),0,10,&SL                      tabulate mean waiting times for all patients
*
SERV   FUNCTION      PF(NEW),S2,T                           tabulate service times of new/return (for check purposes:)

0,STRET/1,STNEW
*-----------------------
STRET  TABLE         PL(SERV),0,1,&SL
STNEW  TABLE         PL(SERV),0,1,&SL
*
* Define Storage:
*----------------
*
       STORAGE       S(CLINIC),(&N*2)                       storage declaration: max 2N patients
*
* Define Performance Measures:
*----------------------------
       INTEGER       &DAY,&RUN
       LET           &DAY=100                               simulate # days
       LET           &RUN=100                               simulate # runs
*
* Collect performance measures for 100 days:
*
       REAL          &IDLE(100),&OVER(100)
       REAL          &AVGWT1(100),&AVGWT2(100),&AVGWTSCH(100),&AVGWTWLK(100),&AVGWTALL(100),&LSS30(100)
       REAL          &WTAPT1(100),&WTAPT2(100),&WTAPT3(100),&WTAPT4(100),&WTAPT5(100)
       REAL          &WTAPT6(100),&WTAPT7(100),&WTAPT8(100),&WTAPT9(100),&WTAPT10(100)
       REAL          &CEARLY(100),&CLATE(100),&CWALK(100)
*
* Averages across 100-days:
*
       REAL          &MIDLE(100),&MOVER(100),&MIDLEPP(100),&MOVERPP(100)
       REAL          &MAVGWT1(100),&MAVGWT2(100),&MAVGWTS(100),&MAVGWTW(100),&MAVGWTA(100),&MLSS30(100)
```

```
        REAL          &MCEARLY(100),&MCLATE(100),&MCWALK(100),&MCALL(100)
        REAL          &MWTAPT1(100),&MWTAPT2(100),&MWTAPT3(100),&MWTAPT4(100),&MWTAPT5(100)
        REAL          &MWTAPT6(100),&MWTAPT7(100),&MWTAPT8(100),&MWTAPT9(100),&MWTAPT10(100)
        REAL          &AVGAPT(100),&SUMSQ(100),&VARAPT(100)
*
* Overall averages across 100 runs: (100x100 simulated days)
*
        REAL          &PMIDLEPP,&PMOVERPP,&PMDOC1,&PMWTEAR,&PMWTLAT,&PMWTSCH,&PMWTWLK
        REAL          &PMWTALL,&PMLS30,&PMFAIR,&PMSEEN,&PMCEAR,&PMCLATE,&PMCWLK


*********************************************************************************************
*                                  Generate Scheduled Patients                              *
*********************************************************************************************
*
        GENERATE      ,,,&N,,9PL,5PF                       N patients generated at time zero
SCHD    ADVANCE       0
        BLET          PF(NO)=N(SCHD)                       assign patient no
        BLET          PL(QPLACE)=PF(NO)                    assign queue no (place in queue)
*
        BLET          PF(NEW)=ML(ASR,PF(NO),2)             assign patient class (new/ret)
        BLET          PL(APT)=ML(ASR,PF(NO),1)             assign appointment time
* Patient class and appointment times are determined by the appointment system, defined by matrix savevalue "ASR"
* (For FCFA sequencing, use FN(NEWRET) to randomly assign new/return patients).
* Next we assign unpunctuality, arrival time & service time to all patients at creation, including no-shows who are
* eventually terminated. This is done to achieve variance reduction by creating identical conditions when comparing
* clinics with different no-show probabilities.
*
AGAIN   BLET          XL(UNPUNC)=RVNORM(7,&MPUN*(-15),25)  assign unpunctuality based on normal dist (mean= 0 or -15
min)
        TEST L        XL(UNPUNC),-100,GOTO                 truncate if earliness > 100 min.
        TRANSFER      ,AGAIN
GOTO    BLET          PL(ARR)=PL(APT)+XL(UNPUNC)           assign arrival time based on unpunctuality
        BLET          PL(SERV)=FN(SERVICE)                 truncated lognormal service times at min. 2, max. 60
minutes
        TEST L        PL(SERV),2,TTT
        BLET          PL(SERV)=2
        TRANSFER      ,NXB
TTT     TEST G        PL(SERV),60,NXB
        BLET          PL(SERV)=60
NXB     TRANSFER      ,FN(FN(NOSHOW))                      route no-shows to block called "NSHOW" based on P_N
SHOWUP  ADVANCE       PL(ARR)                              patient arrivals
        TEST LE       PL(ARR),PL(APT),LATE1                determine if arriving patient is early/late
        BLET          PF(TYPE)=EARLY                       assign patient type 1= early/punctual patient
        TEST L        PL(ARR),&INITIAL,ENTR                for patients arriving before clinic opens
```

```
       PRIORITY       -PL(QPLACE)                          ...we need to specify priorities explicitly
*
* Unless explicit prioritization is done, the first-arrival seizes the doctor without joining the user chain.
* However, we want the earliest appointment, not the earliest arrival, to seize the doctor when the clinic opens.
*
       TRANSFER       ,ENTR
LATE1  BLET           PF(TYPE)=LATE                        assign patient type 2= late patient
       TEST GE        V(PENALTY),1,ENTR                    penalize late patient only if lateness ≥ avg service time
       BLET           PL(QPLACE)=PL(QPLACE)+V(PENALTY)     late patient loses place proportional to lateness
*
ENTR   ENTER          CLINIC                               enter clinic
       GATE FV        DOC                                  limit queue size statistics to time doctor is available
       LINK           LINE,(QPLACE)PL,SZ                   line up in ascending order of appointment time
SZ     SEIZE          DOC                                  capture doctor
       MARK           (SEIZ)PL                             mark start of service

       BLET           PL(WAIT)=PL(SEIZ)-FN(CALWT)          calculate waiting times separately for late/early/walk-in
*
       TEST L         PL(WAIT),0,ADV                       if wait time is negative, truncate to zero
       BLET           PL(WAIT)=0
*
ADV    ADVANCE        PL(SERV)                             advance by previously assigned service time
       RELEASE        DOC                                  release doctor
*
* Every time a patient is served, this deducts 1 from minimum wait assigned to walk-ins, stored in savevalue XFj for
* all walk-ins in line. This keeps track of when to squeeze in walk-ins. Walk-in is squeezed when XFj → 0 or below.
*
       SAVEVALUE      (&N+1)-(&N*2)-,1,XF                  j= 11,...,20 if N= 10 (walk-ins are assigned #'s 11 - 20)
*                                                          j= 21,...,40 if N= 20 (walk-ins are assigned #'s 21 - 40)
* Check if there is a walk-in in line. If yes, fetch its no and put that info into PF(WLKNO) of the scanning Xact.
*
       SCANUCH E      LINE,(TYPE)PF,3,(NO)PF,(WLKNO)PF,UNLK
*
* Test if XFj has reached zero/below (time to squeeze in that walk-in). If no, unlink the next patient in line.
*
       TEST LE        XF(PF(WLKNO)),0,UNLK
*
* Before unlinking the qualifying walk-in, make sure that there is no scheduled patient in line, who arrived earlier
* than that walk-in. If there is such a scheduled patient, see that one next (before the qualifying walk-in). Fi
* we need to check the arrival time of the qualifying walk-in and compare it with arrival times of patients in l:
*
       SCANUCH E      LINE,(NO)PF,PF(WLKNO),(ARR)PL,(WLKARR)PL save Arrival time of walk-in into PL(WLKARR)
       BLET           XL(WLKARR)=PL(WLKARR)                make that info public to use in BV(NXTPAT)
       UNLINK         LINE,SZ,1,BV(NXTPAT)                 unlink using rule BV(NXTPAT)
* BV(NXTPAT) unlinks a patient who has an arrival time ≤XL(WLKARR). This means the next patient to be seen is either
```

```
* the qualifying walk-in, or the scheduled patient who arrived earlier (if there is any). This way, it is ensured
* that no walk-in is served before an earlier-arriving scheduled patient.
*
       TRANSFER       ,LV                                 unlinking Xact leaves clinic
UNLK   UNLINK         LINE,SZ,1                           unlink next patient in line
LV     MARK           (ENDSER)PL                          end of service
       LEAVE          CLINIC                              patient leaves
       TABULATE       FN(WAIT)                            tabulate mean waiting times by patient type
(early/late/walk-in)
       TABULATE       FN(SERV)                            tabulate service times by patient class (new/return)
       TEST E         BV(LESS30),1,CHK                    keep track of # of scheduled patient with wait ≤ 30 min.
       SAVEVALUE      LESS30+,1,XH
*
* For check purposes, collect the following information on patient flow using matrix savevalue "CHECK"
* ------------------
CHK    BLET           ML(CHECK,1,PF(NO))=PL(QPLACE)       mark queue place of patient
       BLET           ML(CHECK,2,PF(NO))=PF(TYPE)         mark type of patient (early/late/walk-in)
       BLET           ML(CHECK,3,PF(NO))=PL(APT)          mark appointment time
       BLET           ML(CHECK,4,PF(NO))=PL(ARR)          mark arrival time
       BLET           ML(CHECK,5,PF(NO))=PL(SEIZ)         mark service start time
       BLET           ML(CHECK,6,PF(NO))=PL(SERV)         mark service time
       BLET           ML(CHECK,7,PF(NO))=PL(ENDSER)       mark service end time
       BLET           ML(CHECK,8,PF(NO))=PL(WAIT)         mark wait time
       BLET           ML(CHECK,9,PF(NO))=PF(NEW)          mark if new/ret
*
* Collect information on waiting times by appointment no using matrix savevalue "WAITNO". This will be used to
* calculate standard deviation of waiting times (FAIRness measure).
*
       BLET           ML(WAITNO,1,PF(NO))=PL(WAIT)        waiting times by appointment no
*
END    TERMINATE      0                                   exit the clinic
*
NSHOW  SAVEVALUE      NOSHOWS+,1,XH                       count no-shows
       BLET           ML(CHECK,3,PF(NO))=PL(APT)          mark appointment time
       TERMINATE      0                                   terminate Xact
*
```

```
**********************************************************************************************
*                                    Generate Walk-ins                                       *
**********************************************************************************************
*
     GENERATE   RVEXPO(8,(&SL/((&PWAL*0.15*&N)+0.00000001))),,,&N,,9PL,5PF      exponential inter-arrival times
*
* The reason for using an epsilon is to be able to automate switching PW values without the problem of division by
* zero. When Pw-> 0, IA-> infinity (no walk-ins).
*
        TEST E          FV(DOC)*SV(CLINIC),1,END            walk-ins are generated only when the clinic is open
MRKWLK  MARK            (ARR)PL                             mark arrival time of walk-ins
        BLET            PF(NO)=N(MRKWLK)+&N                 assign queue # beyond scheduled patients (j= 11,. for
*                                                           N=10)
        BLET            PL(QPLACE)=PF(NO)                   join queue behind scheduled patients
        BLET            PF(TYPE)=WALKIN                     assign patient type 3= walk-in patient
        BLET            PF(NEW)=FN(NEWRET)                  walk-ins are randomly assigned new/return based on %New
        BLET            PL(SERV)=FN(SERVICE)                lognormal service times truncated at min. 2 and max. 60
minutes
        TEST L          PL(SERV),2,NXT1
        BLET            PL(SERV)=2
        TRANSFER        ,NXT
NXT1    TEST G          PL(SERV),60,NXT
        BLET            PL(SERV)=60
NXT     TEST L          CH(LINE),3,LONGER                   assign minimum # of people walk-in will be forced to wait
*                                                           for based on queue length at arrival
        BLET            PF(MINWAIT)=3                       - if walk-in joins short line (<3), assign min. wait of 3
        TRANSFER        ,CNTDWN
LONGER  BLET            PF(MINWAIT)=CH(LINE)                - otherwise, assign a minimum wait = current q-length
*
CNTDWN  BLET            XF(PF(NO))=PF(MINWAIT)+F(DOC)       create a savevalue XFj for walk-ins in order to keep track
*                                                           of countdown on minwait (inc. current patient served).
* For check purposes:
*--------------------
        BLET            ML(CHECK,10,PF(NO))=CH(LINE)        mark LQ (current q-size) when walk-in arrives
        BLET            ML(CHECK,11,PF(NO))=PF(MINWAIT)     mark minwait assigned
        TRANSFER        ,ENTR                               walk-in enters the clinic
*
```

```
***************************************************************************************************
*                                  TIMER ROUTINE TO END SIMULATION                                *
***************************************************************************************************
* An artificial initial period is created before the official start time of the clinic to allow early patients in.
* Clinic closes doors either when the official time is over, or when the last patient leaves (if there is overtime).
* BRESET is used to reinitialize the model after the Initial Period so that statistics are limited to official
* session, only.
*
     GENERATE        0,0,0,1,,9PL,5PF                        create a Xact
     FUNAVAIL        DOC                                     doctor is unavailable at time 0
     ADVANCE         &INITIAL
     BRESET
     FAVAIL          DOC                                     doc is available after initial period is over
     ADVANCE         &SL                                     official session length
     SUNAVAIL        CLINIC                                  clinic closes doors after session is over
     GATE SE         CLINIC                                  ... if clinic is empty
*                                                            if not, simulation ends when last Xact leaves
*
* Collect Performance Measures for Day &I:
*-----------------------------------------
     BLET      &OVER(&I)=C1-&SL                              calculate overtime for day &I
     BLET      &IDLE(&I)=(C1*(1-(FR(DOC)/1000)))             calculate idle time     "
     BLET      &AVGWT1(&I)=TB(EARLY)                         avg. wait of early patients
     BLET      &AVGWT2(&I)=TB(LATE)                          avg. wait of late patients
     BLET      &AVGWTSCH(&I)=((&AVGWT1(&I)*TC(EARLY))+_
               (&AVGWT2(&I)*TC(LATE)))/(TC(EARLY)+TC(LATE))              avg. wait of scheduled patients
     BLET      &AVGWTWLK(&I)=TB(WALKIN)                                  avg. wait of walk-in patients
     BLET      &AVGWTALL(&I)=((&AVGWTSCH(&I)*(TC(EARLY)+TC(LATE)))+_
               (&AVGWTWLK(&I)*TC(WALKIN)))/(TC(EARLY)+TC(WALKIN)+TC(LATE))   avg. wait of all patients
     BLET      &LSS30(&I)=XH(LESS30)/(TC(EARLY)+TC(LATE))                % of scheduled patients wait
*                                                                        < 30 min.
     BLET      &WTAPT1(&I)=ML(CHECK,8,1)                                 waiting times by apt no.
     BLET      &WTAPT2(&I)=ML(CHECK,8,2)
     BLET      &WTAPT3(&I)=ML(CHECK,8,3)
     BLET      &WTAPT4(&I)=ML(CHECK,8,4)
     BLET      &WTAPT5(&I)=ML(CHECK,8,5)
     BLET      &WTAPT6(&I)=ML(CHECK,8,6)
     BLET      &WTAPT7(&I)=ML(CHECK,8,7)
     BLET      &WTAPT8(&I)=ML(CHECK,8,8)
     BLET      &WTAPT9(&I)=ML(CHECK,8,9)
     BLET      &WTAPT10(&I)=ML(CHECK,8,10)
*
     BLET      &CEARLY(&I)=TC(EARLY)                         count # of early patients
     BLET      &CLATE(&I)=TC(LATE)                           count # of late patients
```

```
     BLET      &CWALK(&I)=TC(WALKIN)                      count # of walk-ins
*
* Adjustment was needed for recognizing "null cells", which appear as "0" in the output file. For example, when
* measuring waiting times of late patients, "0" may indicate "zero" waiting time. However, "0" appears also when
* there are no late patients on a particular day. To differentiate the two possibilities, we need to keep track of
* days with no late patients, and take the overall average of waiting times of late patients accordingly.
     TEST E         &CEARLY(&I),0,GG1                     count days with no early patients
     SAVEVALUE      NULL1+,1,XH                           (adjustment needed for wait time of early patients)
GG1  TEST E         &CLATE(&I),0,GG2                       "    " no late patients
     SAVEVALUE      NULL2+,1,XH                           (adjustment needed for wait time of late  patients)
GG2  TEST E         &CWALK(&I),0,GG3                       "    " no walk-ins
     SAVEVALUE      NULL3+,1,XH                           (adjustment needed for wait time of walk-in patients)
*
* A similar problem occurs when measuring waiting time of patients by appointment number. For no-shows, the output
* shows "0" waiting time, however this is actually a "null" cell. A solution is to create an artificial value "777"
* assigned as waiting times of all patients initially. Thus when the value stays, it indicates a no-show case.
* The waiting times with "777" are counted using savevalue "EMPTY" and the overall average calculations are done
* accordingly.
*
GG3  TEST E         ML(WAITNO,1,1),777,EMP1
     SAVEVALUE      EMPTY1+,1,XH
EMP1 TEST E         ML(WAITNO,1,2),777,EMP2
     SAVEVALUE      EMPTY2+,1,XH
EMP2 TEST E         ML(WAITNO,1,3),777,EMP3
     SAVEVALUE      EMPTY3+,1,XH
EMP3 TEST E         ML(WAITNO,1,4),777,EMP4
     SAVEVALUE      EMPTY4+,1,XH
EMP4 TEST E         ML(WAITNO,1,5),777,EMP5
     SAVEVALUE      EMPTY5+,1,XH
EMP5 TEST E         ML(WAITNO,1,6),777,EMP6
     SAVEVALUE      EMPTY6+,1,XH
EMP6 TEST E         ML(WAITNO,1,7),777,EMP7
     SAVEVALUE      EMPTY7+,1,XH
EMP7 TEST E         ML(WAITNO,1,8),777,EMP8
     SAVEVALUE      EMPTY8+,1,XH
EMP8 TEST E         ML(WAITNO,1,9),777,EMP9
     SAVEVALUE      EMPTY9+,1,XH
EMP9 TEST E         ML(WAITNO,1,10),777,TERM
     SAVEVALUE      EMPTY10+,1,XH
*
TERM TERMINATE      1                                     End simulation
*
```

