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**Advanced Parking Management Systems:
Strategic Management of
Intermodal Junctions**

By

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16. Abstract Advanced Parking Management Systems are part of the larger effort to reduce traffic congestion. Such systems utilize variable message signs (VMS) to provide drivers with real time information on the number of open parking spaces at different alternative lots. The hope is that drivers will then go directly to a lot with a sufficient number of open spaces rather than going first to a lot which might already be full. In order to predict the effect of parking availability information on congestion, one needs to know what fraction of drivers will divert to a given lot based on the number of open spaces in each of the lots which appear on a VMS, the driving time to the lots, the walking time from a lot to the destination and so on. Three experiments were run to test alternative models of drivers' lot decisions. One was a standard paper and pencil study; two were run on an advanced driving simulator. It was found that the participants employed two very different decision rules. Two-thirds used a cognitively simple rule which minimized the expected travel time. Using the appropriate rule for a given subject, it was found that over 90% of the decisions could be predicted correctly. Using only the more complex rule, a rule which is currently used, one might predict as few as 33% of the decisions correctly. Thus, the results from this study can be used to improve predictions of drivers' parking choices.			
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CHAPTER 1

MOTIVATION AND OBJECTIVES

Urban traffic congestion worsens each year at an alarming rate. The U.S. Federal Highway Administration forecasts that the severity of traffic congestion will continue to increase at significant rates in all U.S. urban areas, unless specific remediation efforts are undertaken [Kahn, 1992]. The costs of traffic congestion are high. Besides creating the “2-hour” commute, traffic congestion seriously compromises the safety of drivers and passengers on U.S. roadways. In 1995, an estimated 15 million automobile accidents involved 26 million vehicles in the United States. Over 6.6 million accidents were reported to police, and of these, 3.4 million resulted in injuries to motorists, 428,000 of whom were incapacitated [U.S. DOT, 1997]. Over the past 30 years, the U.S. has lost more lives to car accidents than it has lost in all of the wars it has ever fought [Coyner, 1997]. In economic terms, the costs of motor vehicle accidents in 1994 funded through public revenues accounted for \$144 in taxes per household [Coyner, 1997]. Without intervention, we can only expect these costs to increase as more and more motorists occupy our roadways.

Past efforts to relieve traffic congestion have often focused on the expansion of roadway capacity. However, these efforts have their costs, too. Roadway expansion results in considerable displacement and disturbance of residential and public spaces. Furthermore, construction of new roadways requires public funds, which are becoming increasingly scarce [Santiago, 1992]. Large roadway projects are not only costly, but they often do not offer lasting solutions. For example, the

M25 roadway near London was constructed to relieve congestion within the city. Today, it is, itself, the most congested roadway in all of Europe [Emmitt, 1993].

For these reasons, current U.S. transportation agencies are focusing on the optimization of existing infrastructures. Among the most promising solutions is the implementation of advanced traffic management systems (ATMS). Advanced traffic management systems are being designed to provide real-time management of traffic flow [Sobbi, 1995]. More specifically, many ATMS use sophisticated surveillance equipment, real-time, traffic-adaptive control systems, and operator support systems (i.e., expert systems, simulation models, etc.) [Santiago, 1992] to monitor and control access routes to roadways, detect and help facilitate the removal of accidents and stalled vehicles, and re-route traffic in heavily congested areas.

Problems arising from the task of parking contribute considerably to the overall traffic congestion problem [McShane and Meyer, 1982]. Advanced parking management systems (APMS) link information gathered by traffic sensors at selected parking lots to an ATMS where it is processed so that the information can be updated and displayed back to drivers via a signboard, typically on a variable message sign. Variable message signs (VMS) have been proposed as a means to provide drivers with real-time information regarding parking availability in complex parking situations (e.g., airports, sports complexes, shopping districts, convention centers, etc.). The aim of these signs is to provide information to drivers regarding the location and availability of parking spaces in various parking facilities in an attempt to reduce the amount of search time necessary for a driver to find a parking space. Better informed drivers can be expected to reach their destinations more quickly and efficiently, thereby reducing traffic congestion.

The success of ATMS efforts will depend on an understanding of the ways in which drivers respond when given information intended to reduce traffic congestion. The data sources required to build accurate strategies of driver behavior do not yet exist [Santiago, 1992]. The intelligent design of most APMS, in particular, will require the answers to several questions. How do people decide where to park? Are people interested in additional information? If so, what kind of information do drivers need to assist them in selecting a parking lot? How will their decisions be influenced (if at all) by the information provided? And finally, when given accurate information, will drivers' decisions be, in fact, optimal decisions?

Currently, it is not known how drivers decide where to park. It is clear, however, that this choice is influenced by several factors. Drivers who have trouble walking might be expected to choose the lot closest to the final destination, as will, presumably, all drivers in bad weather. More athletic drivers may choose to maximize the average walking time. Drivers who normally choose to minimize the average transit time might, under a tight schedule, choose an alternative with less variability. Drivers might decide in which lot to park based on the neighborhood through which they would need to travel to get from the lot to their final destination (basing their decision, say, on the safety of the area or on whether the walkways will be crowded or relatively empty). Ultimately, it is necessary to determine the broad range of criteria that influence parking decisions to evaluate the ways in which VMS signs might affect traffic flow in complicated parking scenarios.

In addition to determining what criteria influence parking decisions, it is necessary to determine how these decisions are made when parking lots vary on known criteria. The objective of the research described herein is to increase our

knowledge of this decision making process. Having an understanding of how drivers decide where to park will enable traffic engineers to anticipate and better manage traffic congestion. Chapter 2 provides information on past studies conducted in the area of parking decision behavior and motivation for the experiments conducted in this thesis. Chapter 2 also includes an introduction to one framework for modeling decision-making behavior under uncertainty, Expected Utility Theory (EUT), and lists the decision strategies investigated in the first two experiments presented herein.

Chapter 3 describes the first experiment conducted in this study, which was a pencil-and-paper survey designed to determine whether people employ one or a combination of the three hypothetical decision strategies outlined in Chapter 2. The relative importances of the 3 hypothesized strategies are evaluated. Chapter 4 describes the second experiment, which was identical to the first with the exception that subjects' decisions were made in the more realistic context of a driving simulator, rather than on a written survey form. Experiments 1 and 2 are analyzed together, and the results of this analysis motivate the consideration of an alternative decision strategy, a Lexicographic (LEX) choice rule. Chapter 5 describes the third experiment, a second simulator study designed to further investigate and compare the efficacies of METT and LEX at correctly predicting driver behavior. Chapter 6 summarizes the results of the three experiments and sets forth the main conclusions of this thesis.

CHAPTER 2 BACKGROUND

The following literature review begins with an article that proposes a general strategy for parking search behavior in crowded, urban areas. Next, articles that investigate drivers' parking behavior when provided with general parking information are presented and discussed. Finally, an article that examines the effect of an APMS, specifically, on driver decision behavior is reviewed.

Literature Review

The criteria which people use to decide where to park have not been fully studied. Thompson and Richardson [1995] developed an analytical procedure for modeling the parking search behavior of drivers. The strategy assumed that drivers employ a sequential search strategy whereby individual car parks are examined and evaluated one at a time until a choice is made. The essence of the strategy is the assignment of a disutility value to each parking lot examined. In order to understand the idea of a *disutility* it is necessary to introduce some theories of individual decision making. Expected Utility Theory (EUT) is a theory of decision making under uncertainty. The *utility* of an outcome is defined as the benefit that an individual attaches to the outcome. The *utility function* is defined as a mapping between the set of outcomes and a measure of the benefit. Expected Utility Theory allows individuals to have nonlinear utility functions for, say, money and hence have different preferences among gambles with equal expected values. For example, we find that the more money one has, the less he or she values each additional increment

[Coombs, Dawes, & Tversky, 1970]. The expected utility of a gamble, with outcomes x_1, \dots, x_n obtained with probabilities p_1, \dots, p_n , respectively, is

$$E[U] = \sum_{i=1}^n p_i u(x_i) \quad (2.1)$$

where $u(x_i)$ is the utility of the i th outcome.

The idea of a *disutility* is, therefore, a measure of the *cost* that an individual attaches to the outcome. In Thompson and Richardson's study, the disutility is a function of the following costs incurred by choosing a particular lot: in-vehicle travel time (driving to the car park plus finding a space within the park), egress time (time to walk from the parking lot to the final destination), parking fee, expected fine, and expected time spent queuing at the car park entrance. These disutilities were converted into utilities using an additive inverse transformation. A search was terminated when the expected utility of choosing the lot currently being inspected $E[U_j]$ was higher than the expected utility of proceeding to the next parking option $E[U_k], j \neq k$. For example, suppose parking lots A, B, and C have utilities $E[U_A]=3$, $E[U_B]=5$, and $E[U_C]=4$. Suppose further that a driver currently inspecting lot A contemplates the benefit of staying in lot A versus continuing on to inspect lot B. Given the current utilities of each lot, the expected gain in utility of proceeding to lot B is $E[U_B] - E[U_A] = +2$, a positive gain indicating that it is best to continue. On the other hand, the expected gain in utility of proceeding to lot C from lot B is $E[U_C] - E[U_B] = -1$, a negative value indicating that it is best to remain searching for a space in lot B.

The strategy was used to simulate how parking choices might change in response to policy changes (*e.g.*, reducing the allowable parking duration of on-street spaces and increasing the level of enforcement of parking fines.) For example, reducing the allowable parking duration at particular on-street parking spaces resulted in a significant reduction in the average time required to find a space accompanied by an increase in the average egress time. That is, the effect of the parking duration reduction on searching patterns was to encourage motorists to choose car parks in the outer areas, thereby trading off increased walking times for decreased searching times.

Advanced Parking Management Systems have been used to influence positively the parking search experiences of motorists by providing them with information about which they would otherwise be uncertain. In fact, APMS incorporating VMS are the second most widely used information system [Axhausen and Polak, 1996]. Thus, it is surprising that the influence of these systems on drivers' decisions is not more widely documented in the literature. Polak, Vytholkas, and Chatfield [1991], and Khattak and Polak [1991] studied the impact of an experimental parking information system on the behavior of drivers in Nottingham, UK. Parking information was distributed using various media (*e.g.* radio broadcasts, newspaper advertisements, and leaflets). Contact interviews were conducted and mail-back questionnaires were distributed with the objective of investigating the level of penetration of the information and its effect, if any, on driver behavior. Polak *et al.* found that nearly half of the drivers who were aware of radio broadcasts regarding parking availability actively listened to them. Furthermore, over 25% of the listening drivers reported that their decisions with regard to parking type and location were

influenced by the broadcasts, both in the pre-trip and, to a lesser extent, the en-route stages of their trips. Thus, it appears that drivers are generally receptive to parking information provided. However, the fact that driver behavior was influenced primarily in the pre-trip stage led the authors to conclude that complimentary VMS systems are needed.

Axhausen and Polak [1996] studied the effect of an APMS implemented in the Frankfurt city center on the search times required for drivers to find parking. The APMS employed VMS signs distributed about the city center as well as at the city limits. Contact interviews were conducted both before and after the implementation of the APMS. Each driver was asked to report his or her familiarity with the area and the duration of his or her parking search, and to describe the search strategy employed. The survey results indicated that, for drivers with all levels of local familiarity, search times were on average significantly reduced after the implementation of the APMS. However, drivers who reported that they were aware of and used the VMS system had higher average search times than drivers who reported that they were aware of the VMS system, but did not use it. Based on this result, the authors inferred that drivers with a high level of familiarity of the area (and thus lower search times both before and after implementation of the VMS) were less likely to use the VMS than drivers with low to moderate levels of local familiarity.

This thesis differs from the previously published work in this area in a few significant respects. The parking choice strategy proposed by Thompson and Richardson (1996) incorporates in-vehicle travel time, egress time, car park search time, parking fees, expected parking fines, and expected waiting times into the utility function. In addition to those attributes, a number of general subjective parameters

(specified in the strategy as exogenous variables) and stochastic subjective parameters were also included in the utility expression. Although the strategy is quite thorough in that it considers nearly *every* possible consideration, it is unlikely that drivers are able to consider all such attributes in the few moments they have to make a decision whether or not to continue searching for parking. In other words, their strategy may contain too many factors for one individual to realistically consider at one time. The current thesis differs from the work of Thompson and Richardson in two ways. First, we do not set out to create one strategy for the population at large, but rather to investigate a number of very simple choice rules to determine whether different people employ different strategies, a single person employs a combination of strategies, or whether, perhaps, there *does* exist a single strategy to characterize drivers' parking behavior. Secondly, we assume that drivers do not (or cannot) make use of extremely sophisticated choice rules in the short amount of time they have to make a parking decision. Thus, we aim to develop a strategy for explaining drivers' choices based on a minimal number of adjustable parameters.

The studies conducted by Polak *et al.* (1991) investigated driver behavior when pre-trip parking information was provided. However, predicting the effect of informational systems on driver behavior will require examination of driver responses to information provided at the decision point. The work in this thesis differs significantly from the work of Polak, *et al.* in that parking information in this work is disseminated at the decision point. That is, parking information is presented in real-time, and drivers must make their decisions in a matter of seconds.

The work in this thesis will also build on the work of Axhausen and Polak (1995). Axhausen and Polak sought to determine the effect of the *existence* of a

VMS system on driver behavior. However, the study did not attempt to explore how particular information contained in the signs affected drivers' decision behavior. For example, questions like, "How many people will drive to a lot reported on a VMS to have, say, two available spaces?" were not asked. In this way, the current thesis differs from the work of Axhausen and Polak, since this thesis seeks to determine the influence of particular pieces of information presented by the VMS on drivers' decision behavior.

Introduction to Expected Utility Theory

A brief introduction of Expected Utility Theory (EUT) was given in the last section. A more formal introduction is presented here and its applicability to this thesis is described. To predict the decisions that drivers make, it is important to understand the rules that drivers might use to choose one parking lot over another. Expected Utility Theory provides one framework for explaining how drivers might decide where to park. Expected Utility Theory deals with the issue of risky decision making. Risky decisions are made whenever a person is uncertain about the future state of the world [Coombs, Dawes, & Tversky, 1970]. Although variable message signs provide drivers with up-to-the-minute information on parking availability, drivers are still forced to make decisions with less than complete knowledge. For instance, drivers do not know whether a lot will fill between the time they see a sign indicating the availability of parking spaces in a particular lot and the time they actually reach the lot.

Expected Utility Theory assumes that individuals (in this case, drivers) estimate the likelihood of certain future events based on prior experience, beliefs, and/or information provided, and then use those likelihoods to determine the net

worth of a particular decision. It is assumed that an individual's beliefs about the likelihood of an event can be expressed by some probability function (either objective or subjective). An individual would then consider the aggregate benefit of a particular choice by computing a sum of values characterizing the desirabilities of the various possible outcomes weighted by the probabilities of occurrence of those events. Thus, EUT assumes that individuals make choices that maximize the expected utility of an outcome. An equivalent assumption is that individuals make choices so as to *minimize* the expected *disutility* of an outcome. Once again, for the purpose of this thesis, the uncertain event is whether or not a parking lot will fill in the time during which the driver is in transit between the VMS and the parking lot. Thus, a general expression for the expected disutility associated with choosing parking lot i , having k open spaces, when the destination is j can be written:

$$E[DU_{ij}(k)] = [P_{not_full}(k)][DU_{not_full}(i, j)] + [P_{full}(k)][DU_{full}(i, j)] \quad (2.2)$$

That is, the expected disutility is equal to the sum of the disutilities associated with lot i when it is both full and not full upon arrival, weighted by the probability of each event.

Decision Making Strategies

In the first two experiments described in this thesis, EUT was used to investigate drivers' decision-making behavior when provided with real-time parking information. Experiment 1 was a pencil-and-paper parking decision survey. The responses to that survey were compared with the results from a second study (Experiment 2) evaluating decision-making in a driving simulator. The objective of

these studies was to determine which of the following decision strategies might characterize the actual decisions of the subjects:

- 1.) Parking areas are chosen so as to minimize the total expected travel time to one's final destination (METT);
- 2.) Parking areas are chosen such that the distance one walks from the parking lot to the final destination is minimized (MWD); or
- 3.) Parking areas are chosen based on the maximum parking availability (MPA), *i.e.*, the lot with the greatest number of available parking spaces is chosen.

The above choice rules result from the utilization of EUT, each with the application of a particular set of simplifying assumptions. The sections that follow state the assumptions and define the disutility functions associated with each decision rule.

METT Strategy

An METT strategy assumes that individuals derive disutility from the driving, walking and queuing times associated with a particular lot choice. With this assumption, Equation 2.2 may be written as,

$$E[DU_{ij}(k)] = P_{not_full}(k)[DU(t_{d(i)}) + DU(t_{w(ij)})] + P_{full}(k)[DU(t_{d(i)}) + DU(t_{w(ij)}) + DU(t_q)] \quad (2.3)$$

where $t_{d(i)}$ is the time it takes to drive from the VMS to parking lot i , $t_{w(ij)}$ is the time it takes to walk from parking lot i to destination j , and t_q is the queuing time required if a parking lot is full when a driver arrives. $P_{full}(k)$ is the subjective probability that a lot currently containing k open spaces is full when the driver actually arrives. Since the sum of the probabilities is one, Equation 2.3 may be simplified,

$$E[DU_{ij}(k)] = DU(t_{d(i)}) + DU(t_{w(ij)}) + P_{full}(k)DU(t_q)$$

It is further assumed that each disutility is the same linear function of the time required to perform the corresponding task,

$$DU(t_\gamma) = a + bt_\gamma; \quad \gamma = d(i), w(ij), q \quad (2.5)$$

That is, people derive equal disutility from a drive, walk, or wait of the same duration. With this assumption, it can be shown that Equation 2.4 is minimized when the total expected travel time,

$$E[T_{ij}(k)] = t_{d(i)} + t_{w(ij)} + t_q P_{full}(k) \quad (2.6)$$

is minimized.

The above set of assumptions leads to an METT choice rule, in which it is hypothesized that drivers make parking decisions by attempting to minimize the total expected travel time from the VMS to the final destination. Drivers attempting to minimize their total expected travel time would need to assign an actual probability to the event that a parking lot is full when he or she arrives. A possible expression for this probability might be the following linear probability function,

$$P_{full}(k) = \frac{(n - k)}{n} \quad (2.7)$$

where n is the total number of spaces in the lot and k is the number of open spaces in the lot as stated in the VMS.

MWD Strategy

An alternative assumption to the one presented above is that the disutilities drivers derive from driving and queuing are negligible compared to the disutility derived from walking. If this is the case, then, Equation 2.3 can be simplified to,

$$E[DU_{ij}(k)] = P_{not_full}(k)[DU_{walk}] + P_{full}(k)[DU_{walk}] \quad (2.8)$$

or,

$$E[DU_{ij}(k)] = DU_{walk} \quad (2.9)$$

If it is assumed that the disutility of a walk is a function only of the distance walked, and that the disutility of a walk increases with increasing duration, then Equation 2.9 is minimized when the walking time distance is minimized. This set of assumptions leads to the MWD choice rule, where it is hypothesized that drivers make parking decisions by attempting to minimize the walking distance.

MPA Strategy

Finally, we might assume that the total disutility is dominated by the queuing task, and that the driving and walking tasks are negligible in terms of disutility.

Under this assumption, Equation 2.3 is simplified to,

$$E[DU_{ij}(k)] = P_{not_full}(k)(0) + P_{full}(k)[DU_{queue}] \quad (2.10)$$

or,

$$E[DU_{ij}(k)] = P_{full}[DU_{queue}] \quad (2.11)$$

Equation 2.11 is minimized when P_{full} is minimized. Thus, this assumption leads to the MPA choice rule, where it is hypothesized that drivers make parking decisions by attempting to minimize the probability of arriving at a lot and finding it full.

CHAPTER 3
EXPERIMENT 1 (*SURVEY*)

Participants

Fifteen graduate students (12 male and 3 female) were surveyed in the pencil-and-paper survey conducted at the University of Massachusetts at Amherst. The ages of the subjects ranged from 21 to 35 years of age, with an average age of 25.4 years.

Stimulus Material

Subjects were presented with 36 different parking scenarios that were arranged in random order (*Appendix A*). Each of the parking scenarios consisted of a VMS, a destination building and four parking lots labeled Lot A, Lot B, Lot C, and Lot D (see *Figure 1*). Beneath each parking lot was indicated the number of open spaces (out of 100) in the lot. The word “closed” was typed beneath the lots that were not available for parking (*Figure 1*). The parking availability information and the final destination location were the only parameters that varied from scenario to scenario. Note that the “A” presented next to the building graphic in *Figure 1* indicates that the final destination in this scenario is nearest to Lot A.

Experimental Design

Of the 36 parking scenarios, 12 had only two lots available for parking, 12 had only three lots available for parking, and 12 had all four lots available for parking. These scenarios are referred to as 2-lot, 3-lot, and 4-lot scenarios, respectively. The following guidelines were used to counterbalance all of the 2-lot scenarios:

- 1) The number of scenarios in which the lot *nearest* the VMS resulted in the minimum expected travel time was equal to the number of scenarios in which the lot *furthest* from the VMS resulted in the minimum expected travel time.
- 2) The number of scenarios in which the final destination was *nearest* the VMS was equal to the number of scenarios in which the final destination was *furthest* from the VMS.
- 3) The number of scenarios in which the lot *nearest* the VMS had the greatest number of open spaces was equal to the number of scenarios in which the lot *furthest* from the VMS had the greatest number of open spaces.

The counterbalancing for the 3-lot scenarios was very similar. However, in the 3-lot scenarios, there was an equal number of scenarios in which the expected travel time was minimized in the lots nearest and furthest from the VMS, as well as the lot in between these two. Finally, the 4-lot scenarios were constructed such that the number of scenarios resulting in the minimum expected travel time (METT) was equal among all of the four lots (e.g., there were 3 scenarios in which Lot A resulted in the METT, 3 for which Lot B resulted in the METT, etc.).

Once the final set of parking lot scenarios was created, the order in which the scenarios were presented to the subjects was counterbalanced. The first 18 scenarios consisted of six 2-lot, six 3-lot, and six 4-lot scenarios, as did the second 18. Within each set of 18, the order in which the 2-, 3-, and 4-lot scenarios were presented was randomized. This randomization established the final parking scenario ordering, labeled as Figures 1 through 36 in *Appendix A*. Subjects in the survey received packets very similar to *Appendix A*. However, the six pages were randomized such that not all of the subjects were presented the stimuli in the same order.

Procedure

Subjects were asked to review each scenario by considering the location of the destination building relative to the parking lots, and then to select the parking lot they would choose based on the parking availability information provided. A brief summary of the scope of the project and the task the subjects were to perform was given both verbally and in the survey document itself (*Appendix B*). The survey instructions provided subjects with enough information to estimate their total driving, walking, and queuing times. For instance, subjects were told to assume that it would take them 1 minute to drive and 3 minutes to walk each segment of the roadway system. Referring to *Figure 1*, we see that if a subject decided to park in Lot C, it would take the subject 4 minutes to drive to Lot C (4 segments at 1 min/segment) and 9 minutes to walk from Lot C to the destination (3 segments at 3 min/segment). That is, $t_{d(C)} = 4$ minutes and $t_{w(CA)} = 9$ minutes. Subjects were also informed that they could expect to wait 5 minutes for an open space if their chosen lot was full when they arrived (e.g., $t_q = 5$ min).

Results

The raw data collected on each subject for each scenario in the survey is attached as a table in *Appendix C*. In the table, the leftmost column contains figure numbers for the various scenarios presented in *Appendix A*. Each of the other columns contains the letters of the lots chosen by one subject for each of the scenarios. These results are summarized in the form of bar graphs in *Appendix D*, which indicate the number of subjects who chose each particular lot in each scenario, and the predicted METT, MWD, and MPA lots for the scenario.

Subjects' choices differed for 69.4% of the scenarios in the survey. That is, all subjects chose the same parking lot in 11 out of the 36 scenarios. The graphs shown in *Figure 2* display the percentages of subjects' decisions that were consistent with each of the three decision criteria tested (i.e. METT, MWD, and MPA). In some of the parking scenarios, choice of a particular lot was consistent with more than one of the decision criteria. This coincidence of choice rules occurred particularly frequently between MWD and METT lots. Because a section of road may be driven much more quickly than it can be walked, the destination lot tends to coincide with the METT lot, except in cases where the destination lot is very nearly full, such that there is a high probability that choice of the destination lot will result in waiting for an open space. For this reason, two graphs are displayed, one entitled "All Scenarios," which gives the results for all 36 scenarios, and another entitled "Unlike Scenarios," which consists of only those parking scenarios in which lots conforming with METT, MWD, and MPA were all different. *Figure 2* indicates that subjects made choices consistent with METT most often, and that subjects rarely chose parking lots based purely on it having the maximum number of open spaces (MPA). The MWD choice rule also appears to be important to subjects, but a full analysis is postponed until data from a more realistic setting (i.e., a driving simulator) is presented.

Discussion

In the survey study, subjects were presented with stimuli and made decisions in a relatively low-stress, distraction-free environment (*i.e.*, a classroom). However, it is likely that subjects' decision behavior is influenced not only by the options

available, but also by the cognitive load under which the decision is made. For this reason, it is useful to test driver responses using a driving simulator. Previous studies have shown that individuals often perform quite differently on simple paper and pencil tasks than they do on identical driving simulator tasks [Szymkowiak, 1997]. One of the greatest benefits of driving simulators is that they closely mimic the cognitive load present in an actual driving situation. In a simulator, as in a real car, drivers must maneuver the vehicle to keep it on the road, watch out for traffic, navigate roadways, scan for information, and make decisions. Furthermore, the dynamic nature of the driving simulator may create a greater sense of urgency for subjects when making decisions. In haste, subjects might adopt a different, more simple decision strategy than they would in a paper and pencil task.

CHAPTER 4

EXPERIMENT 2 (FIRST SIMULATOR STUDY)

Participants

Experiment 2 utilized a driving simulator. Here, 15 subjects (8 male and 7 female) sat in a driving simulator located in the Human Performance Laboratory at the University of Massachusetts at Amherst (*Figure 3*). The ages of the subjects ranged from 20 to 32 years of age, with an average age of 25.3 years.

Equipment

The driving simulator (Illusion Technologies) consists of a 1995 Saturn SL1, controlled by an Onyx Reality Engine 2 and an Indy computer (both of Silicon Graphics, Inc., Mountain View, CA). The visual database used to represent the driving course was created using Designer's Workbench[®] software developed by Coryphaeus of Los Gatos, CA. Drivers maneuver the simulator car through a virtual world that is presented on screen a few feet in front of the car by a Sony MultiScan Projector (model VPH-1272Q).