```
******************************************************************************************
*                              Customized Reporting Statements                           *
******************************************************************************************
*
     PUTPIC         LINES=1,FILE=REP1sq10
AS CVRET CVNEW UNP PW PN RUN IDLE OVER IdlePP OverPP W(ALL) W(EAR) W(LATE) W(SCHED) W(WALK) LESS30 FAIR #Seen
*
*    PUTPIC         LINES=1,FILE=REP1B10
*AS CVRET CVNEW UNP PW PN RUN FAIR Apt1 Apt2 Apt3 Apt4 Apt5 Apt6 Apt7 Apt8 Apt9 Apt10
*
     PUTPIC         LINES=1,FILE=SUMMsq10
AS CVRET CVNEW UNP PW PN IdlePP OverPP Doc1.5 WTALL Less30 Fair WTEar WTLat WTSch WTW1K #SEEN #EARLY #LATE #WLKIN
*
******************************************************************************************
*        Automate Runs for All Operating Environments (2 &PNSHW x 2 &PWAL x 2 &MPUN x 2 &CVN x 2 &CVR)        *
******************************************************************************************
     DO             &PNSHW=0,1,1              probability of no-shows= 0; then 0.15
     DO             &PWAL=0,1,1               probability of walk-ins= 0; then 0.15
     DO             &MPUN=0,1,1               mean unpunctuality= 0, then -15 min.
     DO             &CVN=1,2,1                CVNew= 0.35, then 0.70
     DO             &CVR=1,2,1                CVRet= 0.35, then 0.70
*
     CLOSE          FILE11                    appointment system files for reading appointment times and sequencing
     CLOSE          FILE21
     CLOSE          FILE12
     CLOSE          FILE22
*
     DO             &M=1,10                   loop for appointment systems - &M is the number of AS
     CLEAR
*
     IF             BV(CV11)=1                                        if CVRet=0.35, CVNew=0.35, then
     GETLIST        FILE=FILE11,(&AS,(ML$ASR(&K,&L),&K=1,&N),&L=1,2)  read appointment systems from FILE11
     ENDIF
     IF             BV(CV21)=1                                        if CVRet=0.70, CVNew=0.35, then FILE21
     GETLIST        FILE=FILE21,(&AS,(ML$ASR(&K,&L),&K=1,&N),&L=1,2)
     ENDIF
     IF             BV(CV12)=1                                        if CVRet=0.35, CVNew=0.70, then FILE12
     GETLIST        FILE=FILE12,(&AS,(ML$ASR(&K,&L),&K=1,&N),&L=1,2)
     ENDIF
     IF             BV(CV22)=1                                        if CVRet=0.70, CVNew=0.70, then FILE22
     GETLIST        FILE=FILE22,(&AS,(ML$ASR(&K,&L),&K=1,&N),&L=1,2)
     ENDIF
*
```

```
*********************************************************************************************
*                                    SET 100 RUNS                                           *
*********************************************************************************************
*
     DO         &J=1,&RUN                     loop for # of runs
     INITIAL    XH(NULL1),0/XH(NULL2),0/XH(NULL3),0
     INITIAL    XH(EMPTY1),0/XH(EMPTY2),0/XH(EMPTY3),0/XH(EMPTY4),0/XH(EMPTY5),0
     INITIAL    XH(EMPTY6),0/XH(EMPTY7),0/XH(EMPTY8),0/XH(EMPTY9),0/XH(EMPTY10),0

     PUTPIC     LINES=3,FILE=REP2A10,(&AS,&J)
     Report for AS    *********        Run-#*
      Day     IDLE     OVER     W(EAR) W(LATE) W(SCHED) W(WALK) W(ALL) LESS30
      ======  ======   ======   ====== ======  ======== ======= ====== ======
*
     PUTPIC     LINES=3,FILE=REP2B10,(&AS,&J)
     Report for AS    *********        Run-#*
      Day     Apt#1    Apt#2    Apt#3    Apt#4    Apt#5    Apt#6   Apt#7    Apt#8   Apt#9   Apt#10
      ======  ======   =====    =====    =====    =====    =====   =====    =====   =====   ======
*
*********************************************************************************************
*                                    SET 100 DAYS                                           *
*********************************************************************************************
*
     DO         &I=1,&DAY                                  loop for # of days
     CLEAR      ML(ASR),XH(NULL1),XH(NULL2),XH(NULL3),_
                XH(EMPTY1),XH(EMPTY2),XH(EMPTY3),XH(EMPTY4),XH(EMPTY5),XH(EMPTY6),XH(EMPTY7),XH(EMPTY8),_
                XH(EMPTY9),XH(EMPTY10)
     INITIAL    ML$WAITNO(1,1-(&N*2)),777                  this is to separate "null" entries from "0" waiting times
*
     RMULT      100000+(50*(100*(&J-1)+(&I-1))),_          set RN1 starting @100,000, increasing 50/day
                600000+(50*(100*(&J-1)+(&I-1))),_          set RN2 starting @600,000, increasing 50/day
                1100000+(50*(100*(&J-1)+(&I-1))),_         set RN3 starting @1,100,000, increasing 50/day
                1600000+(50*(100*(&J-1)+(&I-1))),_         set RN4 starting @1,600,000, increasing 50/day
                2100000+(50*(100*(&J-1)+(&I-1))),_         set RN5 starting @2,100,000, increasing 50/day
                2600000+(50*(100*(&J-1)+(&I-1))),_         set RN6 starting @2,600,000, increasing 50/day
                3100000+(50*(100*(&J-1)+(&I-1))),_         set RN7 starting @3,100,000, increasing 50/day
                3600000+(50*(100*(&J-1)+(&I-1)))           set RN8 starting @3,600,000, increasing 50/day
*
     START      1,NP
*
* Take Average of Performance Measures for each Run #J:
* ---------------------------------------------------
     LET        &MIDLE(&J)=&MIDLE(&J)+&IDLE(&I)
     LET        &MOVER(&J)=&MOVER(&J)+&OVER(&I)
     LET        &MAVGWT1(&J)=&MAVGWT1(&J)+&AVGWT1(&I)
```

```
        LET         &MAVGWT2(&J)=&MAVGWT2(&J)+&AVGWT2(&I)
        LET         &MAVGWTS(&J)=&MAVGWTS(&J)+&AVGWTSCH(&I)
        LET         &MAVGWTW(&J)=&MAVGWTW(&J)+&AVGWTWLK(&I)
        LET         &MAVGWTA(&J)=&MAVGWTA(&J)+&AVGWTALL(&I)
        LET         &MLSS30(&J)=&MLSS30(&J)+&LSS30(&I)
        LET         &MWTAPT1(&J)=&MWTAPT1(&J)+&WTAPT1(&I)
        LET         &MWTAPT2(&J)=&MWTAPT2(&J)+&WTAPT2(&I)
        LET         &MWTAPT3(&J)=&MWTAPT3(&J)+&WTAPT3(&I)
        LET         &MWTAPT4(&J)=&MWTAPT4(&J)+&WTAPT4(&I)
        LET         &MWTAPT5(&J)=&MWTAPT5(&J)+&WTAPT5(&I)
        LET         &MWTAPT6(&J)=&MWTAPT6(&J)+&WTAPT6(&I)
        LET         &MWTAPT7(&J)=&MWTAPT7(&J)+&WTAPT7(&I)
        LET         &MWTAPT8(&J)=&MWTAPT8(&J)+&WTAPT8(&I)
        LET         &MWTAPT9(&J)=&MWTAPT9(&J)+&WTAPT9(&I)
        LET         &MWTAPT10(&J)=&MWTAPT10(&J)+&WTAPT10(&I)
        LET         &MCEARLY(&J)=&MCEARLY(&J)+&CEARLY(&I)
        LET         &MCLATE(&J)=&MCLATE(&J)+&CLATE(&I)
        LET         &MCWALK(&J)=&MCWALK(&J)+&CWALK(&I)
*
```

```
**************************************************************************************************
*                                   REPORT / PERFORMANCE MEASURES PER DAY                        *
**************************************************************************************************
    PUTPIC        LINES=1,FILE=REP2A10,(&I,&IDLE(&I),&OVER(&I),&AVGWT1(&I),&AVGWT2(&I),&AVGWTSCH(&I),_
              &AVGWTWLK(&I),&AVGWTALL(&I),&LSS30(&I))
**** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.***
    PUTPIC        LINES=1,FILE=REP2B10,(&I,&WTAPT1(&I),&WTAPT2(&I),&WTAPT3(&I),_
              &WTAPT4(&I),&WTAPT5(&I),&WTAPT6(&I),&WTAPT7(&I),&WTAPT8(&I),&WTAPT9(&I),&WTAPT10(&I))
**** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.***
*
    PUTPIC        LINES=49,FILE=PFLOW,(&AS,&J,&I,_
                  ML(CHECK,1,1),ML(CHECK,1,2),ML(CHECK,1,3),ML(CHECK,1,4),ML(CHECK,1,5),_
                  ML(CHECK,2,1),ML(CHECK,2,2),ML(CHECK,2,3),ML(CHECK,2,4),ML(CHECK,2,5),_
                  ML(CHECK,3,1),ML(CHECK,3,2),ML(CHECK,3,3),ML(CHECK,3,4),ML(CHECK,3,5),_
                  ML(CHECK,4,1),ML(CHECK,4,2),ML(CHECK,4,3),ML(CHECK,4,4),ML(CHECK,4,5),_
                  ML(CHECK,5,1),ML(CHECK,5,2),ML(CHECK,5,3),ML(CHECK,5,4),ML(CHECK,5,5),_
                  ML(CHECK,9,1),ML(CHECK,9,2),ML(CHECK,9,3),ML(CHECK,9,4),ML(CHECK,9,5),_
                  ML(CHECK,6,1),ML(CHECK,6,2),ML(CHECK,6,3),ML(CHECK,6,4),ML(CHECK,6,5),_
                  ML(CHECK,7,1),ML(CHECK,7,2),ML(CHECK,7,3),ML(CHECK,7,4),ML(CHECK,7,5),_
                  ML(CHECK,8,1),ML(CHECK,8,2),ML(CHECK,8,3),ML(CHECK,8,4),ML(CHECK,8,5),_
                  ML(CHECK,1,6),ML(CHECK,1,7),ML(CHECK,1,8),ML(CHECK,1,9),ML(CHECK,1,10),_
                  ML(CHECK,2,6),ML(CHECK,2,7),ML(CHECK,2,8),ML(CHECK,2,9),ML(CHECK,2,10),_
                  ML(CHECK,3,6),ML(CHECK,3,7),ML(CHECK,3,8),ML(CHECK,3,9),ML(CHECK,3,10),_
                  ML(CHECK,4,6),ML(CHECK,4,7),ML(CHECK,4,8),ML(CHECK,4,9),ML(CHECK,4,10),_
                  ML(CHECK,5,6),ML(CHECK,5,7),ML(CHECK,5,8),ML(CHECK,5,9),ML(CHECK,5,10),_
                  ML(CHECK,9,6),ML(CHECK,9,7),ML(CHECK,9,8),ML(CHECK,9,9),ML(CHECK,9,10),_
                  ML(CHECK,6,6),ML(CHECK,6,7),ML(CHECK,6,8),ML(CHECK,6,9),ML(CHECK,6,10),_
                  ML(CHECK,7,6),ML(CHECK,7,7),ML(CHECK,7,8),ML(CHECK,7,9),ML(CHECK,7,10),_
                  ML(CHECK,8,6),ML(CHECK,8,7),ML(CHECK,8,8),ML(CHECK,8,9),ML(CHECK,8,10),_
                  ML(CHECK,4,11),ML(CHECK,4,12),ML(CHECK,4,13),ML(CHECK,4,14),ML(CHECK,4,15),_
                  ML(CHECK,5,11),ML(CHECK,5,12),ML(CHECK,5,13),ML(CHECK,5,14),ML(CHECK,5,15),_
                  ML(CHECK,9,11),ML(CHECK,9,12),ML(CHECK,9,13),ML(CHECK,9,14),ML(CHECK,9,15),_
                  ML(CHECK,6,11),ML(CHECK,6,12),ML(CHECK,6,13),ML(CHECK,6,14),ML(CHECK,6,15),_
                  ML(CHECK,7,11),ML(CHECK,7,12),ML(CHECK,7,13),ML(CHECK,7,14),ML(CHECK,7,15),_
                  ML(CHECK,8,11),ML(CHECK,8,12),ML(CHECK,8,13),ML(CHECK,8,14),ML(CHECK,8,15),_
                  ML(CHECK,10,11),ML(CHECK,10,12),ML(CHECK,10,13),ML(CHECK,10,14),ML(CHECK,10,15),_
                  ML(CHECK,11,11),ML(CHECK,11,12),ML(CHECK,11,13),ML(CHECK,11,14),ML(CHECK,11,15),_
                  ML(CHECK,4,16),ML(CHECK,4,17),ML(CHECK,4,18),ML(CHECK,4,19),ML(CHECK,4,20),_
                  ML(CHECK,5,16),ML(CHECK,5,17),ML(CHECK,5,18),ML(CHECK,5,19),ML(CHECK,5,20),_
                  ML(CHECK,9,16),ML(CHECK,9,17),ML(CHECK,9,18),ML(CHECK,9,19),ML(CHECK,9,20),_
                  ML(CHECK,6,16),ML(CHECK,6,17),ML(CHECK,6,18),ML(CHECK,6,19),ML(CHECK,6,20),_
                  ML(CHECK,7,16),ML(CHECK,7,17),ML(CHECK,7,18),ML(CHECK,7,19),ML(CHECK,7,20),_
                  ML(CHECK,8,16),ML(CHECK,8,17),ML(CHECK,8,18),ML(CHECK,8,19),ML(CHECK,8,20),_
                  ML(CHECK,10,16),ML(CHECK,10,17),ML(CHECK,10,18),ML(CHECK,10,19),ML(CHECK,10,20),_
                  ML(CHECK,11,16),ML(CHECK,11,17),ML(CHECK,11,18),ML(CHECK,11,19),ML(CHECK,11,20))
```

```
*************          ------------------
Run***                 SCHEDULED-I
Day***                 ------------------
                       Patient#               1     2     3     4     5
                       Appointment No         *.**  *.**  *.**  *.**  *.**
                       Early(1)/Late(2)       *     *     *     *     *
                       Appointment            **.****.****.****.****.**
                       Arrival                **.****.****.****.****.**
                       ServiceStart           **.****.****.****.****.**
                       New(1)/Return(0)       *     *     *     *     *
                       ServiceTime            **.****.****.****.****.**
                       ServiceEnd             **.****.****.****.****.**
                       WaitingTime            **.****.****.****.****.**
                       ------------------
                       Patient#               6     7     8     9     10
                       Appointment No         *.**  *.**  *.**  *.**  *.**
                       Early(1)/Late(2)       *     *     *     *     *
                       Appointment            **.****.****.****.****.**
                       Arrival                **.****.****.****.****.**
                       ServiceStart           **.****.****.****.****.**
                       New(1)/Return(0)       *     *     *     *     *
                       ServiceTime            **.****.****.****.****.**
                       ServiceEnd             **.****.****.****.****.**
                       WaitingTime            **.****.****.****.****.**
                       ------------------
                       WALK-INS-II
                       ------------------
                       Walk-in#               1     2     3     4     5
                       Arrival                *.**  *.**  *.**  *.**  *.**
                       ServiceStart           *.**  *.**  *.**  *.**  *.**
                       New(1)/Return(0)       *     *     *     *     *
                       ServiceTime            *.**  *.**  *.**  *.**  *.**
                       ServiceEnd             *.**  *.**  *.**  *.**  *.**
                       WaitingTime            *.**  *.**  *.**  *.**  *.**
                       ..................
                       Queue lgth @arrival    *.**  *.**  *.**  *.**  *.**
                       MinWaitAssigned        *.**  *.**  *.**  *.**  *.**
                       ------------------
                       Walk-in#               6     7     8     9     10
                       Arrival                *.**  *.**  *.**  *.**  *.**
                       ServiceStart           *.**  *.**  *.**  *.**  *.**
                       New(1)/Return(0)       *     *     *     *     *
                       ServiceTime            *.**  *.**  *.**  *.**  *.**
                       ServiceEnd             *.**  *.**  *.**  *.**  *.**
                       WaitingTime            *.**  *.**  *.**  *.**  *.**
```

```
                    ..................
                    Queue lgth @arrival   *.** *.** *.** *.** *.**
                    MinWaitAssigned       *.** *.** *.** *.** *.**