Stimulus Material

The stimulus provided in the simulator study was similar in content to that which was provided in the survey study, although quite different in terms of format. In the simulator study, the number of open spaces available (out of 100) in each of the four parking lots was displayed on a VMS. Closed lots displayed a red "XX" where the number of open spaces would have been to signify that the lot was not available for parking. *Figure 4* is a snapshot of the graphic database used in this simulation

which provides a sample VMS. Each of the scenarios in the simulation began with a driver positioned behind a stop sign. A brown and white signboard which provided information about the final destination for each scenario was located just beyond the stop sign; the sign identified to which of the four parking lots the destination was nearest. A second snapshot of the graphic database displaying (from the subject's perspective) the first image presented to the subjects can be found in *Figure 5*. Finally, *Figure 6* provides an overview of the roadway used in the simulation.

Experimental Design

The same set of 36 parking scenarios was used in this experiment as were used in Experiment 1. The 36 parking scenarios were presented to the participants in 3 sets of 12 trials. The trial order was fixed for each set of 12, although the order in which the sets were presented to each participant was chosen to ensure that every permutation of the 3 sets (*i.e.*, 1-2-3, 1-3-2, 2-3-1, etc.) was used a nearly equal number of times.

Procedure

The subjects' task in the simulator study was essentially the same as in the survey, although slightly more complicated given the driving task. Each set of 12 trials began with the subject's car sitting at a stop sign. A lead car was in front of the simulator car in every scenario (*Figure 5*). Subjects were instructed not to attempt to pass the lead car at any time during the simulation. The lead car traveled at approximately 32 km/h (20 mph) past the VMS, beyond which it accelerated to 1.5 times the speed of the simulator car. The purpose of the lead car was both to ensure

that subjects drove slowly enough past the VMS to read the information on the parking availability of the various lots, and to provide drivers with the sense that there were other cars on the road with them. Subjects were informed that they could stop and back-up the car if they wanted to re-read the VMS for any reason. As with the survey, subjects were provided a brief summary of the scope of the project and an instruction sheet (*Appendix E*). The instructions provided subjects with the same driving, walking, and queuing times that were given in the pencil-and paper survey. Subjects were given time to familiarize themselves with the driving simulator in a practice session, and were instructed to drive as they would normally. In the practice session, subjects drove the simulator through one complete scenario and were encouraged to practice maneuvering the steering wheel and stopping operations to get a sense of the simulator's manageability. The practice sessions lasted between 5 and 10 minutes, depending on subjects' confidence levels.

Results

The raw data collected on each subject for each scenario in the simulator study is attached as *Appendix F*. Bar graph summaries similar to the ones generated in the pencil-and-paper survey are also available in *Appendix G*. Graphs that display the percentages of decisions consistent with each of the three decision criteria tested are presented in *Figure 7*. Finally, *Figure 8* presents the resulting percentages of decisions consistent with each choice rule in the survey and the simulator side-by-side.

Subjects' choices differed for 25.0% of the scenarios in the driving simulator. That is, all subjects chose the same lot in 27 out of the 36 scenarios in the simulator

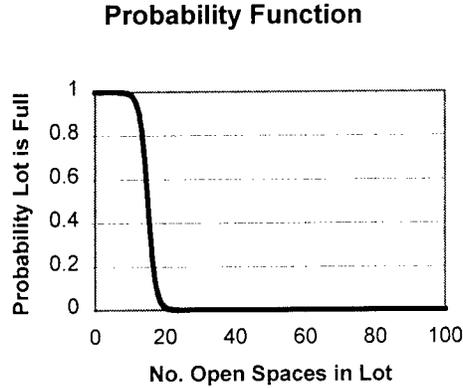
study. Again, the data indicates that drivers rarely used the MPA method of deciding where to park. Furthermore, when the METT lots and the destination lots were not the same, subjects made choices consistent with METT more often than with MWD. Thus, METT appears to be the best way of predicting where drivers will choose to park.

Discussion

Although subjects favored lots resulting in METT, the high proportion of choices not consistent with METT (37.1% and 43.8% for the survey and simulator, respectively) suggested that the assumed probability function, $P_{full}(k)$, used in the initial analysis to compute $E[T_{ij}(k)]$ could be improved to better reflect drivers' perceived probability of finding the lot full upon arrival. Recall that the expected travel times were computed assuming the linear probability function,

$$P_{full}(k) = \frac{(n-k)}{n} \quad (4.1)$$

A more realistic probability function might be one in which subjects perceive nearly a 100% likelihood of arriving at a lot and finding it full until there is some criterion number of open spaces in the parking lot. Above this criterion number, the perceived likelihood may rapidly decrease to nearly zero. There may be another criterion number of spaces (less than 100) at or above which subjects may perceive a nearly 0% likelihood of finding a lot full upon arrival. The following is a graph of an ogival power function which reflects such a perceived probability relationship.



Power functions have been quite effective in psychophysics in mapping physical and psychological dimensions (Kling & Riggs, 1971, and Falmagne 1986). The expected travel times, $E[T_{ij}(k)]$, for the lots were recalculated using the following power function for the perceived probability of arriving at a lot and finding it full:

$$P_{full}(k) = \frac{1}{2} - \frac{1}{2} \left[\frac{(\beta)^{k-\alpha} - (\beta)^{-(k-\alpha)}}{(\beta)^{k-\alpha} + (\beta)^{-(k-\alpha)}} \right] \quad (4.2)$$

Manipulation of the parameter α in the above function adjusts the inflexion point in the ogival function. Manipulation of the parameter β adjusts the steepness of the descent of the function to the x-axis.

Values for the parameters α and β were initially chosen based on an preliminary analysis of data taken from the simulator study. The eleven scenarios for which application of the METT and MWD decision rules resulted in different lot choices were examined. The objective was to identify the minimum number of spaces in the destination lot above which a “typical” subject might be expected to park in that lot. For each subject, the number of open spaces in the destination lot was recorded for two cases. The first case was the case in which the destination lot

was chosen. The second case was that in which a lot other than the destination lot was chosen. Thus, two lists of values were produced for each subject. The minimum value in the first list for a given subject represented the minimum number of open spaces in the destination lot which was deemed acceptable by the subject. The maximum value in the second list represented the maximum number of open spaces in the destination lot which was considered unacceptable by the subject. The subject's criterion number of open spaces was computed as the mean of these two values and corresponds closely to α . For example, *Table 4.1* shows how the criterion number of open spaces was determined for subject #1.

Table 4.1. Criterion number analysis for subject #1

	No. Open Spaces in Destination Lot	
Case 1: Dest. Lot Chosen	$\varepsilon_1 = \{41, 12, 20\}$	Min $\{\varepsilon_1\} = 12$
Case 2: Dest. Lot Not Chosen	$\varepsilon_2 = \{1, 2, 8, 3, 1, 6, 5, 5\}$	Max $\{\varepsilon_2\} = 8$

Thus, the criterion range for subject #1 is 8-12, and the estimated criterion number of open spaces for subject #1 is $\alpha_1 = 10$ spaces. The parameter α used to construct the estimated subjective probability function, $P_{full}(k)$ is an average of the computed values $\{\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_{15}\}$. The parameter β was selected such that the rapidly decreasing region of the ogival function spanned the values between the minimum lower bound and the maximum upper bound of the criterion ranges for all 15 subjects. Application of the above described analysis to the simulator study data resulted in selection of the parameter values $\alpha = 8$ and $\beta = 1.6$.

To verify the above parameterization, a computer algorithm was developed to determine the values of α and β which maximize the agreement between subjects' responses and the hypothesis of an METT choice rule. The FORTAN program PARK (*Appendix H*) steps at user-defined intervals through every possible set $\{\alpha, \beta\}$ bounded by user-defined minimum and maximum α and β values. For each set $\{\alpha, \beta\}$ the program computes the expected travel time $E[T_{ij}(k)]$ for each lot i in each scenario, using Equations 2.6 and 4.2. The program then determines the proportion of subjects choosing the lot having the minimum expected travel time in each scenario. The proportions of subjects making choices consistent with the METT strategy for all $\{\alpha, \beta\}$ combinations are compared, and the sets $\{\alpha, \beta\}$ that result in the maximum agreement are stored in a file.

This program was run on the Experiment 2 data using the parameters given in *Table 4.2*. Several sets $\{\alpha, \beta\}$ yield the maximum agreement with the Experiment 2 data of 93.5%. Among these sets $\{\alpha, \beta\}$ is the set $\{8, 1.6\}$, determined above using an intuitive analysis of the Experiment 2 data. Since this set $\{\alpha, \beta\}$ was determined to be optimal using both the computer algorithm and an intuitive analysis, this parameterization was used in the power probability function 4.2 for analysis of the Experiment 2 results.

Table 4.2. Parameters used for optimal $\{\alpha, \beta\}$ in Experiment 2

	Minimum Value	Maximum Value	Step Size
α	0.1	30	0.1
β	0.1	6	0.05

The effect of this probability function was to change the locations of some of the METT lots, such that the METT and destination lots became coincident in 11 scenarios for which they had previously been different using the linear $P_{full}(k)$ function. *Figure 9* displays the new percentages of decisions consistent with each decision rule. Note that now there are no “Unlike Scenarios,” since there no longer exist scenarios for which application of all 3 choice rules result in different lot choices.

Over 90% of the subjects tested in the driving simulator made choices consistent with minimizing their expected travel time, when the expected travel time, $E_{ij}[T(k)]$, was calculated using the ogival probability function. Thus, the METT choice rule with a probability function of this form might be a satisfactory method for predicting driver behavior.

Note that, regardless of the probability function used, the percentage of decisions consistent with the MWD choice rule was greater in the simulator study than in the survey. A major difference between the driving simulator and survey tests was that subjects in the simulator had less time to make a decision. Subjects in the simulator were told that they could back-up to re-read the VMS if they so desired; however, none of the subjects chose to do so. Instead, subjects made quick decisions. One explanation for the increase in the percentage of decisions consistent with the MWD strategy in the simulator is that subjects were adopting a strategy for scanning the VMS such that they searched first for the information which interested them the most (*e.g.*, the lot nearest the destination). If the destination lot had a number of open spaces above the subject’s criterion number of open spaces and the subject hadn’t time to analyze the remainder of the information, the subject may have simply

decided on the destination lot. If the destination lot did not have a subject's criterion number of open spaces, the subject may have then searched for information regarding the lots adjacent to the destination lot.

CHAPTER 5

EXPERIMENT 3 (SECOND SIMULATOR STUDY)

Introduction and Motivation

In Experiments 1 and 2 presented above, subjects made decisions that were consistent with minimizing their total expected travel time most often. However, a large proportion of drivers chose to minimize their walking distance even when the destination lots did not minimize their total expected travel times. To account for this within the METT strategy, the probability function in the computation of the expected travel time was modified in an attempt to better represent subjects' subjective probability of finding a lot full upon arrival. While the predictive power of the METT strategy was, indeed, improved with the use of a new ogival probability function, the proportion of decisions consistent with minimizing the walking distance was still high. Thus, it is not clear which of the two decision rules subjects use.

In an effort to better explain the data, an evaluation of the decision-making process as a whole was considered. Built into the METT strategy is the assumption that subjects consider all of their options before making a decision. We hypothesize that subjects, perhaps, prioritize their decision criteria, thereby considering options sequentially. Having prioritized their criteria, drivers may make their decisions by evaluating lots one at a time, starting first with the lot that satisfies their highest ranked criterion. This idea of rank ordering decision attributes is a lexicographic (LEX) choice rule [Tversky, 1969]. Simon [1955] and Marschak [1968] show that decision making is influenced by considerations of cognitive effort. Hogarth [1990] explains how different decision strategies require different amounts of computational effort. According to Hogarth, decision problems consist of three basic components:

the alternatives available to the decision maker, events or contingencies that relate actions to outcomes as well as their associated probabilities, and the values associated with the outcomes. He states that, in general, decision tasks become more difficult with more alternatives, multiple contingencies and multiple conflicting dimensions of value. Use of a LEX choice rule involves consideration of fewer alternatives and fewer contingencies than use of an METT choice rule.

The fact that the computation of the expected travel time requires a driver to process all relevant problem information before making a decision makes it more computationally intensive for a driver than the lexicographic strategy, in which choices are based on the most important attributes while other information is (at least temporarily) ignored. Thus, the LEX strategy allows a driver to make decisions with less cognitive effort. It seems reasonable that a diminution in the difficulty of a decision task would allow drivers to make decisions more quickly, an element crucial to a driver who feels an intrinsic need to maintain traffic flow. This might explain why subjects in the survey chose to minimize their expected travel time more often than subjects in the simulator who, given the driving task, felt a greater time constraint (none of the subjects stopped to review the VMS signboard even though they were informed that they could do so).

For a driver to decide in which lot to park, he or she must consider three aspects: the driving task, the walking task, and the possible chore of waiting for an available space if a lot is full upon arrival. Given the high proportion of decisions consistent with minimizing one's walking distance in the preliminary studies, we hypothesize that the walking task is of the greatest concern. Thus, we assume that subjects first consider the lot nearest their destination, and contemplate other lots only

if they decide that the destination lot is undesirable for some reason (in this case, has unacceptable parking availability).

Another important difference between METT and LEX is that in the METT strategy, subjects must estimate the total expected travel time for each of the four lots to identify the lot which minimizes their total expected travel time. The LEX strategy, on the other hand, considers only one value at a time, the number of open spaces in the lot nearest the destination. Here, we assume that subjects have some *a priori* criterion number of open spaces. This criterion number would be based on several considerations of the driving task at hand (*e.g.*, traffic density, weather, one's personal schedule, etc.), and its value might vary slightly from driver to driver. Thus, a decision could be based on a single value (or, more generally, a random variable), rather than a computation that includes a complicated subjective probability function. Factors such as traffic density and weather could then later be manipulated to identify drivers' criterion number of open spaces under several different situations. The contributions of these factors would be much more difficult to incorporate into a probability function.

Objective

In an effort to test the new lexicographic hypothesis, a third experiment was conducted. The objective of this experiment was twofold. First, an attempt was made to identify more precisely the criterion number of open spaces subjects use when deciding where to park. Second, an attempt was made to determine whether the LEX strategy better predicts the choices drivers make when deciding where to park than the METT strategy. To carry out this plan, it was critical to design scenarios

such that lot choices consistent with the LEX and METT choice strategies could be distinguished, regardless of the parameter values.

Participants

Twenty students (11 male and 9 female) from the University of Massachusetts at Amherst were again tested utilizing the driving simulator. The ages of the subjects ranged from 19 to 33 years of age, with an average age of 23 years.

Stimulus Material

Experiment 3 utilized the same driving simulation used in Experiment 2, with modifications made only to the parking availability displayed in the VMS and the final destination. Thirty-six new parking scenarios were designed to achieve the above goals (see *Table 5.1*). Of these 36 scenarios, 10 were created to identify subjects' criterion number of open spaces, 21 were designed to compare the METT and LEX strategies, and the remaining 5 were designed to provide subjects with scenarios that resulted in a relatively obvious choice. These latter 5 scenarios (*Appendix I*) were included so that the subjects were not required to make "difficult" choices 100% of the time. Presenting subjects with a few scenarios that resulted in obvious choices also allowed for an analysis of the rationality of the decision-makers tested.

To identify the criterion number of open spaces, x_c , that subjects use to decide where to park, the parking availability in each of 10 destination lots was increased by one from 3 to 12 open spaces while keeping the availability in all lots immediately adjacent to the destination lot constant (*Appendix J*). Here, only the middle two lots (*i.e.*, Lots "B" and "C") were used as destination lots. This was done so that all of the

destination lots would have two adjacent lots (Lots A & C or Lots B & D). The parking availabilities in lots adjacent to the destination lot were kept constant to isolate the effect of parking availability in the destination lot from that of availabilities in adjacent lots. In other words, if the number of open spaces in the adjacent lots were to vary, it would not be clear whether a subject was basing his or her decision purely on the availability in the destination lot or on some change in the availabilities in the adjacent lots.

Twenty-one of the 36 scenarios were created to compare the METT and LEX strategies. Of these 21 scenarios, 6 (*Appendix K*) were created such that the destination lot contained fewer than the criterion number of open spaces (identified in Experiment 2), but still resulted in the minimum expected travel time as calculated using Equations 2.6 and 4.2, and the parameterization $\{\alpha, \beta\} = \{8, 1.6\}$. Subjects employing an METT method of decision-making were expected to choose the destination lot, while those employing a LEX choice rule were expected to choose one of the other three lots since the availability in the destination lot was “unacceptable.”

Although the parameterization $\{\alpha, \beta\} = \{8, 1.6\}$ was used to calculate $E[T_{ij}(k)]$ in the LVM scenarios, the scenarios were designed such that any $\{\alpha, \beta\}$ combination would result in the lots characterizing an METT choice rule being different from the lots characterizing a LEX choice rule. However, if the criterion number of open spaces that a LEX user establishes to determine whether or not to park in the destination lot is less than or equal to 3 open spaces, then the lot choice characterizing the two decision rules could coincide. For example, consider the first scenario shown in *Appendix K*. The most extreme situation exists when the $\{\alpha, \beta\}$

parameterization leads to $P_{full}(2)=1$ and $P_{full}(50)=0$ resulting in total expected travel times of $E[T_{2,2}(2)]=11$ and $E[T_{4,2}(50)]=14$ for Lot B and Lot D, respectively. Since $E[T_{2,2}(2)] < E[T_{4,2}(50)]$ in this most extreme situation, it is clear that any other $\{\alpha,\beta\}$ combination resulting in $P_{full}(2)<1$ and $P_{full}(50)>0$, will still result in METT users choosing Lot B and LEX users choosing Lot D, provided the LEX user establishes a criterion number greater than 2 open spaces. Performing the same type of analysis on the other 5 LVM scenarios, also results in the lot choices characterizing the METT and LEX rules being distinct.

To counterbalance the LVM scenarios, another 6 scenarios (*Appendix L*) were created identical to the LVM scenarios except that the parking availability in the destination lots was increased to 15 open spaces, a number above the criterion number instead of below the criterion number. Here, we expected subjects employing the LEX choice rule to choose the destination lot regardless of the availabilities in the other parking lots since the destination lot contained what we believed to be greater than most subjects' criterion number of open spaces.

Finally, 9 scenarios were created to test the validity of both the METT and LEX strategies. In these scenarios, the parking availability in the destination lots contained greater than the criterion number of open spaces and also resulted in the minimum expected travel time. Thus, drivers using either METT or LEX choice rules would be expected to park in the destination lot in each of these scenarios. The parking availability in the destination lots of these scenarios contained either 13 or 14 open spaces while the parking availability in the lots upstream and adjacent to the destination lot were incremented by approximately 10 from 17 to 96 open spaces (*Appendix M*). Choosing an adjacent lot would indicate that drivers' decision criteria

are more complex than either the LEX or METT strategies. That is, the influence of parking availability in adjacent lots may be more important than predicted by either of these strategies. Care was taken to keep the expected travel time in the destination lot at least 2 minutes less than that of the adjacent lots. Here, we assume that a 2-minute difference in expected travel time is detectable by subjects. Also, the varying adjacent lots were kept nearer the VMS than the destination lots; otherwise, choice of an adjacent lot would result in the subject having to drive and walk further than they would if he or she had just chosen the destination lot.

Experimental Design

Experiment 3 utilized the same graphic database used in Experiment 2, with changes made only to the number of open spaces provided in the VMS and to the final destination information. Thus, subjects encountered the 36 scenarios in 3 sets of 12. *Appendices I through M* present the 5 different types of strategies used to direct the development of the 36 scenarios for Experiment 3. The strategies used are outlined in *Table 5.1*.

Table 5.1. Strategies used in Experiment 3

Appendix	Scenario Type	Abbreviation	No. of Scenarios in Block	Scenario Purpose
I	Naïve Scenarios	NS	5	Provides some easy, obvious choices.
J	Criterion Scenarios	CS	10	Identify subjects' criterion number of open spaces.
K	LEX vs. METT	LVM	6	Compares the LEX and METT paradigms
L	Counterbalance to LVM	CB	6	Checks subjects consistency using the LEX and/or METT choice rules

Appendix	Scenario Type	Abbreviation	No. of Scenarios in Block	Scenario Purpose
M	Alternative Lot Scenarios	ALS	9	Checks whether availability in alternative lots influence subjects' choice rule

The scenarios were arranged such that each set of 12 trials contained a nearly equal number of scenarios consistent with each scenario type. *Table 5.2* indicates the number of scenarios of each scenario type contained in each of the 3 sets of 12 scenarios:

Table 5.2. Counterbalancing for Experiment 3

Set	Number of Scenarios in each Set Consistent with Types				
	NS	CS	LVM	CB	ALS
1	2	3	2	2	3
2	1	4	2	2	3
3	2	3	2	2	3

Finally, the scenarios were randomized within each set of 12 to establish the final ordering of the scenarios for Experiment 3.

Procedure

The subjects' task was identical to that of the subjects in Experiment 2. That is, subjects were instructed to review the information contained in each VMS and to maneuver the car to the lot of their choice. Subjects were provided with a brief description of the project and written instructions that explained in detail the task they were to perform (see *Appendix N*).

Results

The raw data collected on each subject for each scenario in Experiment 3 is attached as a table in *Appendix O*. The format of the table is identical to the format used in *Appendices C* and *F*. Bar graph summaries, which indicate the number of subjects choosing each particular lot for the NM, CS, LVM, CB, and ALS strategies are presented in *Appendix P*. Finally, *Figure 10* presents the percentage of decisions consistent with the METT and LEX choice rules in the LVM scenarios.

The data were compared with the predictions of the METT and LEX strategies as described below. It was found that neither choice rule completely described all of the subjects' decisions in all of the scenarios. However, most participants made decisions consistent with one or the other of the two choice rules, while few subjects employed a combination of the two. Thus, most participants could be placed in one of two categories: "METT users" or "LEX users." By dividing the data into these two subsets, optimal parameter values for each of the decision strategies were obtained.

Discussion

Analysis of the Experiment 3 data was performed in the following progression. First, the data were analyzed using the PARK algorithm to determine the optimal parameters $\{\alpha, \beta\}$ for the METT strategy. Second, analyses were performed to determine to what extent participants employed a LEX strategy. To do this it was necessary to obtain the criterion number of open spaces employed by subjects to choose one lot over another. Chi-squared analysis of the data collected from the CS scenarios was conducted, and the criterion number was established using a chi-squared minimization technique (described below). Once this criterion number

was established, a second chi-squared analysis was performed to determine whether the LEX choice strategy accurately described *all* of the data in Experiment 3. Since it was found that neither decision strategy completely described all of the data, an analysis of data from the LVM scenarios was undertaken to determine whether participants chose alternately one, then the other strategy or, instead, some participants predominately chose one strategy while others predominately employed the other. It was found that participants employed predominately a single strategy. Finally, with participant data categorized into two subsets (METT users and LEX users), the parameters of both decision rules were optimized using either PARK or a chi-squared minimization technique.

Program PARK was used to determine an optimal $\{\alpha, \beta\}$ parameterization for the power probability function used in the METT strategy to predict subjects' perceived probability of finding a lot full upon arrival. The parameters used to fit the Experiment 3 data are given in *Table 5.3*. A maximum agreement between prediction and experiment of 64.3% was found with $\{\alpha, \beta\} = \{8, 1.5\}$. The degree of agreement is substantially lower than that obtained in Experiment 2. This decrease in percent agreement is expected since the parking scenarios in Experiment 3 were intentionally designed to provide subjects with difficult choices. It is unlikely that drivers will be faced with such "difficult" decisions in practice.

Table 5.3. Parameters used for optimal $\{\alpha, \beta\}$ in Experiment 3

	Minimum Value	Maximum Value	Step Size
α	0.1	30	0.1
β	0.1	6	0.05

To evaluate the efficacy of the LEX strategy for describing the Experiment 3 data, chi-squared analyses were performed. The null hypothesis tested was the hypothesis that subjects employ a LEX choice rule, where the criterion number of open spaces, X_c , is a normally distributed random variable with mean μ and standard deviation σ . In performing the chi-squared analyses, destination lot parking availabilities, x_d , were binned such that the predicted frequencies of acceptance and rejection, $f_{pred,accept}$ and $f_{pred,reject}$, were greater than or equal to five participants. The number of degrees of freedom, df , for a given analysis was then computed as the number of bins less two, the number of parameters.

Initially, the chi-squared analysis was performed on data from the CS scenarios only. The results of the analysis are presented in *Table 5.4*. In the table, x_d represents the number of open spaces in the destination lot, $f_{obs,accept}$ and $f_{obs,reject}$ are the observed frequencies of acceptance and rejection of destination lots having x_d open spaces, and $f_{pred,accept}$ and $f_{pred,reject}$ are the predicted frequencies of acceptance and rejection. The predicted frequencies were computed using the cumulative distribution function for a normally distributed random variable with mean μ and standard deviation σ . The chi-squared analysis was initially performed using a “best guess” of $\{\mu, \sigma\} = \{8.25, 3.79\}$. The chi-squared value was then minimized by iteratively adjusting μ and σ using a Generalized Reduced Gradient (GRG2) nonlinear optimization algorithm available in Microsoft Excel. The minimum chi-squared value of 6.58 ($df = 7 - 2 = 5$) was obtained with $\{\mu, \sigma\} = \{8.77, 4.75\}$. Based on this chi-squared analysis, the null hypothesis cannot be rejected at the 10% significance level. Thus, driver behavior in the CS scenarios might be characterized by a LEX choice rule with a mean criterion number of open spaces of 8.77.

Table 5.4. Chi-squared analysis of CS data for Experiment 3

X_d	$f_{obs,accept}$	$f_{pred,accept}$	$f_{obs,reject}$	$F_{pred,reject}$	$(\chi^2)_i$
3-5	10	9.692	50	50.308	0.0117
6	5	5.606	15	14.394	0.0911
7	10	7.103	10	12.897	1.8325
8	8	8.721	12	11.279	0.1056
9	6	10.394	14	9.606	3.8676
10	12	12.050	8	7.950	0.0005
11-12	31	28.658	9	11.342	0.6749
				$\Sigma_i(\chi^2)_i$	6.584

A similar chi-squared analysis was next performed on data from all scenarios in Experiment 3. The results of this analysis are displayed in Table 5.5. The minimum chi-squared value of 50.1 ($df=9$) was obtained with $\{\mu,\sigma\} = \{7.40,8.28\}$. Based on this analysis, the null hypothesis can be rejected at the 10% significance level. The poor chi-squared value and the large variance of X_c clearly indicate that a simple LEX choice rule does not adequately characterize all subjects.