      ENDDO                                          end of loop for days
*
      LET      &MCEARLY(&J)=&MCEARLY(&J)/&DAY
      LET      &MCLATE(&J)=&MCLATE(&J)/&DAY
      LET      &MCWALK(&J)=&MCWALK(&J)/&DAY
      LET      &MCALL(&J)=&MCEARLY(&J)+&MCLATE(&J)+&MCWALK(&J)
      LET      &MIDLE(&J)=&MIDLE(&J)/&DAY
      LET      &MIDLEPP(&J)=&MIDLE(&J)/&MCALL(&J)
      LET      &MOVER(&J)=&MOVER(&J)/&DAY
      LET      &MOVERPP(&J)=&MOVER(&J)/&MCALL(&J)
      LET      &MAVGWT1(&J)=&MAVGWT1(&J)/(&DAY-XH(NULL1))
      LET      &MAVGWT2(&J)=&MAVGWT2(&J)/(&DAY-XH(NULL2))
      LET      &MAVGWTS(&J)=&MAVGWTS(&J)/&DAY
      LET      &MAVGWTW(&J)=&MAVGWTW(&J)/(&DAY-XH(NULL3)+0.000000001)
      LET      &MAVGWTA(&J)=&MAVGWTA(&J)/&DAY
      LET      &MLSS30(&J)=&MLSS30(&J)/&DAY
      LET      &MWTAPT1(&J)=&MWTAPT1(&J)/(&DAY-XH(EMPTY1))
      LET      &MWTAPT2(&J)=&MWTAPT2(&J)/(&DAY-XH(EMPTY2))
      LET      &MWTAPT3(&J)=&MWTAPT3(&J)/(&DAY-XH(EMPTY3))
      LET      &MWTAPT4(&J)=&MWTAPT4(&J)/(&DAY-XH(EMPTY4))
      LET      &MWTAPT5(&J)=&MWTAPT5(&J)/(&DAY-XH(EMPTY5))
      LET      &MWTAPT6(&J)=&MWTAPT6(&J)/(&DAY-XH(EMPTY6))
      LET      &MWTAPT7(&J)=&MWTAPT7(&J)/(&DAY-XH(EMPTY7))
      LET      &MWTAPT8(&J)=&MWTAPT8(&J)/(&DAY-XH(EMPTY8))
      LET      &MWTAPT9(&J)=&MWTAPT9(&J)/(&DAY-XH(EMPTY9))
      LET      &MWTAPT10(&J)=&MWTAPT10(&J)/(&DAY-XH(EMPTY10))
      LET      &AVGAPT(&J)=(&MWTAPT1(&J)+&MWTAPT2(&J)+&MWTAPT3(&J)+&MWTAPT4(&J)+&MWTAPT5(&J)+_
               &MWTAPT6(&J)+&MWTAPT7(&J)+&MWTAPT8(&J)+&MWTAPT9(&J)+&MWTAPT10(&J))/&N
      LET      &SUMSQ(&J)=(&MWTAPT1(&J)-&AVGAPT(&J))*(&MWTAPT1(&J)-&AVGAPT(&J))+_
               (&MWTAPT2(&J)-&AVGAPT(&J))*(&MWTAPT2(&J)-&AVGAPT(&J))+_
               (&MWTAPT3(&J)-&AVGAPT(&J))*(&MWTAPT3(&J)-&AVGAPT(&J))+_
               (&MWTAPT4(&J)-&AVGAPT(&J))*(&MWTAPT4(&J)-&AVGAPT(&J))+_
               (&MWTAPT5(&J)-&AVGAPT(&J))*(&MWTAPT5(&J)-&AVGAPT(&J))+_
               (&MWTAPT6(&J)-&AVGAPT(&J))*(&MWTAPT6(&J)-&AVGAPT(&J))+_
               (&MWTAPT7(&J)-&AVGAPT(&J))*(&MWTAPT7(&J)-&AVGAPT(&J))+_
               (&MWTAPT8(&J)-&AVGAPT(&J))*(&MWTAPT8(&J)-&AVGAPT(&J))+_
               (&MWTAPT9(&J)-&AVGAPT(&J))*(&MWTAPT9(&J)-&AVGAPT(&J))+_
               (&MWTAPT10(&J)-&AVGAPT(&J))*(&MWTAPT10(&J)-&AVGAPT(&J))
      LET      &VARAPT(&J)=SQRT((&SUMSQ(&J)/(&N-1)))          standard deviation of waiting times
*
```

```
*******************************************************************************************
*                              REPORT / PERFORMANCE MEASURES PER RUN                      *
*******************************************************************************************
*
     PUTPIC     LINES=1,FILE=REP1sq10,(&AS,&CVR,&CVN,&MPUN,&PWAL,&PNSHW,&J,&MIDLE(&J),_
                &MOVER(&J),&MIDLEPP(&J),&MOVERPP(&J),&MAVGWTA(&J),&MAVGWT1(&J),&MAVGWT2(&J),&MAVGWTS(&J),_
                &MAVGWTW(&J),&MLSS30(&J),&VARAPT(&J),&MCALL(&J))
******* * * * * * **** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.***
**.*** **.*** **.*** **.***
*
*    PUTPIC     LINES=1,FILE=REP1B10,(&AS,&CVR,&CVN,&MPUN,&PWAL,&PNSHW,&J,&VARAPT(&J),&MWTAPT1(&J),&MWTAPT2(&J),_
*               &MWTAPT3(&J),&MWTAPT4(&J),&MWTAPT5(&J),&MWTAPT6(&J),&MWTAPT7(&J),&MWTAPT8(&J),&MWTAPT9(&J),_
*               &MWTAPT10(&J))
******* * * * * * **** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.***  **.*** **.*** **.***
*
* Take Overall Average of Performance Measures:
* -------------------------------------------
     LET        &PMCEAR=&PMCEAR+&MCEARLY(&J)
     LET        &PMCLATE=&PMCLATE+&MCLATE(&J)
     LET        &PMCWLK=&PMCWLK+&MCWALK(&J)
     LET        &PMIDLEPP=&PMIDLEPP+&MIDLEPP(&J)
     LET        &PMOVERPP=&PMOVERPP+&MOVERPP(&J)
     LET        &PMWTEAR=&PMWTEAR+&MAVGWT1(&J)
     LET        &PMWTLAT=&PMWTLAT+&MAVGWT2(&J)
     LET        &PMWTSCH=&PMWTSCH+&MAVGWTS(&J)
     LET        &PMWTWLK=&PMWTWLK+&MAVGWTW(&J)
     LET        &PMWTALL=&PMWTALL+&MAVGWTA(&J)
     LET        &PMLS30=&PMLS30+&MLSS30(&J)
     LET        &PMFAIR=&PMFAIR+&VARAPT(&J)
     ENDDO                                          end of loop for runs
*
     LET        &PMCEAR=&PMCEAR/&RUN                count # of early
     LET        &PMCLATE=&PMCLATE/&RUN              count # of late
     LET        &PMCWLK=&PMCWLK/&RUN                count # of walk-ins
     LET        &PMSEEN=&PMCEAR+&PMCLATE+&PMCWLK    count # of total patients seen
     LET        &PMIDLEPP=&PMIDLEPP/&RUN            avg idle time per patient
     LET        &PMOVERPP=&PMOVERPP/&RUN            avg overtime per patient
     LET        &PMWTEAR=&PMWTEAR/&RUN              avg waiting time of early patients
     LET        &PMWTLAT=&PMWTLAT/&RUN              avg waiting time of late patients
     LET        &PMWTSCH=&PMWTSCH/&RUN              avg waiting time of scheduled patients
     LET        &PMWTWLK=&PMWTWLK/&RUN              avg waiting time of walk-in patients
     LET        &PMWTALL=&PMWTALL/&RUN              avg waiting time of patients overall
     LET        &PMDOC1=&PMIDLEPP+1.5*&PMOVERPP     idle + (1.5)*overtime per patient
     LET        &PMLS30=&PMLS30/&RUN                % of scheduled patients with wait < 30 min.
     LET        &PMFAIR=&PMFAIR/&RUN                standard deviation of wait times (fairness)
```

```
*******************************************************************************************************************
*                                               OVERALL REPORT                                                    *
*******************************************************************************************************************
*
     PUTPIC          LINES=1,FILE=SUMMsq10,(&AS,&CVR,&CVN,&MPUN,&PWAL,&PNSHW,&PMIDLEPP,&PMOVERPP,_

     &PMDOC1,&PMWTALL,&PMLS30,&PMFAIR,&PMWTEAR,&PMWTLAT,&PMWTSCH,&PMWTWLK,&PMSEEN,&PMCEAR,&PMCLATE,&PMCWLK)
********* * * * * * **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.*** **.***
**.*** **.*** **.*** **.*** **.*** **.**** **.****
*
* Initialize All Ampervariables:
* ------------------------------
*
     LET        &PMIDLEPP=0
     LET        &PMOVERPP=0
     LET        &PMDOC1=0
     LET        &PMWTEAR=0
     LET        &PMWTLAT=0
     LET        &PMWTSCH=0
     LET        &PMWTWLK=0
     LET        &PMWTALL=0
     LET        &PMLS30=0
     LET        &PMFAIR=0
     LET        &PMCEAR=0
     LET        &PMCLATE=0
     LET        &PMCWLK=0
     LET        &PMSEEN=0
*
     DO         &J=1,&RUN
     LET        &MIDLE(&J)=0
     LET        &MIDLEPP(&J)=0
     LET        &MOVER(&J)=0
     LET        &MOVERPP(&J)=0
     LET        &MAVGWT1(&J)=0
     LET        &MAVGWT2(&J)=0
     LET        &MAVGWTS(&J)=0
     LET        &MAVGWTW(&J)=0
     LET        &MAVGWTA(&J)=0
     LET        &MLSS30(&J)=0
     LET        &MCEARLY(&J)=0
     LET        &MCLATE(&J)=0
     LET        &MCWALK(&J)=0
     LET        &MWTAPT1(&J)=0
     LET        &MWTAPT2(&J)=0
     LET        &MWTAPT3(&J)=0
```