Table 5.5. Chi-squared analysis for all scenarios in Experiment 3

X_d	$f_{obs,accept}$	$f_{pred,accept}$	$f_{obs,reject}$	$f_{pred,reject}$	$(\chi^2)_i$
1-2	35	24.233	65	75.767	6.3142
3-4	12	18.724	48	41.276	3.5101
5	7	7.722	13	12.278	0.1099
6	5	8.660	15	11.340	2.7275
7	10	9.617	10	10.383	0.0294
8	8	10.580	12	9.421	1.3352
9	6	11.534	14	8.466	6.2721
10	12	12.466	8	7.534	0.0463
11	14	13.364	6	6.636	0.0913
12	17	14.216	3	5.784	1.8858
13	65	75.061	35	24.939	5.4069
14	66	62.985	14	17.015	0.6785
>14	219	198.479	1	21.521	21.6889
				$\Sigma_i(\chi^2)_i$	50.1

To determine whether subjects' choices might be described by a combination of METT and LEX choice rules, an analysis of data from the LVM scenarios was undertaken. In the six LVM scenarios, the destination lot contained what we believed to be less than the criterion number of open spaces (*e.g.*, 1, 2, or 3), but still resulted in the minimum expected travel time. Thus, drivers employing an METT choice rule were expected to choose the destination lot, while drivers employing a LEX choice rule were expected to choose one of the other lots. The results for the LVM scenarios are tabulated in *Table 5.6*. The table shows that 36.67% of subjects' choices were consistent with an METT rule and that 63.33% were consistent with a LEX rule. Additionally, 75% of the participants employed one of the two possible choice rules at least 5 out of 6 times. Thus, it is clear that most subjects employ primarily a single decision rule; little evidence exists to support the hypothesis that single subjects employ a combination of the two strategies.

Table 5.6. Results from LVM scenarios of Experiment 3

Subjects	METT Lot Frequency	LEX Lot Frequency	Individual % METT	Individual % LEX
Pilot 1	0	6	0	100
Pilot 2	6	0	100	0
Pilot 3	5	1	83.33	16.67
Subject 1	0	6	0	100
Subject 2	0	6	0	100
Subject 3	0	6	0	100
Subject 4	5	1	83.33	16.67
Subject 5	1	5	16.67	83.33
Subject 6	0	6	0	100
Subject 7	5	2	66.67	33.33
Subject 8	2	4	33.33	66.67
Subject 9	5	1	83.33	16.67
Subject 10	0	6	0	100
Subject 11	3	3	50	50

Subjects	METT Lot Frequency	LEX Lot Frequency	Individual % METT	Individual % LEX
Subject 12	1	5	16.67	83.33
Subject 13	3	3	50	50
Subject 14	2	4	33.33	66.67
Subject 15	0	6	0	100
Subject 16	1	5	16.67	83.33
Subject 17	6	0	100	0
Total	44	76		
% Agreement	36.67%	63.33%		

Given that subjects are divided in terms of their primary decision strategies, the subjects in Experiment 3 were categorized as either METT or LEX users. Having divided the subjects in Experiment 3 into two subsets, the data from all of the scenarios were then re-analyzed to obtain new optimal values for the parameters of the two decision rules. Thus, the optimal parameters $\{\alpha^*, \beta^*\}$ for the METT strategy were re-determined using the PARK program with the data collected from subjects identified as METT users. Similarly, the parameters $\{\mu^*, \sigma^*\}$ for the LEX strategy were re-determined by computing the optimal chi-squared value using the data collected from subjects identified as LEX users.

The chi-squared analysis was performed this time using data collected from the subset of subjects who employed a LEX choice rule at least 83% of the time in the LVM scenarios (*Table 5.7*). The minimum chi-squared value of 8.45 ($df = 7$) was obtained with $\{\mu, \sigma\} = \{8.68, 4.19\}$. Based on this analysis, the null hypothesis cannot be rejected at the 10% significance level. Furthermore, by examining the ratio of the error sum of squares to the total sum of squares (Equation 5.1) it was determined that the LEX strategy with the above parameterization explains 97.5% of the variance.

$$ExplainedVariance = 1 - \left(\frac{\sum_{i=1}^{36} (f_{pred}^i - f_{obs}^i)^2}{\sum_{i=1}^{36} (f_{obs}^i - \bar{f}_{obs})^2} \right) \quad (5.1)$$

where,

$$\bar{f}_{obs} = \frac{\sum_{i=1}^{36} f_{obs}^i}{\#subjects} \quad (5.2)$$

Thus, the decisions of the subset of subjects identified as LEX users in the analysis of the LVM data might be accurately characterized by a LEX choice rule with a mean criterion number of open spaces of 8.68. Moreover, the parameters μ and σ are in reasonable agreement with those determined in the chi-squared analysis for all subjects in the CS scenarios.

Table 5.7. Chi-squared analysis for subjects identified as LEX users

x_d	$f_{obs,accept}$	$f_{pred,accept}$	$f_{obs,reject}$	$f_{pred,reject}$	$(\chi^2)_i$
1-2	2	2.323	48	47.677	0.0471
3-4	1	3.065	29	26.935	1.5499
5-6	6	4.506	14	15.494	0.6396
7-8	10	7.794	10	12.206	1.0231
9-10	10	11.540	10	8.460	0.4859
11-12	17	14.962	3	5.038	1.1017
13	41	42.444	9	7.556	0.3252
14	34	35.922	6	4.078	1.0088
>14	109	106.064	1	3.936	2.2712
				$\Sigma_i(\chi^2)_i$	8.4526

The program PARK was used to determine optimal parameters $\{\alpha^*, \beta^*\}$ for the METT strategy using the data collected from the subset of subjects who employed an METT choice rule at least 83% of the time in the LVM scenarios. The minimum,

maximum, and step size values for the parameters α and β used to fit this data (*i.e.*, α_{\min} , α_{\max} , α_{step} , etc.) are identical to those given in *Table 5.4* (above). A maximum agreement between prediction and experiment of 80.1% was found with $\{\alpha, \beta\} = \{8.1, 1.2\}$. If we increase the subject pool to include subjects who employed METT at least 67% of the time, the maximum agreement is 79.2% with $\{\alpha, \beta\} = \{8, 1.1\}$. Finally, if the data analysis includes subjects employing METT at least 33% of the time a maximum agreement of 78.6% is found with $\{\alpha, \beta\} = \{8.1, 1.3\}$. Recall that when we include all subjects in the analysis (*i.e.*, LEX users as well as METT users) the maximum agreement drops to 64.3%. Thus, when we include these last few LEX users, we strongly limit the ability of the METT strategy to describe the data.

Finally, analysis of the data collected from the ALS scenarios must be mentioned. Recall that in these 9 scenarios the parking availability in the destination lots alternated between 13 and 14 while the parking availability in the lots upstream and adjacent to the destination lots were increased by approximately 10 from 17 in the first scenario to 96 in the ninth scenario. The objective of these ALS scenarios was to determine whether participants were influenced not only by the parking availability in the destination lots, but also by the availability in lots adjacent to the destination lot. Results from these scenarios indicated that 6 of the 20 participants were influenced by the increasing availability in the upstream adjacent lots. Although this indicates that the decision strategy employed by drivers is likely to be more complicated than either the METT or LEX strategies predict, it has been shown that the METT and LEX predictions provide powerful approximations of the actual decision behavior of the participants tested.

CHAPTER 6

CONCLUSION

Enhancing our understanding of the criteria drivers use when making parking decisions is essential to the successful implementation of APMS. We began this study by performing a pencil-and-paper survey (Experiment 1) to determine which of three hypothetical decision rules most accurately describes drivers' choices when deciding where to park. The first decision rule investigated assumed that drivers might chose parking lots that contained the greatest number of open spaces. This strategy was referred to as the MPA (maximize parking availability) decision strategy. The second decision rule assumed that drivers might chose lots in such a way as to minimize the walking distance from the parking lot to the final destination. This decision rule was called the MWD (minimize walking distance) decision strategy. The final strategy assumed that drivers might choose lots that minimize the total expected travel time (denoted METT) from the VMS to the final destination. These choice rules result from the utilization of Expected Utility Theory (see Chapter 2). Results from Experiment 1 suggested that when subjects were given as much time as they desired and could concentrate on only the decision task at hand, they made choices consistent with the METT strategy most often (63%). The MWD and MPA strategies were chosen less often (31% and 7%, respectively).

The same decision strategies were then tested in a more realistic setting. Experiment 2 evaluated the aforementioned decision rules using a driving simulator in which participants maneuvered an actual car through a virtual world. Results from Experiment 2, showed trends similar to those found in Experiment 1, with drivers choosing lots consistent with the METT strategy most frequently (56%), the MWD

strategy less often (40%), and the MPA strategy least often (3%). All of the above results with respect to the METT choice rule assumed that drivers used a linear probability function (Equation 2.7) to compute the probability that a given lot would be full upon arrival.

Although participants clearly favored the METT choice strategy, the high proportion of decisions not consistent with METT suggested that the linear probability function assumed might be improved to better reflect drivers' perceived probability of arriving at a lot and finding it full. Thus, different forms of the subjective probability function were then investigated. We found that using instead an ogival power function with optimal parameters (determined using a computer algorithm) the proportion of subjects' responses consistent with the METT choice rule in Experiment 2 could be increased to 94 percent. Thus, the METT choice rule employing a power probability function in the computation of the expected travel time appeared to be a satisfactory tool for describing driver behavior in the simulated parking situation.

By utilizing survey questions and a driving simulation, we were able to investigate both the static and dynamic preferences of drivers. While the results from Experiments 1 and 2 clearly demonstrated a preference among participants in terms of choice rule (*i.e.*, METT), we found that, regardless of the probability function used, the percentage of decisions consistent with the MWD choice rule were greater in Experiment 2 (the simulator) than in Experiment 1 (the survey). Thus, subjects' dynamic responses seem to differ on average from their static responses. Research into the literature revealed that individual decision making is influenced by considerations of cognitive effort. Use of EUT to identify alternatives that minimize

ones expected travel time involves a great deal of computational effort since one must first estimate the expected travel times associated with each lot choice before identifying the alternative with the minimum travel time. It is likely, then, that the increased cognitive load associated with the simulated driving task, which encourages subjects to make decisions in real-time, caused some subjects to adopt a simpler decision strategy. To account for this, we hypothesized that drivers might employ a lexicographic (LEX) choice rule in which decision attributes are prioritized so that only a subset of options that satisfy ones highest ranked criterion are considered while other information can be ignored. Thus, a LEX choice rule describes a decision strategy that is both simple and efficient. A third experiment was then conducted to compare the efficacy of the METT strategy with that of the LEX strategy.

Experiment 3 was designed to test the LEX strategy and determine whether or not it could describe drivers' decisions more accurately than the METT strategy. The LEX strategy assumed that drivers first consider parking in the lot nearest the final destination, and that the acceptance of this "destination" lot is dependent upon ones criterion number of open spaces. Thus, if the destination lot contains a number of open spaces above ones criterion number, say, X_c , then we assume that LEX users drive directly to this lot without ever even considering other options. Results of Experiment 3 established that X_c could be described as a normally distributed random variable with mean $\mu = 8.68$ and standard deviation $\sigma = 4.17$.

An additional goal of Experiment 3 was to determine whether subjects employ one or a combination of decision strategies when deciding where to park. Scenarios were designed such that the lot choices characterizing METT users were different from the lot choices characterizing LEX users in a given scenario, regardless of the

parameterizations in each strategy. Analysis of the data from those scenarios revealed that participants primarily employ a single strategy and rarely use a combination of strategies. This information allowed the partitioning of subject data into one of two categories, METT users and LEX users.

With this distinction made, each subset of data could be used to optimize the parameters involved with each strategy. Analysis of the data for subjects identified as LEX users yielded optimal mean and standard deviation values for X_c of $\{\mu^*, \sigma^*\} = \{8.68, 4.17\}$, resulting in an explained variance of 97.5%. Use of PARK with data from subjects identified as METT users resulted in a maximum agreement of 80.1% with parameter values $\{\alpha^*, \beta^*\} = \{8.1, 1.2\}$. It must be noted that not all of the data in Experiment 3 could be explained. Two subjects employed an METT choice rule 33% of the time and a LEX choice rule 67% of the time in the LVM scenarios, and two others employed each choice rule half of the time. Thus, we were not able to classify the decisions made by all of the participants.

The goal of this thesis was to develop simple strategies that characterize the majority of decisions made by drivers in a parking task. Two such decision rules have been identified. The first, a choice rule based on Expected Utility Theory successfully described 94% of the decisions made in Experiment 2, a simulated driving task. Experiment 3 was a second simulated driving task designed to further test the METT strategy by presenting participants with more challenging decision choices. In this experiment, it was found that approximately two-thirds of the participants utilized the second, less computationally intensive, lexicographic choice rule. The remaining one third of the participants in Experiment 3 utilized the METT choice rule. Thus, two very promising decision strategies involving a minimum

number of parameters have been identified that can be used to predict driver decision behavior in parking situations.

Throughout this research many simplifying assumptions were necessary to formulate the two simple decision strategies. For example, both the METT and LEX strategies assume that parking availability is the primary factor affecting parking decision behavior. However, it is reasonable to assume that other factors such as weather conditions, traffic density, and time of day will also heavily influence individual decision behavior. Additionally, all of the participants tested in this thesis were students, either graduate or undergraduate, from the university. It is difficult to say whether or not the decision strategies would be employed to the same extent and/or with the same optimal parameterization when applied to a broader range of the population. Future research should focus on two primary areas. First, it will be necessary to test the two decision strategies on different demographic populations. These populations should include older adults, parents toting children, professionals, groups with varying levels of physical capacity, etc. As with the younger adults, both sets of parking scenarios should be presented to the above groups. Once the percentage of employment of the METT and LEX strategies is identified and optimal parameters established for the general population, other factors such as weather, traffic density and time of day should be systematically examined.