```
     LET        &MWTAPT4(&J)=0
     LET        &MWTAPT5(&J)=0
     LET        &MWTAPT6(&J)=0
     LET        &MWTAPT7(&J)=0
     LET        &MWTAPT8(&J)=0
     LET        &MWTAPT9(&J)=0
     LET        &MWTAPT10(&J)=0
     LET        &AVGAPT(&J)=0
     LET        &SUMSQ(&J)=0
     LET        &VARAPT(&J)=0
     ENDDO
*
     ENDDO                                  next appointment system
     ENDDO                                  next CV_Ret
     ENDDO                                  next CV_New
     ENDDO                                  next unpunctuality
     ENDDO                                  next probability of walk-ins
     ENDDO                                  next probability of no-shows
**********************************************************************************************************************
     END                                    End of Model-File Execution
**********************************************************************************************************************
```

APPENDIX B. Statistical Analysis of Empirical Data

Empirical data were collected from a primary care clinic in a New York metropolitan hospital, which provides service to about 300,000 outpatients a year. Data collection was conducted through observation, where patient arrival times, appointment times, consultation start and consultation end times were recorded. Secondary data on the percentage of no-shows and walk-ins was obtained from the monthly reports of various clinics.

It is generally considered better to use a theoretical distribution rather than the empirical distribution function directly in the simulation model. Such an approach has the advantage of simulating cases beyond those observed empirically (p. 327, Law and Kelton, 1991). The results of the statistical analysis on input parameters are discussed in the following sections.

1. SERVICE TIMES

Data on service times of return and new patients were collected on the same doctor. Sample size is 90 and 35 for return and new patients, respectively. First, we test the null hypothesis that the means of service times for new and return patients are equal. Nonparametric Mann-Whitney-Wilcoxon test results reject the null hypothesis at the 95 percent confidence level (W= 1075, p-value= 0.0059). These results support prior research, which generally found that the service times of new patients were significantly higher than the service times of return patients (Nuffield Provincial Hospitals Trust 1965;

Partridge 1992; Hart 1995). Next, we test the null hypothesis that the variances of consultation times for new and return patients are equal. The results of F-test reveal no evidence of a significant difference at alpha 0.05 ($F = 0.6981$, p-value = 0.1596).

1.1. Service Times of Return Patients

The shape of the histogram of service times suggest that the underlying distribution is skewed to the right. This is supported by the fact that the mean is greater than the median (15.5> 14.0), and skewness is greater than zero (0.707> 0) (see Table 1). It is unlikely that the true distribution is exponential, since the coefficient of variation is not close to 1.

Table 1. Summary Statistics for the Service Time Data (Return Patients)

Summary Statistic	Value
Minimum	6.00
Maximum	29.00
Mean	15.50
Median	14.00
Variance	25.38
Standard Deviation	5.037
Coefficient of Variation	0.325
Skewness	0.707
Kurtosis	0.156

We investigate the lognormal, gamma and Weibull distributions, all of which may follow shapes similar to that of the histogram of the service time data (see Figure 2). A comparison of the P-P and Q-Q plots shows that these plots are more linear for the lognormal distribution, indicating a better fit (Figure 1). Next, we calculate the maximum-likelihood estimates (MLEs) of the parameters for the lognormal distribution.

The shape parameter σ is 0.32, and the scale parameter μ is 2.69. Using these parameters, a frequency comparison is conducted as shown in Figure 2. In general, the agreement between the fitted lognormal distribution and the empirical service time data seems reasonable. After these heuristic procedures, we pursue a more formal goodness-of-fit test. The Kolmogorov-Smirnov test results show that we can not reject the lognormal distribution at alpha 0.05. From Table 2, the adjusted K-S statistic 0.808 is less than the critical value $c'_{0.95}$= 0.895 (see Ch. 6 in Law and Kelton, 1991).

Figure 2. Frequency Comparisons for the Fitted Lognormal Distribution and the Service Time Data (Return)

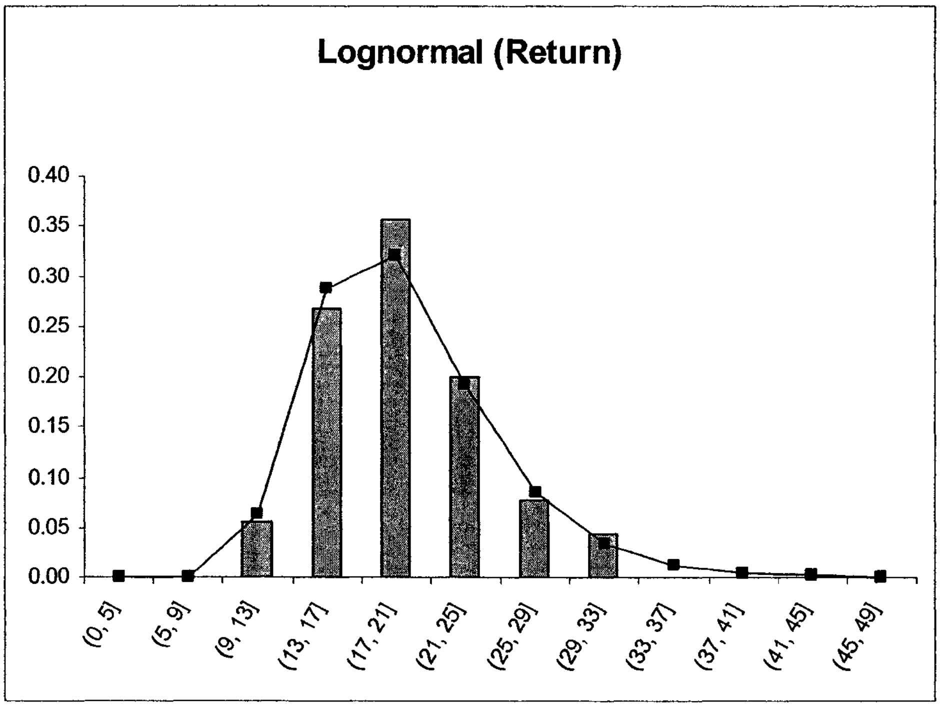
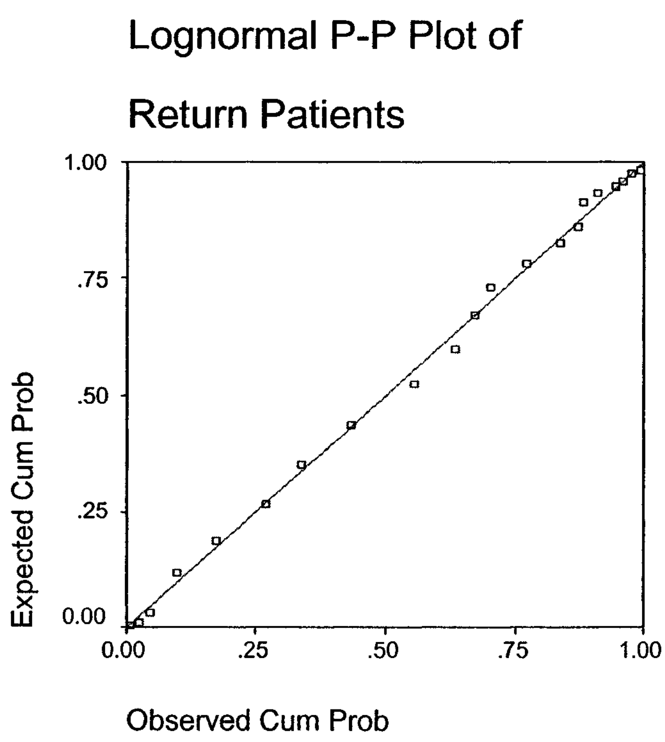


Figure 1. P-P and Q-Q Plots for the Lognormal Distribution for the Service Time Data (Return)



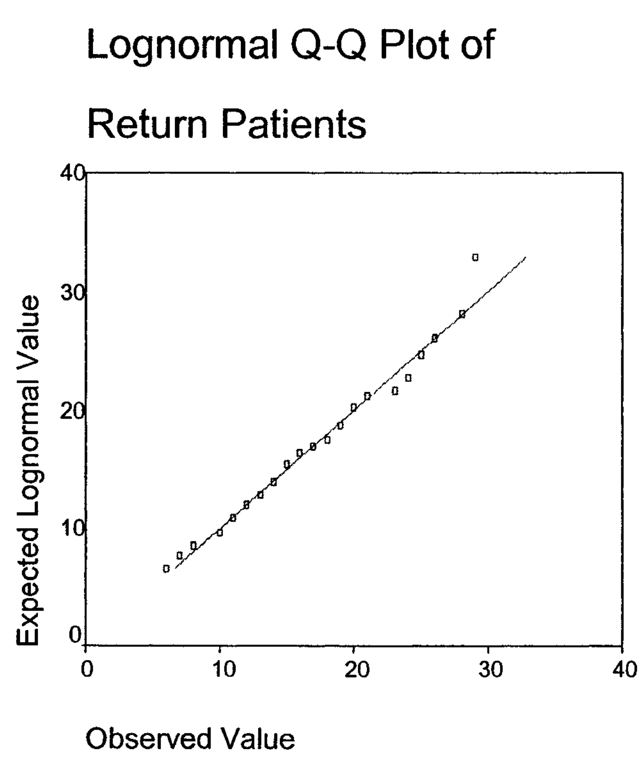


Table 2. One-Sample Kolmogorov-Smirnov Test for the Service Time Data (Return)[1]

N		90
Normal Parameters	Mean	2.6887
	Std. Deviation	.32606
Most Extreme Differences	Absolute	.085
	Positive	.074
	Negative	-.085
Kolmogorov-Smirnov Z		.808
Asymp. Sig. (2-tailed)		.532

[1] K-S test is for the Normal distribution, where X_i's are logarithms of the original data points we have hypothesized to have a lognormal distribution

1.2. Service Times of New Patients

The same analysis is repeated for the service time data of new patients. Table 3 summarizes the statistics. Similar to the case with return patients, the P-P and Q-Q plots suggest that the lognormal distribution is a better fit to our empirical data compared to gamma and Weibull (see Figure 3).

Table 3. Summary Statistics for the Service Time Data (New Patients)

Summary Statistic	Value
Minimum	10.00
Maximum	40.00
Mean	19.09
Median	18.00
Variance	46.96
Standard Deviation	6.85
Coefficient of Variation	0.36
Skewness	1.13
Kurtosis	1.33

Figure 4 shows the frequency comparisons of empirical service time data with the lognormal distribution. The MLEs for the shape parameter σ is 0.34, and the scale parameter μ is 2.89. Next, we conduct the Kolmogorov-Smirnov test for goodness of fit. The adjusted K-S statistic 0.598 is less than the critical value $c'_{0.95}$= 0.895 (see Table 4).

Therefore, we accept the null hypothesis that population service times are from a lognormal distribution at level $\alpha = 0.05$. To summarize, the results of our heuristic and formal goodness-of-fit tests indicate that the lognormal distribution is a good fit for our service time data for both new and return patients.

Figure 4. Frequency Comparisons for the Fitted Lognormal Distribution and the Service Time Data (New)

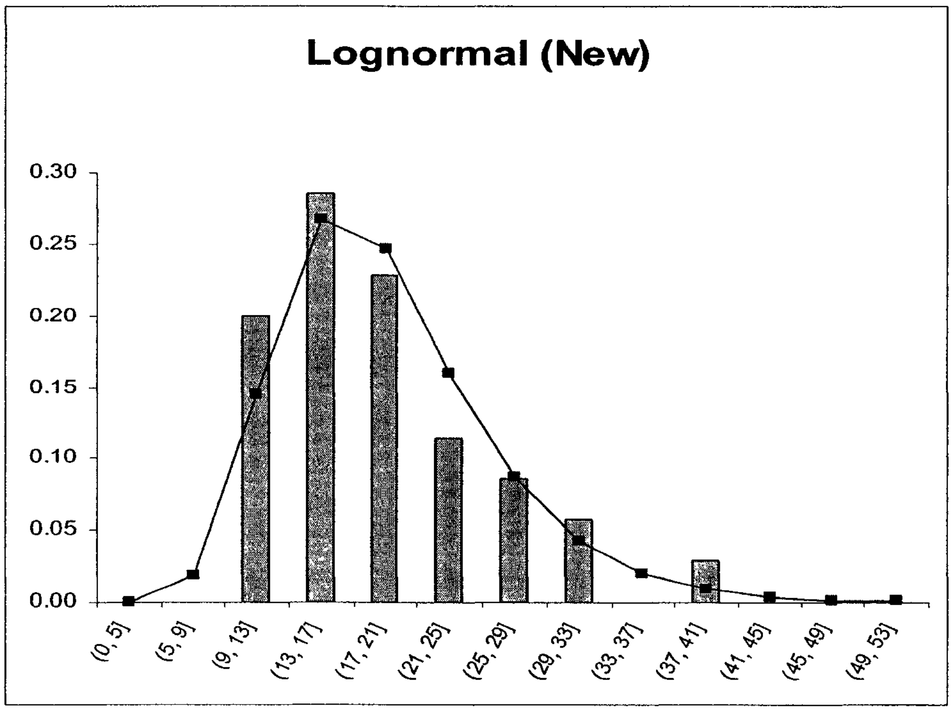
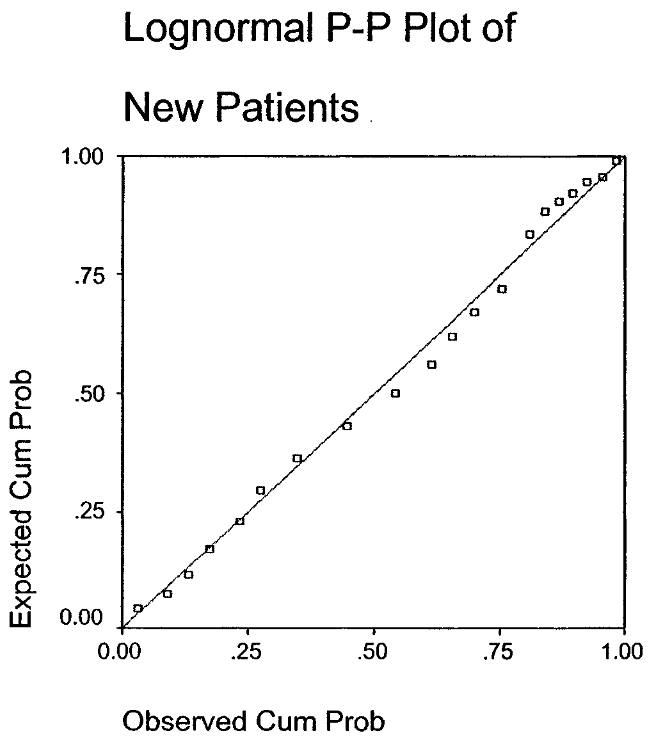


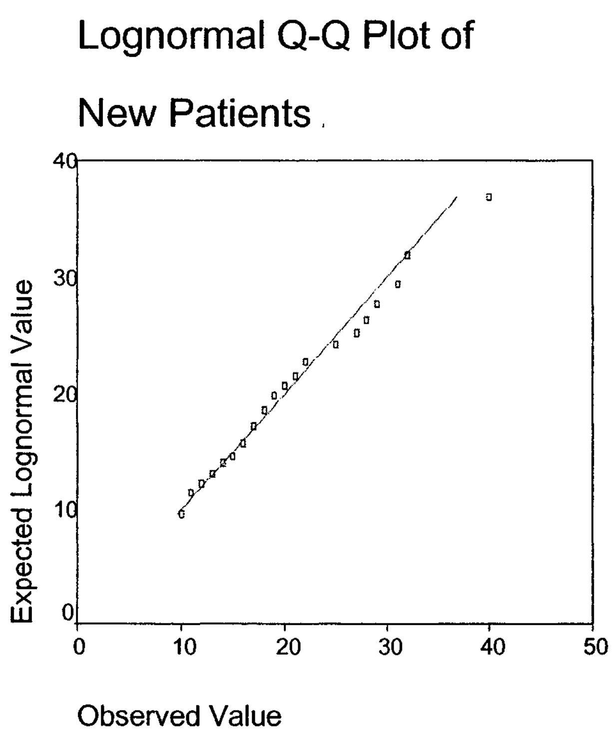
Table 4. One-Sample Kolmogorov-Smirnov Test for the Service Time Data (New)[1]

N		35
Normal Parameters	Mean	2.8909
	Std. Deviation	.33982
Most Extreme Differences	Absolute	.101
	Positive	.101
	Negative	-.075
Kolmogorov-Smirnov Z		.598
Asymp. Sig. (2-tailed)		.867

K-S test is for the Normal distribution, where X_i's are logarithms of the original data points we have hypothesized to have a lognormal distribution

Figure 3. P-P and Q-Q Plots for the Lognormal Distribution for the Service Time Data (New)





2. PATIENT UNPUNCTUALITY

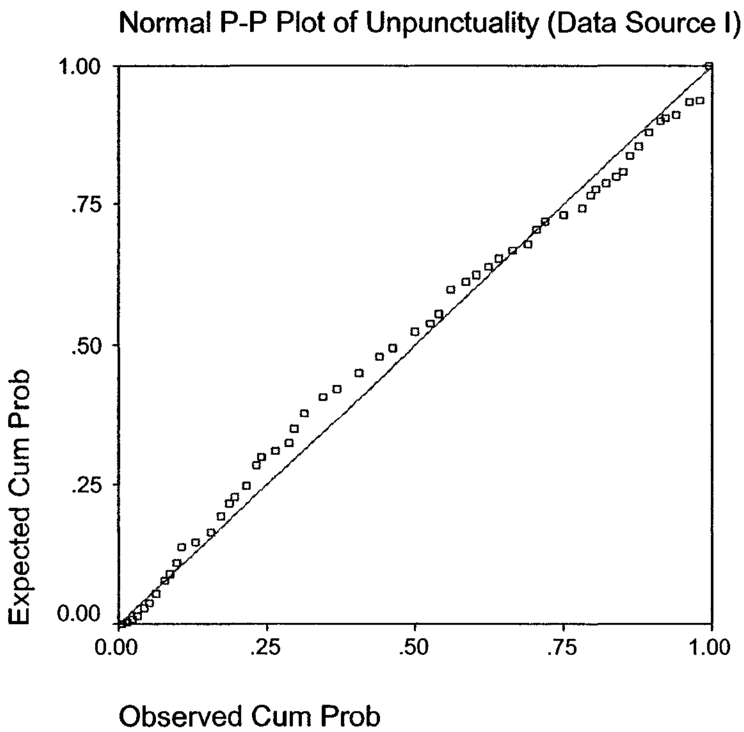
Empirical data were collected on unpunctuality of patients by recording the deviation of patients' arrivals from their appointment times. The shape of the histogram suggests that the normal distribution might be a good fit (Figure 6). Even though the mean is not equal to the median, it is fairly close, as one would expect in a symmetric distribution (-16.62 vs. -15.00). Possible applications of normal distribution include errors of various types (Law and Kelton, 1991), and patients' unpunctuality may be thought of as deviations or "errors" from the appointment times.

Figure 5 presents the P-P and Q-Q plots. Once again, we find the P-P plot to be reasonably linear, indicating a good fit between the normal and empirical distribution. Q-Q plot, which amplifies the differences that exist between the tails of the distribution function, suggests a poorer fit. This might be due to sample size that is possibly excluding the extreme cases in the tail areas. Next, we conduct the Kolmogorov-Smirnov test to assess formally if the normal distribution provides a good fit. Since the adjusted K-S statistic 0.834 is less than $c'_{0.95}$= 0.895, we could not reject the null (See Table 8). Thus, we conclude that the normal distribution provides a sufficiently good representation for modeling the unpunctuality of patients in our simulation experiments.

Table 7. Summary Statistics for the Unpuctuality Data

Summary Statistic	Value
Minimum	-105
Maximum	80
Mean	-16.62
Median	-15
Variance	732.79
Standard Deviation	27.07
Coefficient of Variation	-1.63
Skewness	-0.337
Kurtosis	1.81

Figure 5. P-P and Q-Q Plots for the Normal Distribution for the Unpunctuality Data



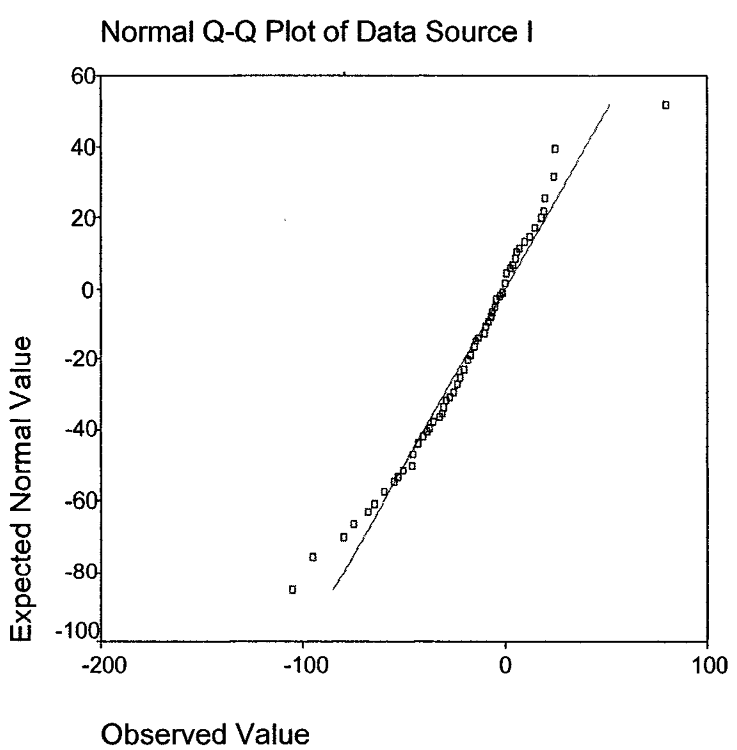


Figure 6. Frequency Comparisons for the Fitted Normal Distribution and the Unpunctuality Data

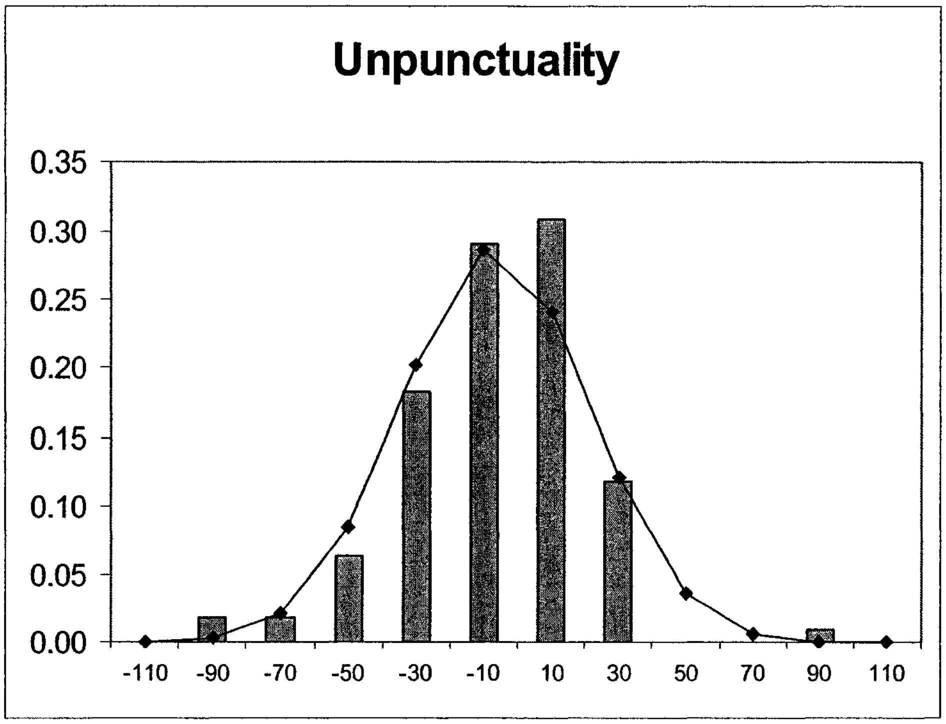


Table 8. One-Sample Kolmogorov-Smirnov Test for the Unpunctuality Data

N		110
Normal Parameters	Mean	-16.6182
	Std. Deviation	27.07007
Most Extreme Differences	Absolute	.080
	Positive	.053
	Negative	-.080
Kolmogorov-Smirnov Z		.834
Asymp. Sig. (2-tailed)		.490

3. NO-SHOW AND WALK-IN RATES

Table 10 lists no-show and walk-in rates reported in seventy-eight clinics of the New York metropolitan hospital during January-February 2002 (sample size is 34,897 patients). The average no-show rate across all clinics is 38%, and the average walk-in rate is 16%. These rates are higher than most of the P_W and P_N values studied in the literature.

There are major differences among specialties in terms of no-show and walk-in rates observed. Few clinics, such as peripheral vascular diseases, have zero walk-ins. The highest walk-in rates are observed in mental health, pediatrics, and hepatology. Sixty-four percent of the clinics have no-show probabilities above 30 percent. Clinics such as colposcopy, mental health, and peripheral vascular diseases have the lowest no-show rates, whereas clinics such as pediatrics neurology and family planning have the highest no-show rates.

Table 10. No-Show and Walk-in Rates Observed in Clinics (78 clinics, 34,897 patients Jan-Feb 2002)

Clinic Name	% No-Shows	Clinic Name	% No-Shows	Clinic Name	% Walk-ins	Clinic Name	% Walk-ins
Adolescent Colposcopy	0%	Proctology	37%	Developmental Eval	0%	Cardiac	13%
Pediatrics	0%	Medicine (Team 3)	38%	OBS Initial -- Chc	0%	Gynecology	13%
Peripheral Vascular Diseases	0%	Adult Med	39%	Peripheral Vascular Diseases	0%	OBS Prenatal	13%
Chest TB	0%	Adult Eve & Weekends	39%	Obstetrics --Chc	2%	Arthritis	13%
Mental Health	0%	Developmental Eval	39%	Healthy Baby (Well)	3%	Infectious Disease	13%
Well Baby	1%	Pediatrics Hematology	41%	Ear Nose Throat	4%	Chc-Gyn	13%
Peds Med (Homecrest)	3%	Orthopedic	41%	Pediatrics Allergy	4%	Pediatrics Cardiac	14%
OBS Initial -- Chc	12%	Medicine (Team 5)	41%	Pediatrics Renal	4%	Pediatrics Cardiac	15%