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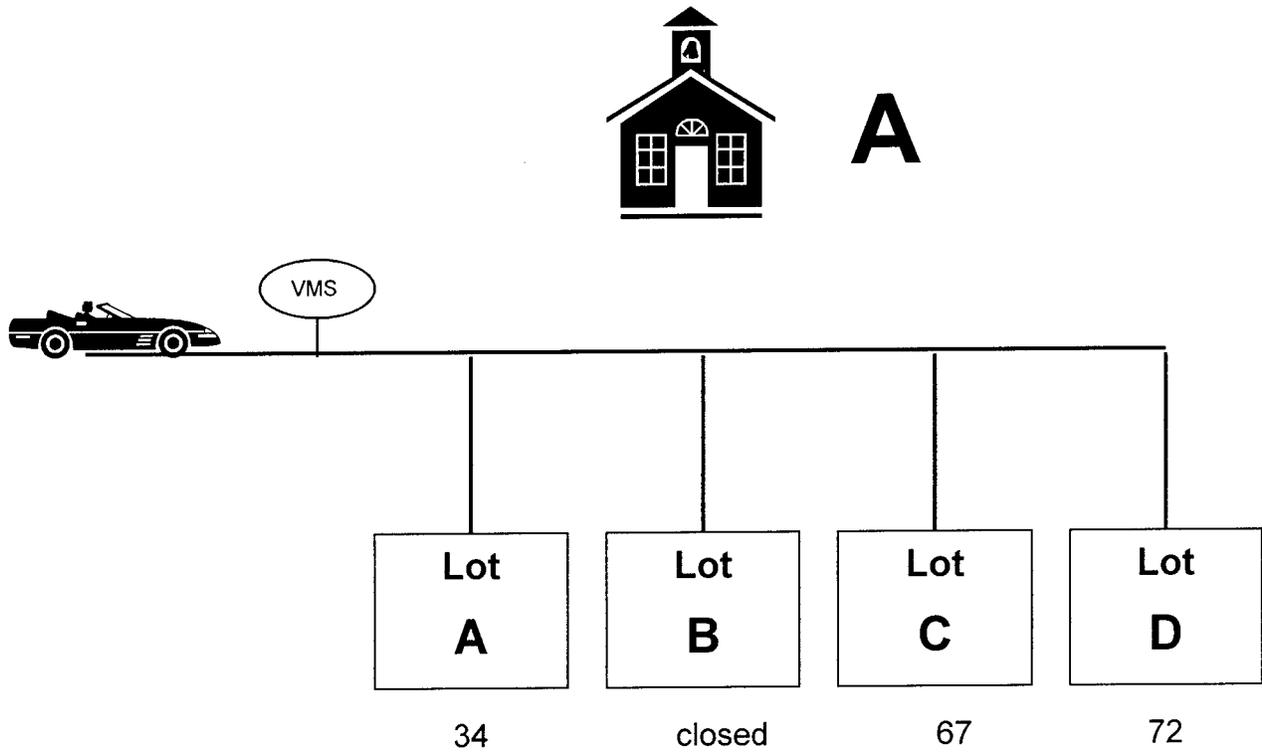


Figure 1. Sample Scenario Used in Survey Study

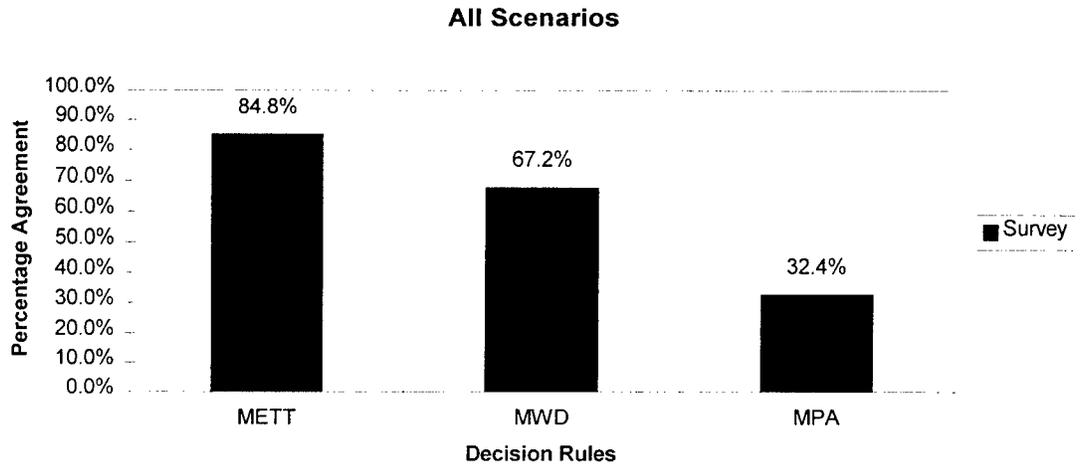


Figure 2 (a). Survey Results Using All Parking Scenarios

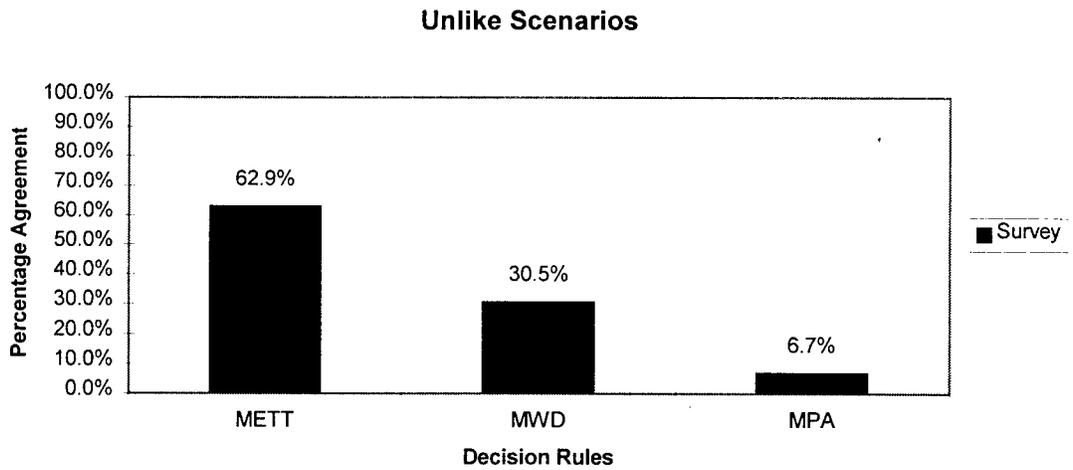


Figure 2 (b). Survey Results using Scenarios with Distinct Choice Rules

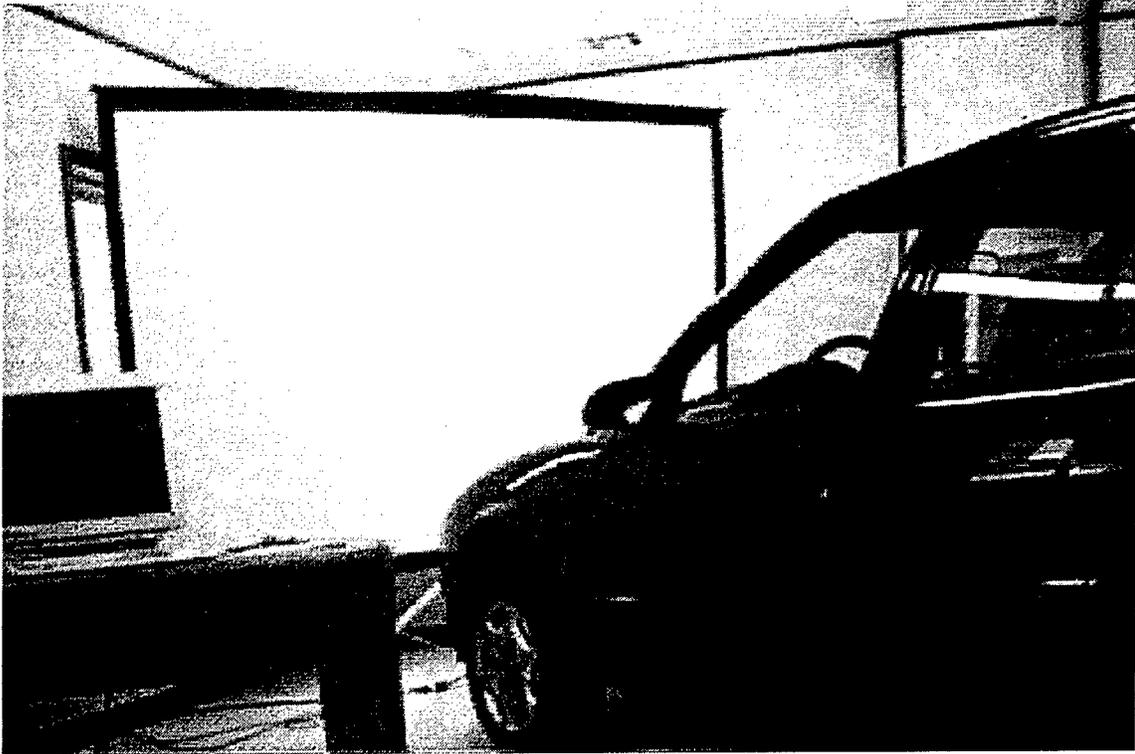


Figure 3. University of Massachusetts Driving Simulator

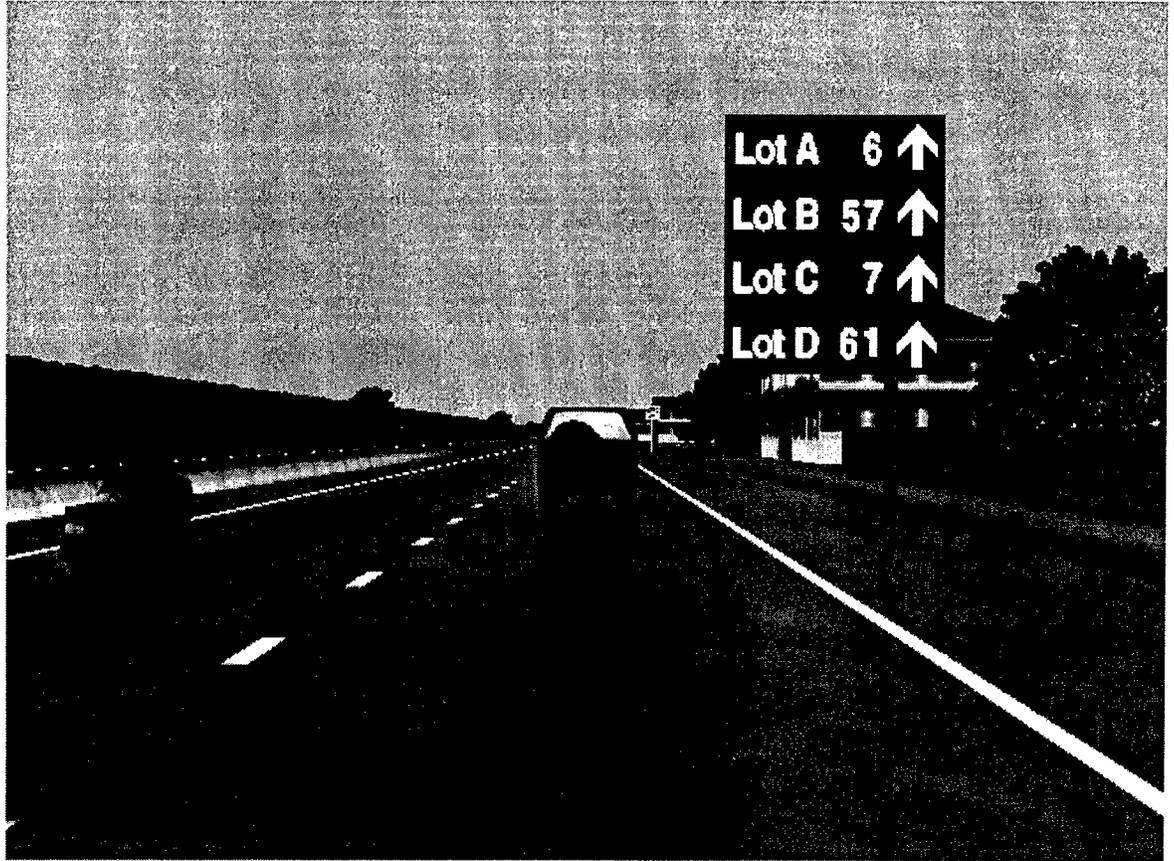


Figure 4. VMS used in Simulator Study

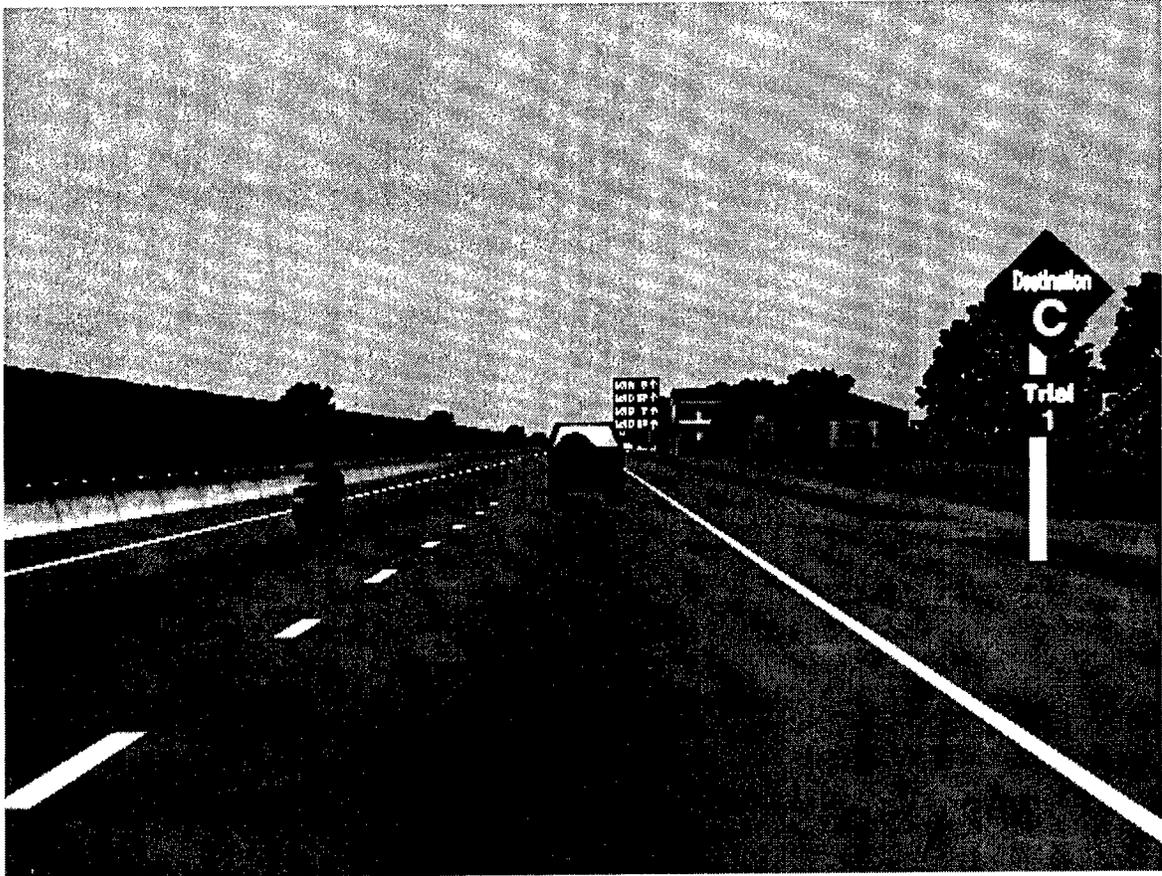


Figure 5. First Image Seen by Subjects in Driving Simulator Study

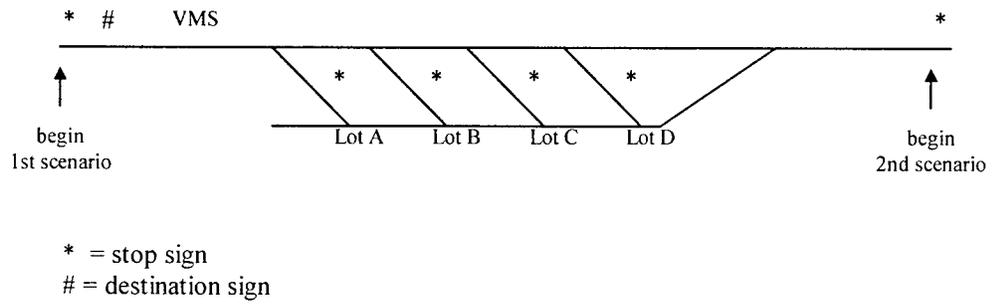


Figure 6. Roadway structure used in Simulation Study

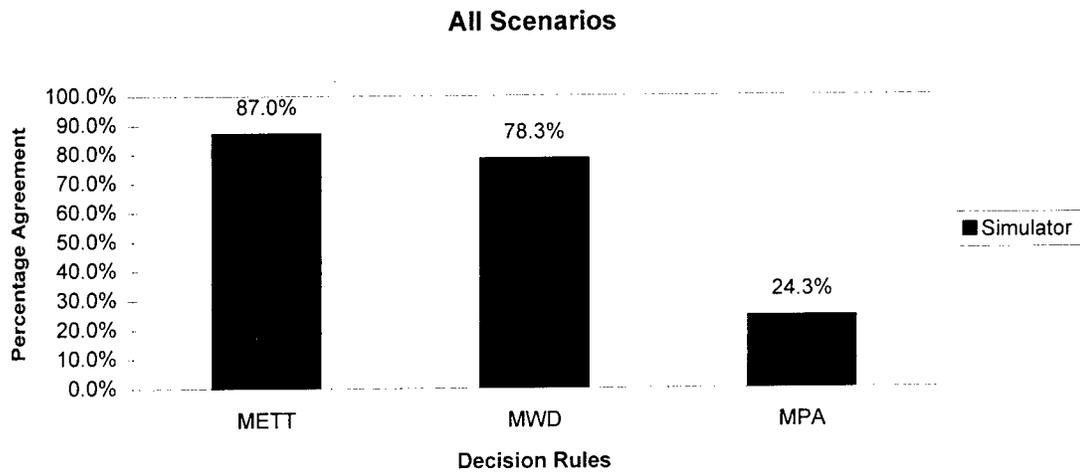


Figure 7 (a). Simulator Results Using All Parking Scenarios

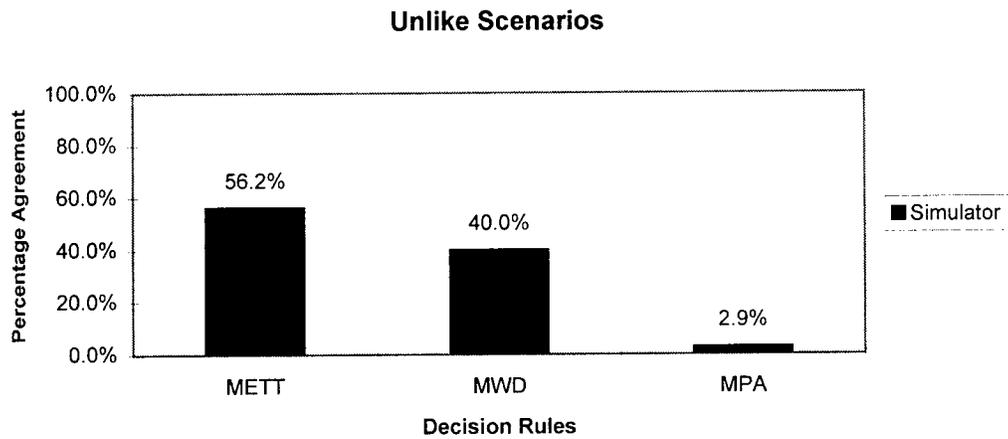


Figure 7 (b). Simulator Results using Scenarios with Distinct Choice Rules

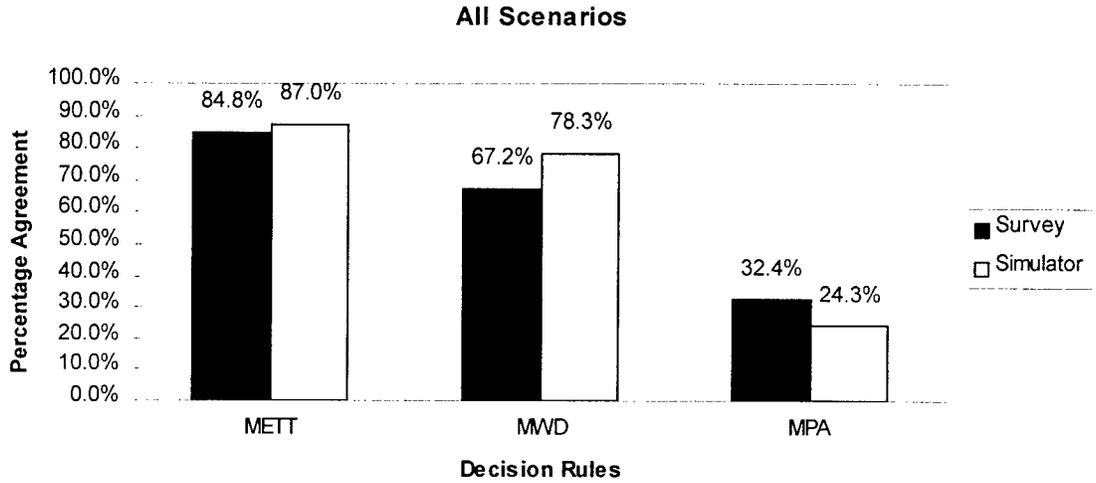


Figure 8 (a). Survey and Simulator Results Using All Parking Scenarios

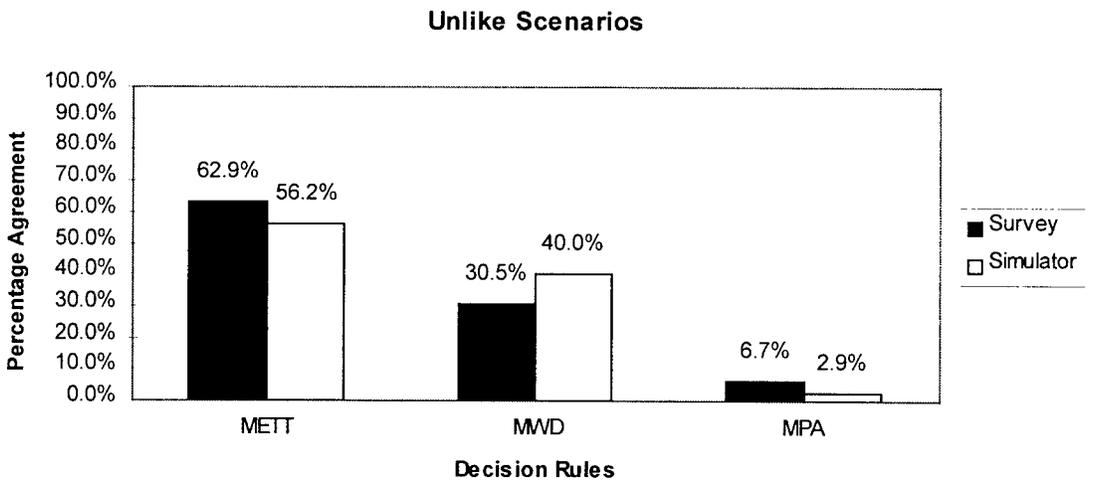


Figure 8 (b). Survey & Simulator Results using Scenarios with Distinct Choice Rules

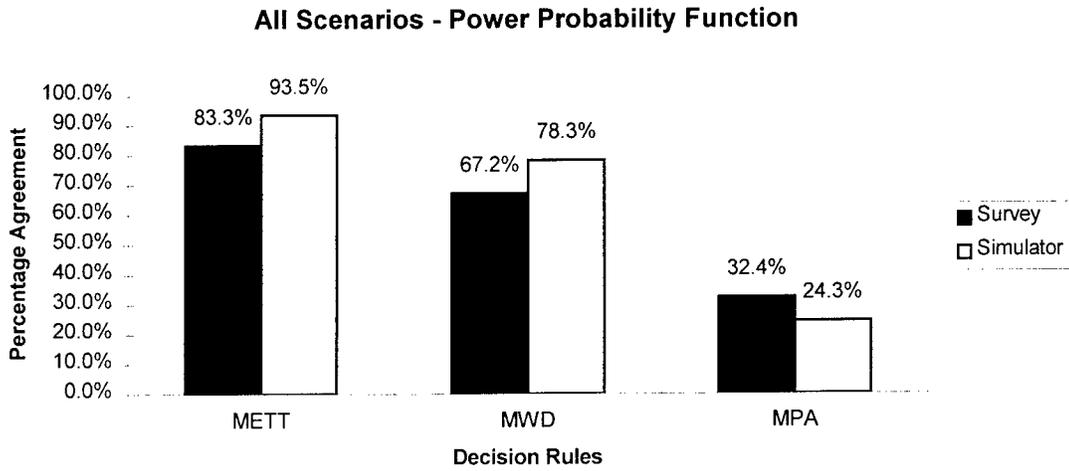


Figure 9. Survey and Simulator Results Using the Power Probability Function

LVM Scenarios

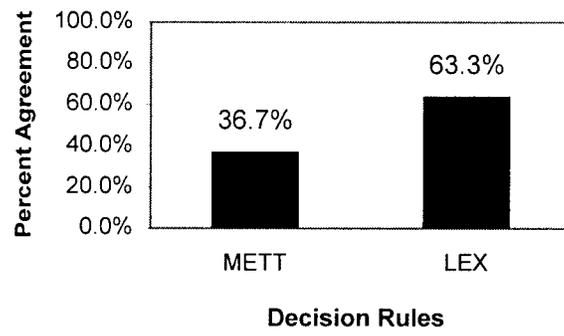
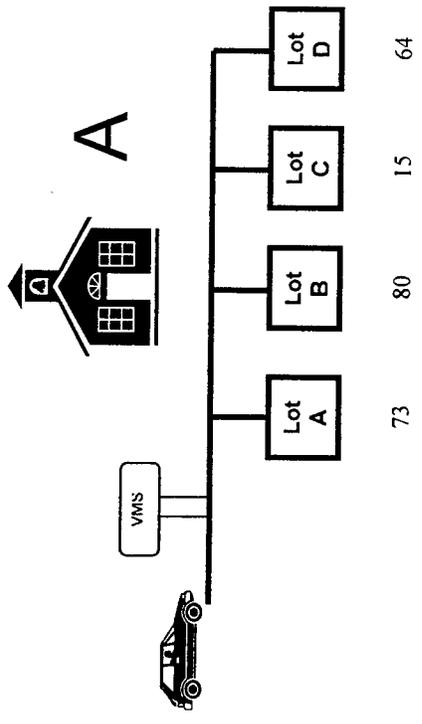
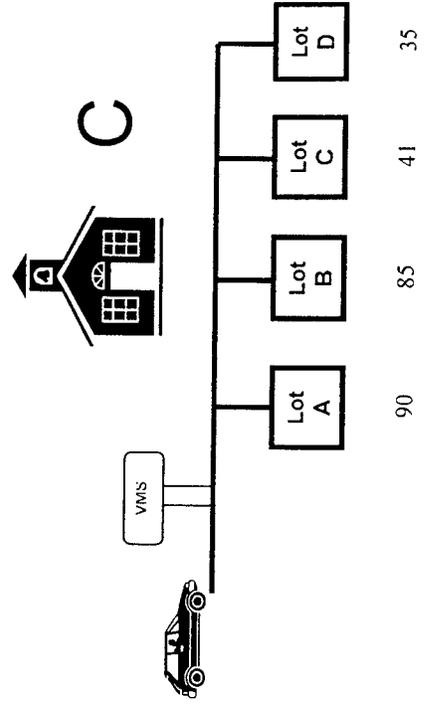