OBS Initial	18%	Dermatology	41%	Neurology	4%	OBS Initial	15%
Oncology	20%	Breast Surgery	42%	Genital-Urinary	5%	Audiology (Eval)	15%
Special Medical Cln	20%	Gyn Tumor	43%	Allergy	5%	Hematology	15%
Allergy	21%	Medicine (Team 6)	44%	Special Medical Cln	5%	Adolescent Comp Care	16%
OBS Prenatal	21%	Neurology	44%	Pediatrics GYN	5%	Adult Med	17%
OBS Screening	22%	Arthritis	44%	Peds Eve & Weekends	6%	Gyn	17%
Pediatrics Allergy	24%	Chc- Medicine	45%	Chc- Family Plan	6%	Orthopedic	17%
Healthy Mom (OBS PP)	24%	Pediatrics Mental Hygiene	45%	Diabetes	6%	Medicine (Team 2)	17%
Renal	25%	Medicine (Team 2)	46%	Gastro-intestinal	6%	OBS Prenatal	17%
OBS Prenatal	25%	Pediatrics Endocrine	46%	Osteoporosis	7%	Proctology	17%
OBS High Risk	26%	Pediatrics Cardiac	46%	Medicine (Team 5)	7%	Chest Surgery	18%
Healthy Baby (Well)	27%	Gynecology	46%	Healthy Mom (OBS PP)	7%	Podiatry (non-routine)	18%
Obstetrics --Chc	27%	Gyn -	46%	Pediatrics Endocrine	7%	Medicine (Team 4)	19%
Genital-Urinary	27%	Rehabilitation	48%	Podiatry Non-Routine	8%	Well Baby	19%
Infectious Disease	28%	Peds Eve & Weekends	49%	Adult Endocrine	8%	Pediatrics Mental Hygiene	19%
Medicine (Team 7)	28%	Ophthalmology	49%	OBS Post Partum	8%	Ophthalmology	22%
Hematology	29%	Peds Pulmonology Asth	49%	Renal	9%	Pediatrics Bay	22%
Pain Management	29%	Pediatrics Cardiac	49%	Adolescent Colposcopy	9%	Medicine (Team 7)	22%
Diabetes	29%	Pediatrics GYN	49%	Gyn Tumor	9%	Surgery	23%
Medicine (Team 4)	30%	Podiatry (non-routine)	50%	Pediatrics	9%	Medicine (Primary Care 1)	23%
Audiology (Eval)	30%	OBS Post Partum	50%	Breast Surgery	10%	Peds Med (Homecrest)	24%
Adult Endocrine	30%	Pediatrics Renal	51%	OBS Screening	10%	Minor Surgery	25%
Minor Surgery	31%	Chest Non-TB	53%	Medicine (Team 3)	10%	Chc- Medicine	25%
Medicine (Primary Care 1)	31%	Pediatrics - Chc	54%	Pediatrics Hematology	11%	Rehabilitation	27%
Hepatology	33%	Osteoporosis	54%	OBS High Risk	11%	Chest TB	28%
Plastic Surgery	34%	Gastro-intestinal	55%	Adult Eve & Weekends	12%	Pain Management	31%
Ear Nose Throat	34%	Chc-Gyn	56%	Chest Non-TB	12%	Peds Pulmonology Asth	34%
Podiatry Non-Routine	35%	Adolescent Comp Care	57%	Dermatology	12%	Mental Health	35%
Chest Surgery	35%	Chc- Family Plan	59%	Plastic Surgery	12%	Pediatrics - Chc	42%
Surgery	35%	Pediatrics	60%	Medicine (Team 6)	12%	Pediatrics Neurology	56%
Cardiac	36%	Pediatrics Neurology	67%	Oncology	13%	Hepatology	61%
		TOTAL	**38%**			**TOTAL**	**16%**

APPENDIX C. Pilot Runs for Setting β_i and k_i-Values in OFFSET and DOME Rules

The formulations of the variable-block rules, OFFSET and DOME, require setting multipliers β_i, and early/delay parameters k_i (see Section 4.1.1). The goal of this pre-study is to choose the β_i, k_i–values to simulate in the main experiments. Analysis is done at two stages. First, the decision factor β_i is investigated fixing k_i at one level. And next, the decision factor k_i is investigated, this time fixing β_i.

1. DECISION FACTOR β_i

The formulation of the OFFSET rule, introduced by Ho and Lau (1992), requires two multipliers; β_1 and β_2. In their simulation study, the authors reported that (β_1, β_2) combinations of (0.15, 0.30) and (0.25, 0.50) performed the best. During our pilot study, we used these original β_1 and β_2 values. However, for the environments that we investigated, β_2= 0.50 resulted in appointment times beyond the clinic end time. During our pilot runs, this was corrected by setting the appointment times at roughly 10 minutes before the clinic end time.

The DOME rule uses a third multiplier, β_3. After some experimentation, we decided to test this factor at two levels: 0.05 and 0.25. When investigating β_i, we fixed k_1 and k_2–values at 5 and 9, respectively, for clinics with N= 10 patients (similarly, k_1= 10 and k_2= 18 for N= 20). For simplicity, throughout the analysis the (k_1, k_2) combination is referred to as (5, 9), even though it actually implies (10, 18) for N= 20. Table 1 lists the set of OFFSET and DOME rules that result from the combinations of β_i, and k_i-values chosen during our pilot study. The details on formulations of appointment rules can be found in Table 1 in Appendix D.

Table 1. OFFSET and DOME Rules Tested

Rule	Parameters
OFF1530	β_1=0.15, β_2= 0.30, k= 5
OFF2550	β_1=0.25, β_2= 0.50, k= 5
D153005	β_1=0.15, β_2= 0.30, β_3= 0.05, k_1= 5, k_2= 9
D153025	β_1=0.15, β_2= 0.30, β_3= 0.25, k_1= 5, k_2= 9
D255005	β_1=0.25, β_2= 0.50, β_3= 0.05, k_1= 5, k_2= 9
D255025	β_1=0.25, β_2= 0.50, β_3= 0.25, k_1= 5, k_2= 9

The eight appointment rules listed in Table 1, are investigated under 64 clinic environments (2 N x 2 CV_{Ret} x 2 CV_{New} x 2 P_W x 2 P_N x 2 Unp). The levels chosen for all experimental factors are summarized in Table 2.

Table 2. Summary of Experimental Factors

Decision Factor	**Levels**
β_1	0.15, 0.25
β_2	0.30, 0.50
β_3	0.05, 0.25

Environmental Factor	**Levels**
Number of patients per session (N)	10, 20
Coefficient of variation for return patients (CV_{Ret})	0.35, 0.70
Coefficient of variation for new patients (CV_{New})	0.35, 0.70
Probability of walk-ins (P_W)	0, 0.15
Probability of no-shows (P_N)	0, 0.15
Mean unpunctuality of patients (Unp)	-15, 0 min.

The dependent variable used in the full-factorial model is the total cost equation [9] presented in Section 4.4. TC1, TC10, and TC100 correspond to C_d/C_p ratios of 1, 10 and 100, respectively. For example, TC1 is the total cost of the system when doctor's time is assumed equally valuable as patient's time. Similarly, TC10 (TC100) is the total cost when doctor's time is assumed 10 (100) times more valuable than patient's time.

ANOVA test results are shown in Table 3 for dependent variables TC1, TC10 and TC100. Since our goal is to compare appointment rules, we focus our discussion on the two-way and three-way interactions of RULE with environmental factors. For the sake of brevity, only the significant three-way interactions are included in ANOVA table. The results show that all two-way interactions are significant at alpha 0.05, except for RULE*CV_{Ret} for TC100. Also, interaction plots reveal that almost all of the interactions are infatuating effects. Exceptions include the RULE*P_W and RULE*P_W*N interactions, which show cross effects (See Figure 1). Therefore, when comparing appointment rules, we limit the range of operating environments to four (2 N x 2 P_W), fixing the rest of the factors at one level (P_N= 0, CV_{Ret}= 0.35, CV_{New}= 0.35, and Unp= -15 minutes). This limitation will not effect the rankings of appointment rules.

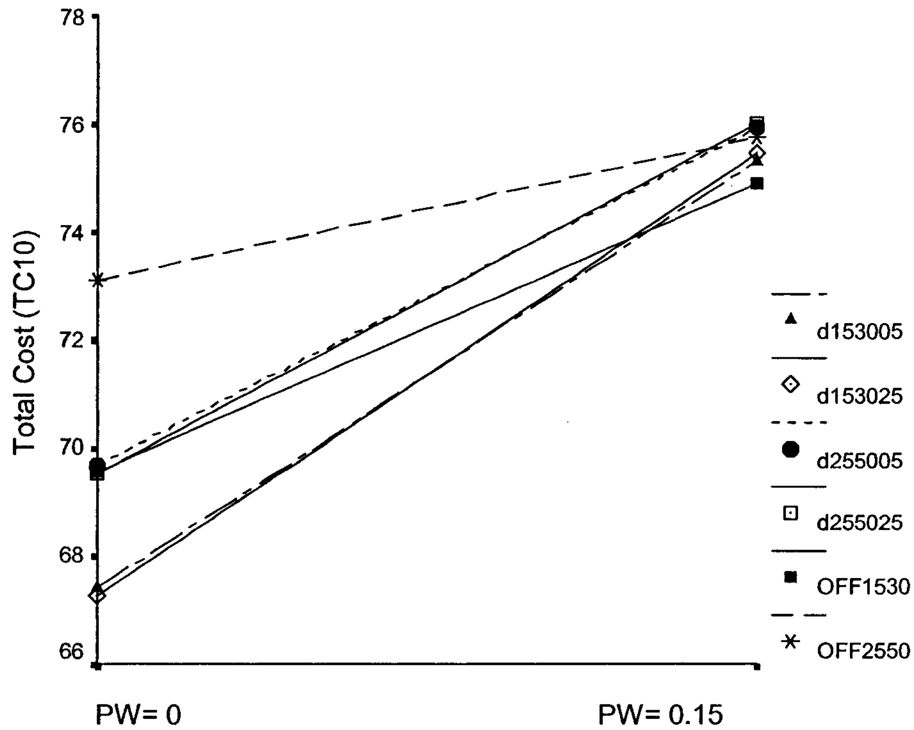
Tukey's test is conducted for pairwise comparisons of appointment rules in each environment to detect significant differences at 95 percent confidence level. Table 4 shows rankings of rules for performance measures TC1, TC10 and TC100. In this section, we avoid direct comparison of OFFSET and DOME rules, which will be done during the main experiments. Rather, we focus on comparing appointment rules based on their β_i and k_i–values. In environments with zero walk-ins (#1 and #3), OFFSET and DOME rules with (β_1, β_2) combinations of (0.15, 0.30) perform better compared to those with (0.25, 0.50). There are no significant differences between β_3 values tested at alpha 0.05. In environments with high walk-ins (#2 and 4), there are no significant differences among the β_1, β_2 and β_3 values tested. As a result, we choose β_1= 0.15, β_2= 0.30, and β_3= 0.05 to formulate OFFSET and DOME rules for the main experiments. Since the results indicated that the effect of β_3 was insignificant in all environments, the choice for β_3 was completely arbitrary.

Table 4. Rankings of β_i Combinations in DOME and OFFSET Rules [1]

Env # 1		**Env # 2**		**Env # 3**		**Env # 4**	
P_W= 0, N= 10		P_W = 0.15, N= 10		P_W = 0, N= 20		P_W = 0.15, N= 20	
Rule	**TC1**	**Rule**	**TC1**	**Rule**	**TC1**	**Rule**	**TC1**
OFF1530	15.14^{A}	OFF2550	26.11^{A}	OFF1530	8.58^{A}	OFF2550	18.84^{A}
OFF2550	15.28^{A}	OFF1530	26.59^{A}	OFF2550	8.89^{B}	OFF1530	19.26^{A}
d153005	15.91^{B}	d255005	27.85^{B}	d153005	9.02^{B}	d255005	19.87^{B}
d153025	16.01^{B}	d153005	27.98^{B}	d153025	9.10^{B}	d255025	19.98^{B}
d255005	16.13^{B}	d255025	28.00^{B}	d255005	9.34^{C}	d153005	20.10^{B}
d255025	16.23^{B}	d153025	28.12^{B}	d255025	9.41^{C}	d153025	20.22^{B}
Rule	**TC10**	**Rule**	**TC10**	**Rule**	**TC10**	**Rule**	**TC10**
d153025	64.00^{A}	OFF1530	88.40^{A}	d153025	25.97^{A}	OFF2550	42.43^{A}
d153005	64.11^{A}	d153005	89.07^{A}	d153005	25.98^{A}	OFF1530	42.64^{A}
d255025	65.62^{B}	OFF2550	89.14^{A}	OFF1530	26.28^{A}	d255005	43.62^{B}
d255005	65.73^{B}	d153025	89.23^{A}	d255025	27.24^{B}	d153005	43.67^{B}
OFF1530	66.73^{B}	d255005	89.55^{A}	d255005	27.27^{B}	d255025	43.77^{B}
OFF2550	70.07^{C}	d255025	89.71^{A}	OFF2550	28.01^{C}	d153025	43.82^{B}
Rule	**TC100**	**Rule**	**TC100**	**Rule**	**TC100**	**Rule**	**TC100**
d153025	543.97^{A}	d153005	699.99^{A}	d153025	194.72^{A}	OFF1530	276.47^{A}
d153005	546.05^{A}	d153025	700.24^{A}	d153005	195.54^{A}	OFF2550	278.32^{A}
d255025	559.54^{B}	OFF1530	706.52^{AB}	OFF1530	203.31^{B}	d153005	279.29^{A}
d255005	561.71^{B}	d255005	706.60^{AB}	d255025	205.53^{B}	d153025	279.80^{A}
OFF1530	582.70^{C}	d255025	706.84^{AB}	d255005	206.55^{B}	d255005	281.13^{A}
OFF2550	617.99^{D}	OFF2550	719.41^{B}	OFF2550	219.27^{C}	d255025	281.64^{A}

[1] Appointment rules joined by the same superscript are not significantly different at alpha 0.05.

Figure 1. Two-Way Interaction RULE * P_W



Three-Way Interaction RULE * P_W * N

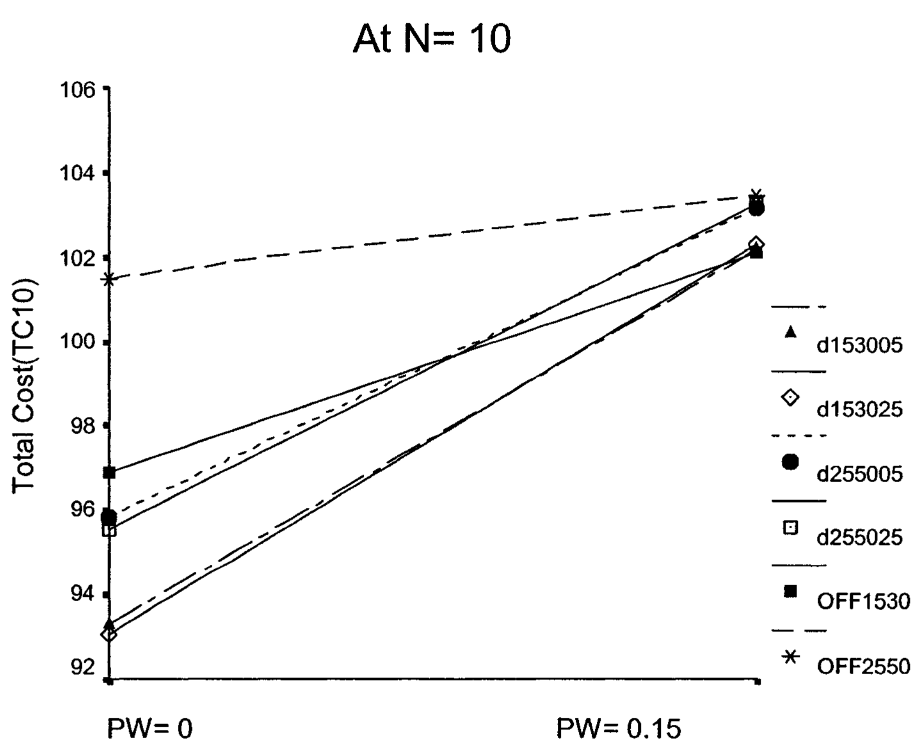


Table 3. ANOVA on Performance Measures TC1, TC10, TC100

	DF	TC1
Corrected Model	151	5573
Intercept	1	8009838
RULE	5	735
RULE * PW	5	198
RULE * PN	5	148
RULE * UNP	5	91
RULE * N	5	55
RULE * CVNEW	5	9
RULE * CVRET	5	2
RULE * PW * N	5	12
RULE * PN * N	5	9
RULE * UNP * N	5	4
RULE * UNP * PN	5	2
R-SQUARE		.957

	DF	TC10
Corrected Model	151	11168
Intercept	1	10456815
RULE	5	434
RULE * PW	5	337
RULE * PN	5	183
RULE * N	5	149
RULE * UNP	5	60
RULE * CVNEW	5	18
RULE * CVRET	5	1*
RULE * PW * N	5	52
RULE * PN * N	5	25
RULE * UNP * N	5	15
RULE * CVNEW * N	5	5
RULE * UNP * PW	5	4
RULE * UNP * PN	5	4
R-SQUARE		.978

	DF	TC100
Corrected Model	151	12412
Intercept	1	8910564
RULE	5	955
RULE * PW	5	313
RULE * N	5	291
RULE * PN	5	153
RULE * UNP	5	53
RULE * CVNEW	5	19
RULE * CVRET	5	2*
RULE * PW * N	5	60
RULE * PN * N	5	25
RULE * UNP * N	5	16
RULE * CVNEW * N	5	6
RULE * UNP * PW	5	5
RULE * UNP * PN	5	4
R-SQUARE		.980

* Insignificant at alpha 0.05.

Environmental Factors: PN: probability of no-shows; PW: probability of walk-ins; UNP: unpunctuality of patients; CVNEW: coefficient of variation for new patients; CVRET: coefficient of variation for return patients
Decision Factor: RULE: appointment rule

2. DECISION FACTOR k_i

For the OFFSET rule, this study uses Ho and Lau's (1992) best performing early/delay parameter k= 5 for N= 10. A simulation experiment is conducted to choose the best k_2 for the DOME rule, which is simulated for the first time in the literature. Note that when analyzing the decision factor β_i in the previous Section 1, (k_1, k_2) values were fixed at (5, 9). Here, two more levels are tested; (3, 7), and (3, 9). Again, these (k_1, k_2) values are adjusted for clinic size, corresponding to (10, 18), (6, 14), and (6, 18) for N= 20. The β_i parameters are fixed at β_1=0.15, β_2= 0.30, and β_3= 0.25, based on results from Section 1. Decision factors and environmental factors are summarized in Table 5.

Table 5. Summary of Experimental Factors

Decision Factor	**Levels**
(k_1, k_2) combination	(3, 7), (3, 9) and (5, 9)

Environmental Factor	**Levels**
Number of patients per session (N)	10, 20
Coefficient of variation for return patients (CV_{Ret})	0.35, 0.70
Coefficient of variation for new patients (CV_{New})	0.35, 0.70
Probability of walk-ins (P_W)	0, 0.15
Probability of no-shows (P_N)	0, 0.15
Mean unpunctuality of patients (Unp)	-15, 0 min.

ANOVA tests results shown in Table 6 indicate that all two-way interactions are significant at α= 0.05 for dependent variables TC1, TC10 and TC100. Interaction plots reveal that the RULE*P_W and RULE*P_N interactions have cross effects. This implies that the performance rankings of appointment rules change for different values of P_W and P_N (see Figure 2). The rest of the two-way interactions show only infatuating effects, and thus they are less interesting. We continue our analysis by limiting the range of environments to four (2 P_N x 2 P_W), fixing the rest of the environmental factors at one level (N= 10, CV_{Ref}= 0.35, CV_{New} = 0.35, and Unp= -15 minutes).

Tukey's test is conducted for pairwise comparisons at alpha level 0.05. Table 7 summarizes the statistical results, providing rankings of appointment rules in terms of TC1, TC10 and TC100. Appointment rules joined by the same superscript are not significantly different at alpha 0.05. The results show that (5, 9) appears as the best (k_1, k_2) combination with lowest total cost in 10 out of the 12 cases. As a result, we choose k_1= 5, and k_2= 9 for the DOME rules simulated in our main experiments.

Table 7. Rankings of (k_1, k_2) Combinations in DOME Rules [1]

Env # 1		Env # 2		Env # 3		Env # 4	
P_W= 0, P_N= 0		P_W= 0.15, P_N= 0		P_W= 0, P_N= 0.15		P_W= 0.15, P_N= 0.15	
Rule	**TC1**	**Rule**	**TC1**	**Rule**	**TC1**	**Rule**	**TC1**
(3, 9)	15.98 ^{A}	(3, 9)	27.79 ^{A}	(5, 9)	14.90 ^{A}	(3, 9)	22.75 ^{A}
(5, 9)	16.25 ^{A}	(5, 9)	28.40 ^{A}	(3, 9)	14.91 ^{A}	(5, 9)	22.90 ^{A}
(3, 7)	17.12 ^{B}	(3, 7)	29.66 ^{B}	(3, 7)	15.15 ^{A}	(3, 7)	23.67 ^{B}
Rule	**TC10**	**Rule**	**TC10**	**Rule**	**TC10**	**Rule**	**TC10**
(5, 9)	64.79 ^{A}	(5, 9)	90.06 ^{A}	(3, 7)	81.26 ^{A}	(5, 9)	89.04 ^{A}
(3, 7)	65.13 ^{A}	(3, 7)	92.14 ^{B}	(5, 9)	83.31 ^{B}	(3, 7)	89.31 ^{A}
(3, 9)	69.43 ^{B}	(3, 9)	93.36 ^{B}	(3, 9)	87.86 ^{C}	(3, 9)	93.11 ^{B}
Rule	**TC100**	**Rule**	**TC100**	**Rule**	**TC100**	**Rule**	**TC100**
(3, 7)	545.16 ^{A}	(5, 9)	706.65 ^{A}	(3, 7)	742.37 ^{A}	(3, 7)	745.68 ^{A}
(5, 9)	550.18 ^{A}	(3, 7)	716.90 ^{A}	(5, 9)	767.43 ^{B}	(5, 9)	750.45 ^{A}
(3, 9)	603.93 ^{B}	(3, 9)	749.01 ^{B}	(3, 9)	817.42 ^{C}	(3, 9)	796.64 ^{B}

[1] Appointment rules joined by the same superscript are not significantly different at alpha 0.05.

Table 6. ANOVA on Performance Measures TC1, TC10, TC100[1]

	DF	TC1
Corrected Model	85	4667
Intercept	1	3049855
RULE	2	1832.51
RULE * PN	2	208.78
RULE * PW	2	134.55
RULE * N	2	110.59
RULE * UNP	2	103.30
RULE * CVNEW	2	24.91
RULE * CVRET	2	13.87
RULE * CVNEW * N	2	11.69
RULE * PW * N	2	5.81
RULE * PN * N	2	4.64
RULE * UNP * PN	2	3.74
R-SQUARE		.954

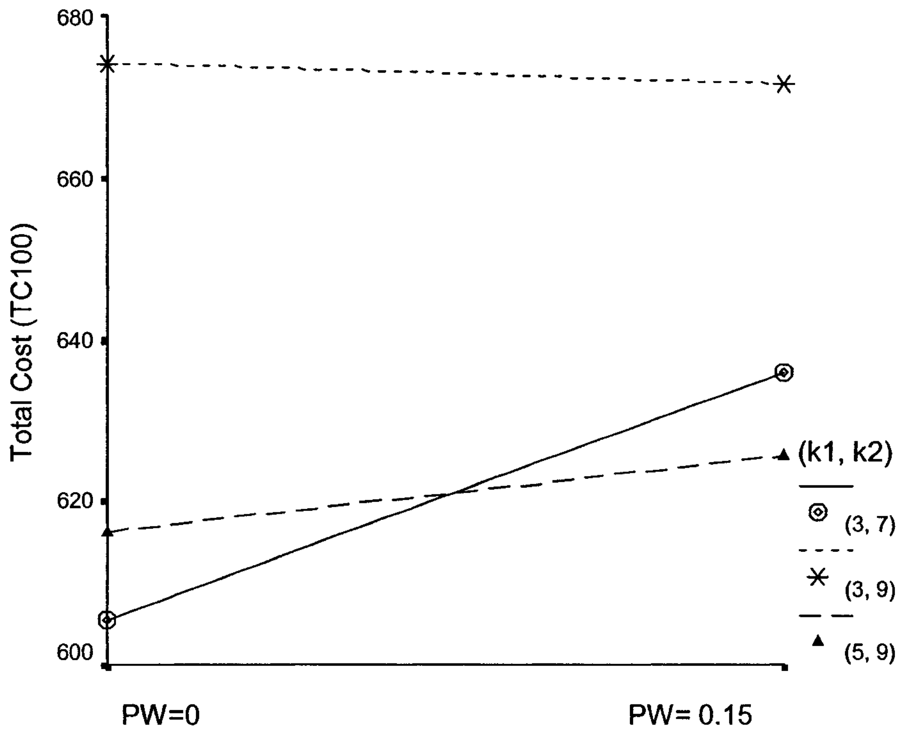
	DF	TC10
Corrected Model	85	9124
Intercept	1	4282401
RULE	2	1253
RULE * N	2	286
RULE * PW	2	229
RULE * PN	2	166
RULE * UNP	2	71
RULE * CVNEW	2	10
RULE * CVRET	2	4
RULE * UNP * PW	2	7
RULE * UNP * PN	2	6
RULE * UNP * N	2	5
R-SQUARE		.976

	DF	TC100
Corrected Model	85	10482
Intercept	1	3950134
RULE	2	2917
RULE * N	2	311
RULE * PW	2	225
RULE * PN	2	126
RULE * UNP	2	57
RULE * CVNEW	2	31
RULE * CVRET	2	12
RULE * UNP * PW	2	10.12
RULE * UNP * PN	2	6.60
RULE * UNP * N	2	5.68
R-SQUARE		.979

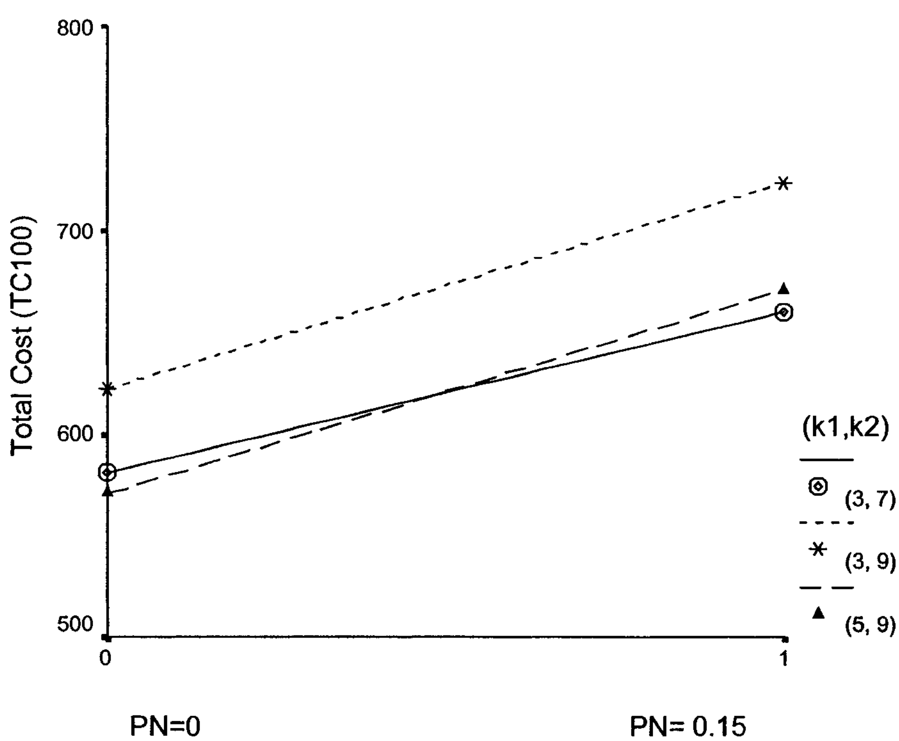
[1] All significant at alpha 0.05.

Environmental Factors: PN: probability of no-shows; PW: probability of walk-ins; UNP: unpunctuality of patients; CVNEW: coefficient of variation for new patients; CVRET: coefficient of variation for return patients
Decision Factor: RULE: appointment rule

Figure 2. Two-way interaction: RULE * P_W



Two-way interaction: RULE * PN



APPENDIX D. Formulation of Appointment Systems

The formulae for appointment rules require specifying the mean service times (μ) for calculating appointment times, t_i. Some rules, such as OFFSET and DOME also require the standard deviation of service times (σ) in their formulation (see Section 4.1.1). Recall that mean service times were different for the eight hypothetical clinic simulated, as summarized in Table VI of Section 4.3.2. This table is partially repeated here for the ease of illustrating how these μ-values were used in formulating appointment systems.

Table 1. Hypothetical Clinics Simulated

Environmental Factor	**Clinic 1**	**Clinic 2**
Number of patients per clinic session(N)	10	20
Percentage of new patients (*%New*)	0.40	0.40
Ratio of the mean consultation time of new patients to the mean consultation time of return patients (μ_{New}/μ_{Ret})	2	2
Mean consultation time of new patients (μ_{New})	30 min.	15 min.
Mean consultation time of return patients (μ_{Ret})	15 min.	7.5 min.
Mean consultation time of all patients (μ)	21 min.	10.5 min.
Clinic session length (T)	210 min.	210 min.

When formulating AS without interval-adjustment, the overall μ was used in setting the appointment interval-lengths. On the other hand, when formulating appointment systems with interval-adjustment, appointment intervals were calculated separately for new/return patients using μ_{Ret} and μ_{New}-values. For example, if the individual-block/fixed-interval rule combined with NEW_BEG sequencing without interval adjustment (IBFI/NEW_BEG-0) was to be simulated in Clinic 1, then all appointment intervals would be set equal to 21 minutes, and four new patients would be assigned to blocks at the beginning of the session. For the same AS with interval-adjustment (IBFI/NEW_BEG-1), four appointment slots assigned for new patients would be set equal to 30 minutes, and the rest six slots would be set equal to 15 minutes.

As mentioned earlier, the variable-block rules of OFFSET and DOME also require the standard deviation of service times (σ) in their formulation. The calculation of overall σ-values are not as straightforward as μ-values. In fact, for all combinations of CV_{Ret} and CV_{New}, the overall CV-value need to be determined based on the particular percentage of new patients. For this reason, 5000 service times were simulated to approximate the overall σ-values for each environment (2 CV_{Ret} x 2 CV_{New}). The results are summarized in Table 2 for Clinics 1 and 2 (since OFFSET and DOME rules were only simulated during pilot runs and Part I, the analysis was necessary for these two clinics, only). Note that due to truncation of service times, some of the σ_{New} and σ_{Ret}-values are different than the theoretical values that would be obtained using the formula $\sigma = CV/\mu$. In Tables 3-5, the reader may find the details on all appointment systems simulated in this study during pilot runs, as well as the main experiments (Part I and II). Each column specifies appointment times, t_i, for patients i= 1 through N. Negative values indicate that the patient is called prior to clinic start time, which is set at zero.

Table 2. Mean and Standard Deviation of Service Times Used in Formulation of AS

Simulated CV_{Ret} , CV_{New} values	Clinic	μ_{Ret}	μ_{New}	Overall μ	σ_{Ret}	σ_{New}	Overall σ
CV_{Ret}= 0.35, CV_{New}= 0.35	1	15	30	21	5.25	10.20^T	10.71
	2	7.5	15	10.5	2.625	5.25	5.46
CV_{Ret}= 0.35, CV_{New}= 0.70	1	15	30	21	5.25	16.20^T	13.02
	2	7.5	15	10.5	2.625	9.90^T	7.67
CV_{Ret}= 0.70, CV_{New}= 0.35	1	15	30	21	9.90^T	10.20^T	12.39
	2	7.5	15	10.5	5.025^T	5.25	6.405
CV_{Ret} = 0.70, CV_{New}= 0.70	1	15	30	21	9.90^T	16.20^T	14.49
	2	7.5	15	10.5	5.025^T	9.90^T	8.40

^{T} Truncation effect

Table 3. DOME and OFFSET Rules Tested During Pilot Runs

OFFSET1 has β_1=0.15, β_2=0.30, k=5
OFFSET2 has β_1=0.25, β_2=0.50, k=5
DOME1 has β_1=0.15, β_2=0.30, β_3=0.05, k_1=5, k_2=9
DOME2 has β_1=0.15, β_2=0.30, β_3=0.25, k_1=5, k_2=9
DOME3 has β_1=0.25, β_2=0.50, β_3=0.05, k_1=5, k_2=9
DOME4 has β_1=0.25, β_2=0.50, β_3=0.25, k_1=5, k_2=9
DOME5 has β_1=0.15, β_2=0.30, β_3=0.25, k_1=3, k_2=7
DOME6 has β_1=0.15, β_2=0.30, β_3=0.25, k_1=3, k_2=9

Clinic 1, N= 10, CV_{Ret}= 0.35, CV_{New}= 0.35										
OFFSET1	-6.4	16.2	38.8	61.4	84.0	108.2	132.4	156.6	180.8	200.0
OFFSET2	-10.7	13.0	36.7	60.3	84.0	110.4	136.7	163.1	189.4	200.0
DOME 1	-6.4	16.2	38.8	61.4	84.0	108.2	132.4	156.6	168.0	188.5
DOME 2	-6.4	16.2	38.8	61.4	84.0	108.2	132.4	156.6	168.0	186.3
DOME 3	-10.7	13.0	36.7	60.3	84.0	110.4	136.7	163.1	168.0	188.5
DOME 4	-10.7	13.0	36.7	60.3	84.0	110.4	136.7	163.1	168.0	186.3
DOME 5	-3.2	19.4	42.0	66.2	90.4	114.6	126.0	144.3	162.7	181.0
DOME 6	-3.2	19.4	42.0	66.2	90.4	114.6	138.8	163.1	168.0	186.3
Clinic 1, N= 10, CV_{Ret}= 0.35, CV_{New}= 0.70										
OFFSET1	-7.8	15.2	38.1	61.1	84.0	108.9	133.8	158.7	183.6	200.0
OFFSET2	-13.0	11.3	35.5	59.8	84.0	111.5	139.0	166.5	194.0	200.0
DOME 1	-7.8	15.2	38.1	61.1	84.0	108.9	133.8	158.7	168.0	188.4
DOME 2	-7.8	15.2	38.1	61.1	84.0	108.9	133.8	158.7	168.0	185.8
DOME 3	-13.0	11.3	35.5	59.8	84.0	111.5	139.0	166.5	168.0	188.4
DOME 4	-13.0	11.3	35.5	59.8	84.0	111.5	139.0	166.5	168.0	185.8
DOME 5	-3.9	19.1	42.0	66.9	91.8	116.7	126.0	143.8	161.5	179.3
DOME 6	-3.9	19.1	42.0	66.9	91.8	116.7	141.6	166.5	168.0	185.8
Clinic 1, N= 10, CV_{Ret}= 0.70, CV_{New}= 0.35										
OFFSET1	-7.4	15.4	38.3	61.1	84.0	108.7	133.4	158.2	182.9	200.0
OFFSET2	-12.4	11.7	35.8	59.9	84.0	111.2	138.4	165.6	192.8	200.0
DOME 1	-7.4	15.4	38.3	61.1	84.0	108.7	133.4	158.2	168.0	188.4
DOME 2	-7.4	15.4	38.3	61.1	84.0	108.7	133.4	158.2	168.0	185.9
DOME 3	-12.4	11.7	35.8	59.9	84.0	111.2	138.4	165.6	168.0	188.4
DOME 4	-12.4	11.7	35.8	59.9	84.0	111.2	138.4	165.6	168.0	185.9
DOME 5	-3.7	19.1	42.0	66.7	91.4	116.2	126.0	143.9	161.8	179.7
DOME 6	-3.7	19.1	42.0	66.7	91.4	116.2	140.9	165.6	168.0	185.9
Clinic 1, N= 10, CV_{Ret}= 0.70, CV_{New}= 0.70										
OFFSET1	-8.7	14.5	37.7	60.8	84.0	109.4	134.7	160.1	185.4	200.0
OFFSET2	-14.5	10.1	34.8	59.4	84.0	112.3	140.5	168.8	197.0	200.0
DOME 1	-8.7	14.5	37.7	60.8	84.0	109.4	134.7	160.1	168.0	188.3
DOME 2	-8.7	14.5	37.7	60.8	84.0	109.4	134.7	160.1	168.0	185.4
DOME 3	-14.5	10.1	34.8	59.4	84.0	112.3	140.5	168.8	168.0	188.3
DOME 4	-14.5	10.1	34.8	59.4	84.0	112.3	140.5	168.8	168.0	185.4
DOME 5	-4.3	18.8	42.0	67.4	92.7	118.1	126.0	143.4	160.8	178.1
DOME 6	-4.3	18.8	42.0	67.4	92.7	118.1	143.4	168.8	168.0	185.4

Table 3. DOME and OFFSET Rules Tested During Pilot Runs (Cont'ed)

Clinic 2, N= 20, CV_{Ret}= 0.35, CV_{New}= 0.35																				
OFFSET1	-7.4	4.0	15.3	26.6	37.9	49.2	60.5	71.9	83.2	94.5	106.6	118.8	130.9	143.1	155.2	167.3	179.5	191.6	200.0	200.0
OFFSET2	-12.3	-0.4	11.5	23.3	35.2	47.0	58.9	70.8	82.6	94.5	107.7	121.0	134.2	147.4	160.7	173.9	187.1	200.0	200.0	200.0
DOME 1	-7.4	4.0	15.3	26.6	37.9	49.2	60.5	71.9	83.2	94.5	106.6	118.8	130.9	143.1	155.2	167.3	178.5	179.5	187.6	196.8
DOME 2	-7.4	4.0	15.3	26.6	37.9	49.2	60.5	71.9	83.2	94.5	106.6	118.8	130.9	143.1	155.2	167.3	179.5	178.5	188.7	198.9
DOME 3	-12.3	-0.4	11.5	23.3	35.2	47.0	58.9	70.8	82.6	94.5	107.7	121.0	134.2	147.4	160.7	173.9	178.5	187.1	188.7	199.0
DOME 4	-12.3	-0.4	11.5	23.3	35.2	47.0	58.9	70.8	82.6	94.5	107.7	121.0	134.2	147.4	160.7	173.9	178.5	187.1	187.6	196.8
DOME 5	-4.1	7.2	18.5	29.9	41.2	52.5	64.6	76.8	88.9	101.1	113.2	125.3	136.5	137.5	145.6	154.8	163.9	173.0	182.2	191.3
DOME 6	-4.1	7.2	18.5	29.9	41.2	52.5	64.6	76.8	88.9	101.1	113.2	125.3	137.5	149.6	161.7	173.9	178.5	186.0	187.6	196.8
Clinic 2, N= 20, CV_{Ret}= 0.35, CV_{New}= 0.70																				
OFFSET1	-10.4	1.3	13.0	24.6	36.3	47.9	59.6	71.2	82.9	94.5	107.3	120.1	132.9	145.7	158.5	171.3	184.1	196.9	200.0	200.0
OFFSET2	-17.3	-4.8	7.6	20.0	32.4	44.8	57.3	69.7	82.1	94.5	108.8	123.2	137.5	151.8	166.2	180.5	194.8	200.0	200.0	200.0
DOME 1	-10.4	1.3	13.0	24.6	36.3	47.9	59.6	71.2	82.9	94.5	107.3	120.1	132.9	145.7	158.5	171.3	178.5	184.1	187.1	195.7
DOME 2	-10.4	1.3	13.0	24.6	36.3	47.9	59.6	71.2	82.9	94.5	107.3	120.1	132.9	145.7	158.5	171.3	178.5	184.1	188.6	198.7
DOME 3	-17.3	-4.8	7.6	20.0	32.4	44.8	57.3	69.7	82.1	94.5	108.8	123.2	137.5	151.8	166.2	178.5	180.5	188.6	194.8	198.7
DOME 4	-17.3	-4.8	7.6	20.0	32.4	44.8	57.3	69.7	82.1	94.5	108.8	123.2	137.5	151.8	166.2	178.5	180.5	187.1	194.8	195.7
DOME 5	-5.8	5.9	17.6	29.2	40.9	52.5	65.3	78.1	90.9	103.7	116.5	129.3	136.5	142.1	145.1	153.7	162.3	170.8	179.4	188.0
DOME 6	-5.8	5.9	17.6	29.2	40.9	52.5	65.3	78.1	90.9	103.7	116.5	129.3	142.1	154.9	167.7	178.5	180.5	187.1	193.3	195.7
Clinic 2, N= 20, CV_{Ret}= 0.70, CV_{New}= 0.35																				
OFFSET1	-8.7	2.8	14.3	25.7	37.2	48.7	60.1	71.6	83.0	94.5	106.9	119.3	131.8	144.2	156.6	169.0	181.5	193.9	200.0	200.0
OFFSET2	-14.4	-2.3	9.8	21.9	34.0	46.1	58.2	70.3	82.4	94.5	108.2	121.9	135.6	149.3	163.0	176.7	190.4	200.0	200.0	200.0
DOME 1	-8.7	2.8	14.3	25.7	37.2	48.7	60.1	71.6	83.0	94.5	106.9	119.3	131.8	144.2	156.6	169.0	178.5	181.5	187.4	196.3
DOME 2	-8.7	2.8	14.3	25.7	37.2	48.7	60.1	71.6	83.0	94.5	106.9	119.3	131.8	144.2	156.6	169.0	178.5	181.5	188.7	198.9
DOME 3	-14.4	-2.3	9.8	21.9	34.0	46.1	58.2	70.3	82.4	94.5	108.2	121.9	135.6	149.3	163.0	176.7	178.5	188.7	190.4	198.9
DOME 4	-14.4	-2.3	9.8	21.9	34.0	46.1	58.2	70.3	82.4	94.5	108.2	121.9	135.6	149.3	163.0	176.7	178.5	187.4	190.4	196.3
DOME 5	-4.8	6.7	18.1	29.6	41.0	52.5	64.9	77.3	89.8	102.2	114.6	127.0	136.5	139.5	145.4	154.3	163.2	172.1	181.0	189.9
DOME 6	-4.8	6.7	18.1	29.6	41.0	52.5	64.9	77.3	89.8	102.2	114.6	127.0	139.5	151.9	164.3	176.7	178.5	187.4	189.1	196.3
Clinic 2, N= 20, CV_{Ret}= 0.70, CV_{New}= 0.70																				
OFFSET1	-11.3	0.4	12.2	23.9	35.7	47.5	59.2	71.0	82.7	94.5	107.5	120.5	133.6	146.6	159.6	172.6	185.6	198.7	200.0	200.0
OFFSET2	-18.9	-6.3	6.3	18.9	31.5	44.1	56.7	69.3	81.9	94.5	109.2	123.9	138.6	153.3	168.0	182.7	197.4	200.0	200.0	200.0
DOME 1	-11.3	0.4	12.2	23.9	35.7	47.5	59.2	71.0	82.7	94.5	107.5	120.5	133.6	146.6	159.6	172.6	178.5	185.6	186.9	195.3
DOME 2	-11.3	0.4	12.2	23.9	35.7	47.5	59.2	71.0	82.7	94.5	107.5	120.5	133.6	146.6	159.6	172.6	178.5	185.6	188.6	198.7
DOME 3	-18.9	-6.3	6.3	18.9	31.5	44.1	56.7	69.3	81.9	94.5	109.2	123.9	138.6	153.3	168.0	178.5	182.7	188.6	197.4	198.7
DOME 4	-18.9	-6.3	6.3	18.9	31.5	44.1	56.7	69.3	81.9	94.5	109.2	123.9	138.6	153.3	168.0	178.5	182.7	186.9	195.3	197.4
DOME 5	-6.3	5.5	17.2	29.0	40.7	52.5	65.5	78.5	91.6	104.6	117.6	130.6	136.5	143.6	144.9	153.3	161.7	170.1	178.5	186.9
DOME 6	-6.3	5.5	17.2	29.0	40.7	52.5	65.5	78.5	91.6	104.6	117.6	130.6	143.6	156.7	169.7	178.5	182.7	188.6	195.7	198.7

Table 4. Rules Tested During Main Runs - Part I

Clinic 1, N= 10, CV_{Ret}= 0.35, CV_{New}= 0.35

IBFI	0	21	42	63	84	105	126	147	168	189
OFFSET	-6.42	16.185	38.79	61.4	84	108.21	132.42	156.63	180.84	200
DOME	-6.42	16.185	38.79	61.4	84	108.21	132.42	156.63	168	188.47
2BEG	0	0	21	42	63	84	105	126	147	168
2BEG_DOME	-6.42	-6.42	16.185	38.79	61.4	84	108.21	132.42	156.63	168
MBFI	0	0	42	42	84	84	126	126	168	168
MB_DOME	-6.42	-6.42	38.79	38.79	84	84	132.42	132.42	168	168

Clinic 1, N= 10, CV_{Ret}= 0.35, CV_{New}= 0.70

IBFI	0	21	42	63	84	105	126	147	168	189
OFFSET	-7.8	15.15	38.1	61.05	84	108.9	133.8	158.7	183.6	200
DOME	-7.8	15.15	38.1	61.05	84	108.9	133.8	158.7	168	188.35
2BEG	0	0	21	42	63	84	105	126	147	168
2BEG_DOME	-7.8	-7.8	15.15	38.1	61.05	84	108.9	133.8	158.7	168
MBFI	0	0	42	42	84	84	126	126	168	168
MB_DOME	-7.8	-7.8	38.1	38.1	84	84	133.8	133.8	168	168

Clinic 1, N= 10, CV_{Ret}= 0.70, CV_{New}= 0.35

IBFI	0	21	42	63	84	105	126	147	168	189
OFFSET	-7.44	15.42	38.28	61.14	84	108.72	133.44	158.16	182.88	200
DOME	-7.44	15.42	38.28	61.14	84	108.72	133.44	158.16	168	188.38
2BEG	0	0	21	42	63	84	105	126	147	168
2BEG_DOME	-7.44	-7.44	15.42	38.28	61.14	84	108.72	133.44	158.16	168
MBFI	0	0	42	42	84	84	126	126	168	168
MB_DOME	-7.44	-7.44	38.28	38.28	84	84	133.44	133.44	168	168

Clinic 1, N= 10, CV_{Ret}= 0.70, CV_{New}= 0.70

IBFI	0	21	42	63	84	105	126	147	168	189
OFFSET	-8.7	14.48	37.65	60.83	84	109.35	134.7	160.05	185.4	200
DOME	-8.7	14.48	37.65	60.83	84	109.35	134.7	160.05	168	188.28
2BEG	0	0	21	42	63	84	105	126	147	168
2BEG_DOME	-8.7	-8.7	14.48	37.65	60.83	84	109.35	134.7	160.05	168
MBFI	0	0	42	42	84	84	126	126	168	168
MB_DOME	-8.7	-8.7	37.65	37.65	84	84	134.7	134.7	168	168

Table 4. Rules Tested During Main Runs - Part I (Cont'ed)

Clinic 2, N= 20, CV_{Ret}= 0.35, CV_{New}= 0.35

IBFI	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189	199.5
OFFSET	-7.37	3.95	15.27	26.59	37.91	49.22	60.54	71.86	83.18	94.5	106.64	118.78	130.91	143.05	155.19	167.33	179.47	191.6	200	200
DOME	-7.37	3.95	15.27	26.59	37.91	49.22	60.54	71.86	83.18	94.5	106.64	118.78	130.91	143.05	155.19	167.33	179.47	178.5	188.73	198.95
2BEG	0	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189
2BEG_DOME	-7.37	-7.37	3.95	15.27	26.59	37.91	49.22	60.54	71.86	83.18	94.5	106.64	118.78	130.91	143.05	155.19	167.33	179.47	178.5	188.73
MBFI	0	0	21	21	42	42	63	63	84	84	105	105	126	126	147	147	168	168	189	189
MB_DOME	-7.37	-7.37	15.27	15.27	37.91	37.91	60.54	60.54	83.18	83.18	106.64	106.64	130.91	130.91	155.19	155.19	179.47	179.47	188.73	188.73

Clinic 2, N= 20, CV_{Ret}= 0.35, CV_{New}= 0.70

IBFI	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189	199.5
OFFSET	-10.35	1.3	12.95	24.6	36.25	47.9	59.55	71.2	82.85	94.5	107.3	120.1	132.9	145.7	158.5	171.3	184.1	196.9	200	200
DOME	-10.35	1.3	12.95	24.6	36.25	47.9	59.55	71.2	82.85	94.5	107.3	120.1	132.9	145.7	158.5	171.3	178.5	184.1	188.62	198.73
2BEG	0	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189
2BEG_DOME	-10.35	-10.35	1.3	12.95	24.6	36.25	47.9	59.55	71.2	82.85	94.5	107.3	120.1	132.9	145.7	158.5	171.3	178.5	184.1	188.62
MBFI	0	0	21	21	42	42	63	63	84	84	105	105	126	126	147	147	168	168	189	189
MB_DOME	-10.35	-10.35	12.95	12.95	36.25	36.25	59.55	59.55	82.85	82.85	107.3	107.3	132.9	132.9	158.5	158.5	178.5	178.5	188.62	188.62

Clinic 2, N= 20, CV_{Ret}= 0.70, CV_{New}= 0.35

IBFI	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189	199.5
OFFSET	-8.65	2.81	14.3	25.7	37.2	48.7	60.1	71.6	83.0	94.5	106.9	119.3	131.8	144.2	156.6	169.03	181.5	193.9	200	200
DOME	-8.65	2.81	14.3	25.7	37.2	48.7	60.1	71.6	83.0	94.5	106.9	119.3	131.8	144.2	156.6	169.03	178.5	181.5	188.7	198.9
2BEG	0	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189
2BEG_DOME	-8.65	-8.65	2.81	14.3	25.7	37.2	48.7	60.1	71.6	83.0	94.5	106.9	119.3	131.8	144.2	156.6	169.0	178.5	181.5	188.7
MBFI	0	0	21	21	42	42	63	63	84	84	105	105	126	126	147	147	168	168	189	189
MB_DOME	-8.65	-8.65	14.3	14.3	37.2	37.2	60.1	60.1	83.0	83.0	106.9	106.9	131.8	131.8	156.6	156.61	178.5	178.5	188.7	188.7

Clinic 2, N= 20, CV_{Ret}= 0.70, CV_{New}= 0.70

IBFI	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189	199.5
OFFSET	-11.34	0.42	12.18	23.94	35.7	47.46	59.22	70.98	82.74	94.5	107.52	120.54	133.56	146.58	159.6	172.62	185.64	198.66	200	200
DOME	-11.34	0.42	12.18	23.94	35.7	47.46	59.22	70.98	82.74	94.5	107.52	120.54	133.56	146.58	159.6	172.62	178.5	185.64	188.58	198.86
2BEG	0	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189
2BEG_DOME	-11.34	-11.34	0.42	12.18	23.94	35.7	47.46	59.22	70.98	82.74	94.5	107.52	120.54	133.56	146.58	159.6	172.62	178.5	185.64	188.68
MBFI	0	0	21	21	42	42	63	63	84	84	105	105	126	126	147	147	168	168	189	189
MB_DOME	-11.34	-11.34	12.18	12.18	35.7	35.7	59.22	59.22	82.74	82.74	107.52	107.52	133.56	133.56	159.6	159.6	178.5	178.5	188.58	188.68

Table 5. Rules Tested During Main Runs - Part II

Clinic 1, N= 10, $\%New$= 0.40, μ_{New}/μ_{Ret}= 2

IBFI/ALTER-0	0	21	42	63	84	105	126	147	168	189
IBFI/ALTER-1	0	30	45	60	90	105	120	150	165	180
	N	R	R	N	R	R	N	R	R	N
IBFI/NEW_BEG-0	0	21	42	63	84	105	126	147	168	189
IBFI/NEW_BEG-1	0	30	60	90	120	135	150	165	180	195
	N	N	N	N	R	R	R	R	R	R
IBFI/RET_BEG-0	0	21	42	63	84	105	126	147	168	189
IBFI/RET_BEG-1	0	15	30	45	60	75	90	120	150	180
	R	R	R	R	R	R	N	N	N	N
2BEG/ALTER-0	0	0	21	42	63	84	105	126	147	168
2BEG/ALTER-1	0	0	30	45	60	90	105	120	150	165
	N	R	R	N	R	R	N	R	R	N
2BEG/NEW_BEG-0	0	0	21	42	63	84	105	126	147	168
2BEG/NEW_BEG-1	0	0	30	60	90	120	135	150	165	180
	N	N	N	N	R	R	R	R	R	R
2BEG/RET_BEG-0	0	0	21	42	63	84	105	126	147	168
2BEG/RET_BEG-1	0	0	15	30	45	60	75	90	120	150
	R	R	R	R	R	R	N	N	N	N
MBFI/ALTER-0	0	0	42	42	84	84	126	126	168	168
MBFI/ALTER-1	0	0	45	45	90	90	120	120	165	165
	N	R	R	N	R	R	N	R	R	N
MBFI/NEW_BEG-0	0	0	42	42	84	84	126	126	168	168
MBFI/NEW_BEG-1	0	0	60	60	120	120	150	150	180	180
	N	N	N	N	R	R	R	R	R	R
MBFI/RET_BEG-0	0	0	42	42	84	84	126	126	168	168
MBFI/RET_BEG-1	0	0	30	30	60	60	90	90	150	150
	R	R	R	R	R	R	N	N	N	N

Table 5. Rules Tested During Main Runs - Part II (Cont'ed)

Clinic 2, N= 20, $\%New$= 0.40, μ_{New}/μ_{Ret}= 2

IBFI/ALTER-0	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189	199.5
IBFI/ALTER-1	0	15	22.5	37.5	45	52.5	67.5	75	82.5	97.5	105	112.5	127.5	135	142.5	157.5	165	172.5	187.5	195
	N	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	N
IBFI/NEW_BEG-0	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189	199.5
IBFI/NEW_BEG-1	0	15	30	45	60	75	90	105	120	127.5	135	142.5	150	157.5	165	172.5	180	187.5	195	202.5
	N	N	N	N	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R
IBFI/RET_BEG-0	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189	199.5
IBFI/RET_BEG-1	0	7.5	15	22.5	30	37.5	45	52.5	60	67.5	75	82.5	90	105	120	135	150	165	180	195
	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N	N	N	N	N
2BEG/ALTER-0	0	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189
2BEG/ALTER-1	0	0	15	22.5	37.5	45	52.5	67.5	75	82.5	97.5	105	112.5	127.5	135	142.5	157.5	165	172.5	187.5
	N	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	N
2BEG/NEW_BEG-0	0	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189
2BEG/NEW_BEG-1	0	0	15	30	45	60	75	90	105	120	127.5	135	142.5	150	157.5	165	172.5	180	187.5	195
	N	N	N	N	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R
2BEG/RET_BEG-0	0	0	10.5	21	31.5	42	52.5	63	73.5	84	94.5	105	115.5	126	136.5	147	157.5	168	178.5	189
2BEG/RET_BEG-1	0	0	7.5	15	22.5	30	37.5	45	52.5	60	67.5	75	82.5	90	105	120	135	150	165	180
	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N	N	N	N	N
MBFI/ALTER-0	0	0	21	21	42	42	63	63	84	84	105	105	126	126	147	147	168	168	189	189
MBFI/ALTER-1	0	0	22.5	22.5	45	45	67.5	67.5	82.5	82.5	105	105	127.5	127.5	142.5	142.5	165	165	187.5	187.5
	N	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	N
MBFI/NEW_BEG-0	0	0	21	21	42	42	63	63	84	84	105	105	126	126	147	147	168	168	189	189
MBFI/NEW_BEG-1	0	0	30	30	60	60	90	90	120	120	135	135	150	150	165	165	180	180	195	195
	N	N	N	N	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R
MBFI/RET_BEG-0	0	0	21	21	42	42	63	63	84	84	105	105	126	126	147	147	168	168	189	189
MBFI/RET_BEG-1	0	0	15	15	30	30	45	45	60	60	75	75	90	90	120	120	150	150	180	180
	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N	N	N	N	N

Table 5. Rules Tested During Main Runs - Part II (Cont'ed)

Clinic 3, N= 10, $\%New$= 0.40, μ_{New}/μ_{Ret}= 1.33

IBFI/ALTER-0	0	17	34	51	68	85	102	119	136	153
IBFI/ALTER-1	0	20	35	50	70	85	100	120	135	150
	N	R	R	N	R	R	N	R	R	N
IBFI/NEW_BEG-0	0	17	34	51	68	85	102	119	136	153
IBFI/NEW_BEG-1	0	20	40	60	80	95	110	125	140	155
	N	N	N	N	R	R	R	R	R	R
IBFI/RET_BEG-0	0	17	34	51	68	85	102	119	136	153
IBFI/RET_BEG-1	0	15	30	45	60	75	90	110	130	150
	R	R	R	R	R	R	N	N	N	N
2BEG/ALTER-0	0	0	17	34	51	68	85	102	119	136
2BEG/ALTER-1	0	0	20	35	50	70	85	100	120	135
	N	R	R	N	R	R	N	R	R	N
2BEG/NEW_BEG-0	0	0	17	34	51	68	85	102	119	136
2BEG/NEW_BEG-1	0	0	20	40	60	80	95	110	125	140
	N	N	N	N	R	R	R	R	R	R
2BEG/RET_BEG-0	0	0	17	34	51	68	85	102	119	136
2BEG/RET_BEG-1	0	0	15	30	45	60	75	90	110	130
	R	R	R	R	R	R	N	N	N	N
MBFI/ALTER-0	0	0	34	34	68	68	102	102	136	136
MBFI/ALTER-1	0	0	35	35	70	70	100	100	135	135
	N	R	R	N	R	R	N	R	R	N
MBFI/NEW_BEG-0	0	0	34	34	68	68	102	102	136	136
MBFI/NEW_BEG-1	0	0	40	40	80	80	110	110	140	140
	N	N	N	N	R	R	R	R	R	R
MBFI/RET_BEG-0	0	0	34	34	68	68	102	102	136	136
MBFI/RET_BEG-1	0	0	30	30	60	60	90	90	130	130
	R	R	R	R	R	R	N	N	N	N

Table 5. Rules Tested During Main Runs - Part II (Cont'ed)

Clinic 4, N= 20, %New= 0.40, μ_{New}/μ_{Ret}= 1.33

IBFI/ALTER-0	0	8.5	17	25.5	34	42.5	51	59.5	68	76.5	85	93.5	102	110.5	119	127.5	136	144.5	153	161.5
IBFI/ALTER-1	0	10	17.5	27.5	35	42.5	52.5	60	67.5	77.5	85	92.5	102.5	110	117.5	127.5	135	142.5	152.5	160
	N	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	N
IBFI/NEW_BEG-0	0	8.5	17	25.5	34	42.5	51	59.5	68	76.5	85	93.5	102	110.5	119	127.5	136	144.5	153	161.5
IBFI/NEW_BEG-1	0	10	20	30	40	50	60	70	80	87.5	95	102.5	110	117.5	125	132.5	140	147.5	155	162.5
	N	N	N	N	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R
IBFI/RET_BEG-0	0	8.5	17	25.5	34	42.5	51	59.5	68	76.5	85	93.5	102	110.5	119	127.5	136	144.5	153	161.5
IBFI/RET_BEG-1	0	7.5	15	22.5	30	37.5	45	52.5	60	67.5	75	82.5	90	100	110	120	130	140	150	160
	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N	N	N	N	N
2BEG/ALTER-0	0	0	8.5	17	25.5	34	42.5	51	59.5	68	76.5	85	93.5	102	110.5	119	127.5	136	144.5	153
2BEG/ALTER-1	0	0	10	17.5	27.5	35	42.5	52.5	60	67.5	77.5	85	92.5	102.5	110	117.5	127.5	135	142.5	152.5
	N	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	N
2BEG/NEW_BEG-0	0	0	8.5	17	25.5	34	42.5	51	59.5	68	76.5	85	93.5	102	110.5	119	127.5	136	144.5	153
2BEG/NEW_BEG-1	0	0	10	20	30	40	50	60	70	80	87.5	95	102.5	110	117.5	125	132.5	140	147.5	155
	N	N	N	N	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R
2BEG/RET_BEG-0	0	0	8.5	17	25.5	34	42.5	51	59.5	68	76.5	85	93.5	102	110.5	119	127.5	136	144.5	153
2BEG/RET_BEG-1	0	0	7.5	15	22.5	30	37.5	45	52.5	60	67.5	75	82.5	90	100	110	120	130	140	150
	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N	N	N	N	N
MBFI/ALTER-0	0	0	17	17	34	34	51	51	68	68	85	85	102	102	119	119	136	136	153	153
MBFI/ALTER-1	0	0	17.5	17.5	35	35	52.5	52.5	67.5	67.5	85	85	102.5	102.5	117.5	117.5	135	135	152.5	152.5
	N	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	R	N	R	N
MBFI/NEW_BEG-0	0	0	17	17	34	34	51	51	68	68	85	85	102	102	119	119	136	136	153	153
MBFI/NEW_BEG-1	0	0	20	20	40	40	60	60	80	80	95	95	110	110	125	125	140	140	155	155
	N	N	N	N	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R
MBFI/RET_BEG-0	0	0	17	17	34	34	51	51	68	68	85	85	102	102	119	119	136	136	153	153
MBFI/RET_BEG-1	0	0	15	15	30	30	45	45	60	60	75	75	90	90	110	110	130	130	150	150
	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N	N	N	N	N

Table 5. Rules Tested During Main Runs - Part II (Cont'ed)

Clinic 5, N= 10, $\%New$= 0.20, μ_{New}/μ_{Ret}= 2

IBFI/ALTER-0	0	18	36	54	72	90	108	126	144	162
IBFI/ALTER-1	0	30	45	60	75	90	120	135	150	165
	N	R	R	R	R	N	R	R	R	R
IBFI/NEW_BEG-0	0	18	36	54	72	90	108	126	144	162
IBFI/NEW_BEG-1	0	30	60	75	90	105	120	135	150	165
	N	N	R	R	R	R	R	R	R	R
IBFI/RET_BEG-0	0	18	36	54	72	90	108	126	144	162
IBFI/RET_BEG-1	0	15	30	45	60	75	90	105	120	150
	R	R	R	R	R	R	R	R	N	N
2BEG/ALTER-0	0	0	18	36	54	72	90	108	126	144
2BEG/ALTER-1	0	0	30	45	60	75	90	120	135	150
	N	R	R	R	R	N	R	R	R	R
2BEG/NEW_BEG-0	0	0	18	36	54	72	90	108	126	144
2BEG/NEW_BEG-1	0	0	30	60	75	90	105	120	135	150
	N	N	R	R	R	R	R	R	R	R
2BEG/RET_BEG-0	0	0	18	36	54	72	90	108	126	144
2BEG/RET_BEG-1	0	0	15	30	45	60	75	90	105	120
	R	R	R	R	R	R	R	R	N	N
MBFI/ALTER-0	0	0	36	36	72	72	108	108	144	144
MBFI/ALTER-1	0	0	45	45	75	75	120	120	150	150
	N	R	R	R	R	N	R	R	R	R
MBFI/NEW_BEG-0	0	0	36	36	72	72	108	108	144	144
MBFI/NEW_BEG-1	0	0	60	60	90	90	120	120	150	150
	N	N	R	R	R	R	R	R	R	R
MBFI/RET_BEG-0	0	0	36	36	72	72	108	108	144	144
MBFI/RET_BEG-1	0	0	30	30	60	60	90	90	120	120
	R	R	R	R	R	R	R	R	N	N

Table 5. Rules Tested During Main Runs - Part II (Cont'ed)

Clinic 6, N= 20, $\%New$= 0.20, μ_{New}/μ_{Ret}= 2

IBFI/ALTER-0	0	9	18	27	36	45	54	63	72	81	90	99	108	117	126	135	144	153	162	171
IBFI/ALTER-1	0	15	22.5	30	37.5	45	60	67.5	75	82.5	90	105	112.5	120	127.5	135	150	157.5	165	172.5
	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R
IBFI/NEW_BEG-0	0	9	18	27	36	45	54	63	72	81	90	99	108	117	126	135	144	153	162	171
IBFI/NEW_BEG-1	0	15	30	45	60	67.5	75	82.5	90	97.5	105	112.5	120	127.5	135	142.5	150	157.5	165	172.5
	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
IBFI/RET_BEG-0	0	9	18	27	36	45	54	63	72	81	90	99	108	117	126	135	144	153	162	171
IBFI/RET_BEG-1	0	7.5	15	22.5	30	37.5	45	52.5	60	67.5	75	82.5	90	97.5	105	112.5	120	135	150	165
	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N
2BEG/ALTER-0	0	0	9	18	27	36	45	54	63	72	81	90	99	108	117	126	135	144	153	162
2BEG/ALTER-1	0	0	15	22.5	30	37.5	45	60	67.5	75	82.5	90	105	112.5	120	127.5	135	150	157.5	165
	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R
2BEG/NEW_BEG-0	0	0	9	18	27	36	45	54	63	72	81	90	99	108	117	126	135	144	153	162
2BEG/NEW_BEG-1	0	0	15	30	45	60	67.5	75	82.5	90	97.5	105	112.5	120	127.5	135	142.5	150	157.5	165
	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
2BEG/RET_BEG-0	0	0	9	18	27	36	45	54	63	72	81	90	99	108	117	126	135	144	153	162
2BEG/RET_BEG-1	0	0	7.5	15	22.5	30	37.5	45	52.5	60	67.5	75	82.5	90	97.5	105	112.5	120	135	150
	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N
MBFI/ALTER-0	0	0	18	18	36	36	54	54	72	72	90	90	108	108	126	126	144	144	162	162
MBFI/ALTER-1	0	0	22.5	22.5	37.5	37.5	60	60	75	75	90	90	112.5	112.5	127.5	127.5	150	150	165	165
	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R
MBFI/NEW_BEG-0	0	0	18	18	36	36	54	54	72	72	90	90	108	108	126	126	144	144	162	162
MBFI/NEW_BEG-1	0	0	30	30	60	60	75	75	90	90	105	105	120	120	135	135	150	150	165	165
	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
MBFI/RET_BEG-0	0	0	18	18	36	36	54	54	72	72	90	90	108	108	126	126	144	144	162	162
MBFI/RET_BEG-1	0	0	15	15	30	30	45	45	60	60	75	75	90	90	105	105	120	120	150	150
	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N

Table 5. Rules Tested During Main Runs - Part II (Cont'ed)

Clinic 7, N= 10, %New= 0.20, $\mu\mu_{New}/\mu_{Ret}$= 1.33

IBFI/ALTER-0	0	16	32	48	64	80	96	112	128	144
IBFI/ALTER-1	0	20	35	50	65	80	100	115	130	145
	N	R	R	R	R	N	R	R	R	R
IBFI/NEW_BEG-0	0	16	32	48	64	80	96	112	128	144
IBFI/NEW_BEG-1	0	20	40	55	70	85	100	115	130	145
	N	N	R	R	R	R	R	R	R	R
IBFI/RET_BEG-0	0	16	32	48	64	80	96	112	128	144
IBFI/RET_BEG-1	0	15	30	45	60	75	90	105	120	140
	R	R	R	R	R	R	R	R	N	N
2BEG/ALTER-0	0	0	16	32	48	64	80	96	112	128
2BEG/ALTER-1	0	0	20	35	50	65	80	100	115	130
	N	R	R	R	R	N	R	R	R	R
2BEG/NEW_BEG-0	0	0	16	32	48	64	80	96	112	128
2BEG/NEW_BEG-1	0	0	20	40	55	70	85	100	115	130
	N	N	R	R	R	R	R	R	R	R
2BEG/RET_BEG-0	0	0	16	32	48	64	80	96	112	128
2BEG/RET_BEG-1	0	0	15	30	45	60	75	90	105	120
	R	R	R	R	R	R	R	R	N	N
MBFI/ALTER-0	0	0	32	32	64	64	96	96	128	128
MBFI/ALTER-1	0	0	35	35	65	65	100	100	130	130
	N	R	R	R	R	N	R	R	R	R
MBFI/NEW_BEG-0	0	0	32	32	64	64	96	96	128	128
MBFI/NEW_BEG-1	0	0	40	40	70	70	100	100	130	130
	N	N	R	R	R	R	R	R	R	R
MBFI/RET_BEG-0	0	0	32	32	64	64	96	96	128	128
MBFI/RET_BEG-1	0	0	30	30	60	60	90	90	120	120
	R	R	R	R	R	R	R	R	N	N

Table 5. Rules Tested During Main Runs - Part II (Cont'ed)

Clinic 8, N= 20, %New= 0.20, μ_{New}/μ_{Ret}= 1.33

IBFI/ALTER-0	0	8	16	24	32	40	48	56	64	72	80	88	96	104	112	120	128	136	144	152
IBFI/ALTER-1	0	10	17.5	25	32.5	40	50	57.5	65	72.5	80	90	97.5	105	112.5	120	130	137.5	145	152.5
	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R
IBFI/NEW_BEG-0	0	8	16	24	32	40	48	56	64	72	80	88	96	104	112	120	128	136	144	152
IBFI/NEW_BEG-1	0	10	20	30	40	47.5	55	62.5	70	77.5	85	92.5	100	107.5	115	122.5	130	137.5	145	152.5
	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
IBFI/RET_BEG-0	0	8	16	24	32	40	48	56	64	72	80	88	96	104	112	120	128	136	144	152
IBFI/RET_BEG-1	0	7.5	15	22.5	30	37.5	45	52.5	60	67.5	75	82.5	90	97.5	105	112.5	120	130	140	150
	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N
2BEG/ALTER-0	0	0	8	16	24	32	40	48	56	64	72	80	88	96	104	112	120	128	136	144
2BEG/ALTER-1	0	0	10	17.5	25	32.5	40	50	57.5	65	72.5	80	90	97.5	105	112.5	120	130	137.5	145
	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R
2BEG/NEW_BEG-0	0	0	8	16	24	32	40	48	56	64	72	80	88	96	104	112	120	128	136	144
2BEG/NEW_BEG-1	0	0	10	20	30	40	47.5	55	62.5	70	77.5	85	92.5	100	107.5	115	122.5	130	137.5	145
	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
2BEG/RET_BEG-0	0	0	8	16	24	32	40	48	56	64	72	80	88	96	104	112	120	128	136	144
2BEG/RET_BEG-1	0	0	7.5	15	22.5	30	37.5	45	52.5	60	67.5	75	82.5	90	97.5	105	112.5	120	130	140
	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N
MBFI/ALTER-0	0	0	16	16	32	32	48	48	64	64	80	80	96	96	112	112	128	128	144	144
MBFI/ALTER-1	0	0	17.5	17.5	32.5	32.5	50	50	65	65	80	80	97.5	97.5	112.5	112.5	130	130	145	145
	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R	N	R	R	R	R
MBFI/NEW_BEG-0	0	0	16	16	32	32	48	48	64	64	80	80	96	96	112	112	128	128	144	144
MBFI/NEW_BEG-1	0	0	20	20	40	40	55	55	70	70	85	85	100	100	115	115	130	130	145	145
	N	N	N	N	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
MBFI/RET_BEG-0	0	0	16	16	32	32	48	48	64	64	80	80	96	96	112	112	128	128	144	144
MBFI/RET_BEG-1	0	0	15	15	30	30	45	45	60	60	75	75	90	90	105	105	120	120	140	140
	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	N	N	N	N

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