Figure 10. Experiment 3 Results from LVM Scenarios

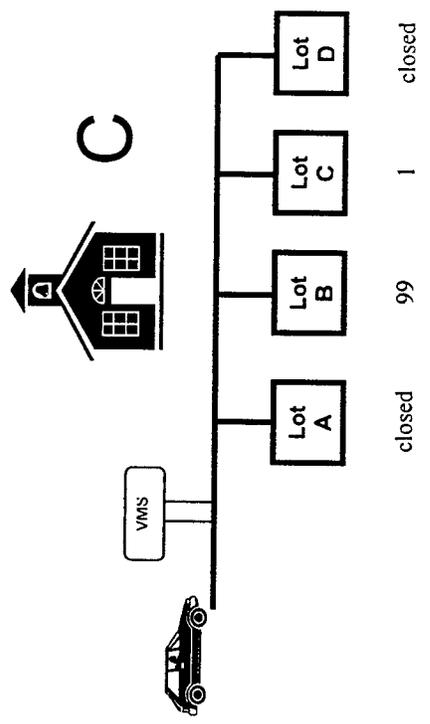
APPENDIX A
PARKING SCENARIOS FOR EXPERIMENTS 1 & 2



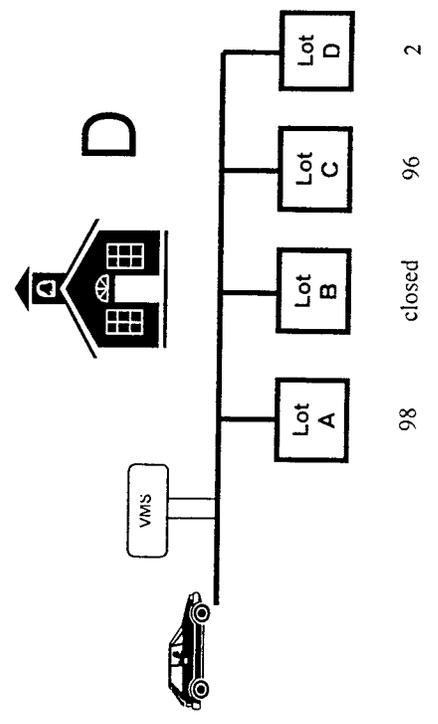
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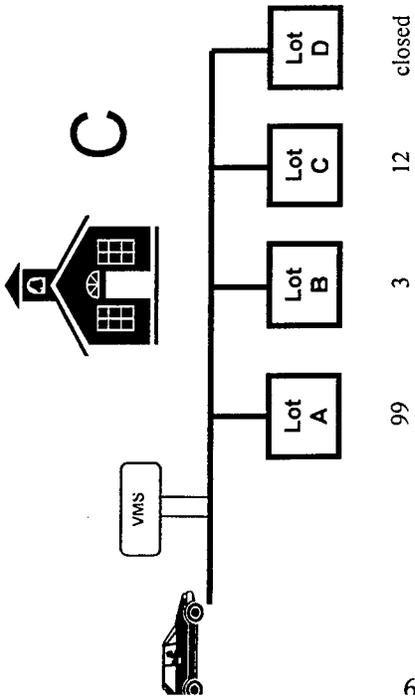
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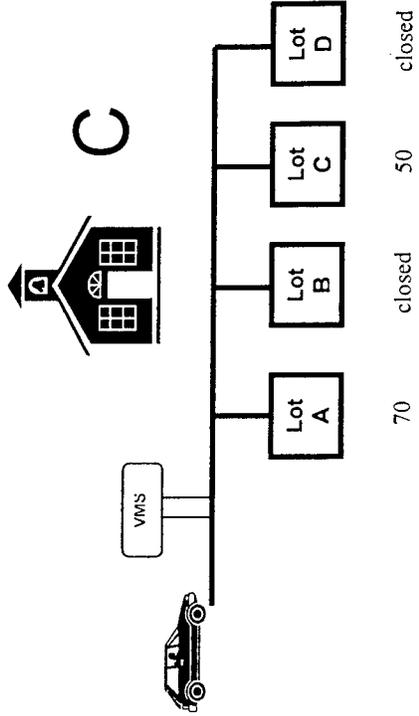
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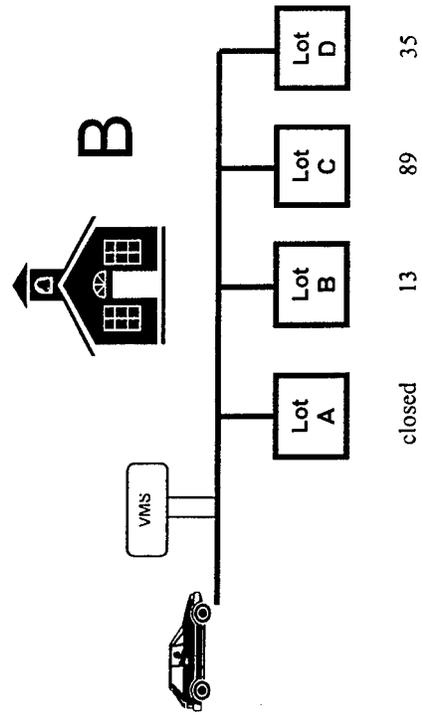
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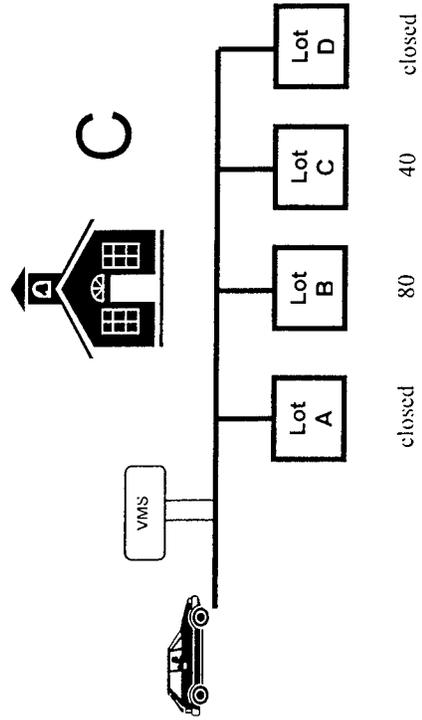
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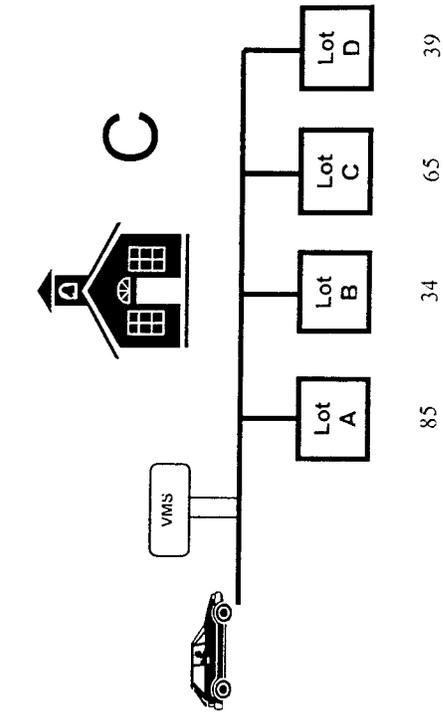
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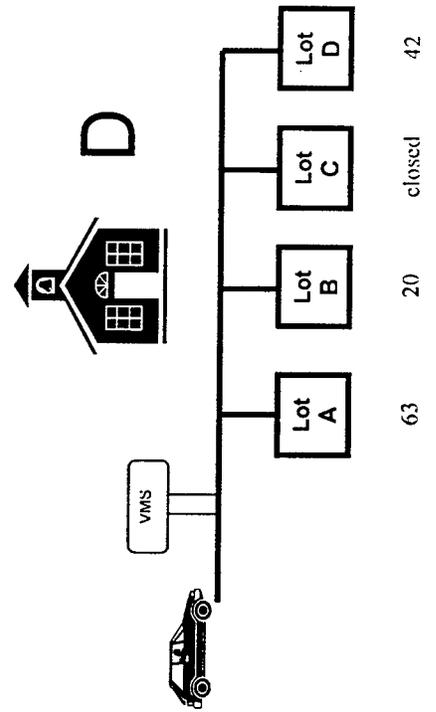
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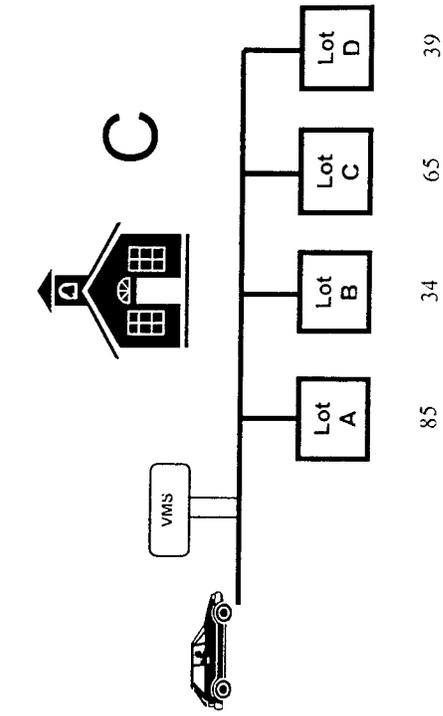
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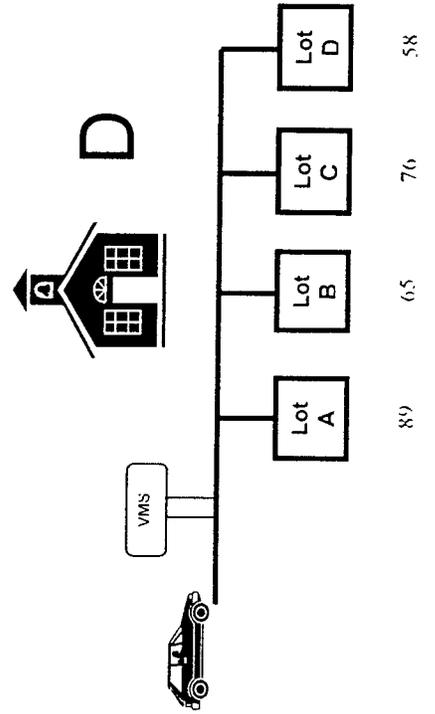
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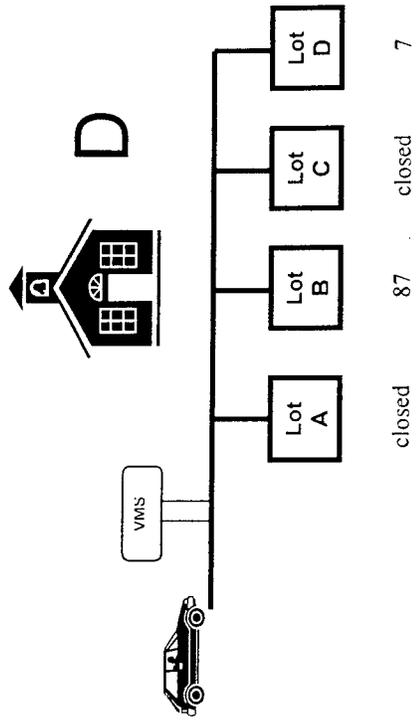
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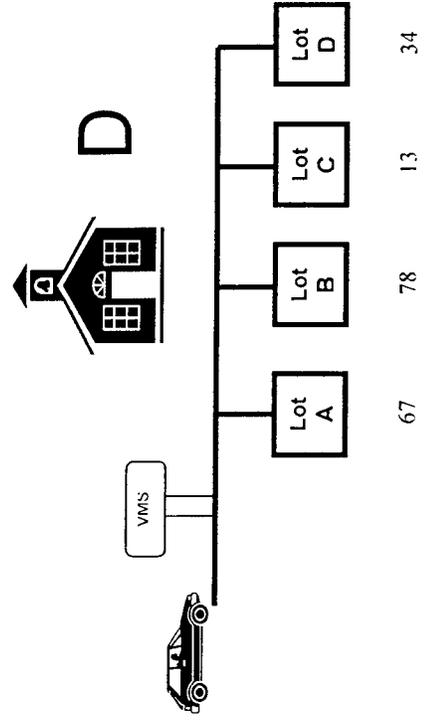
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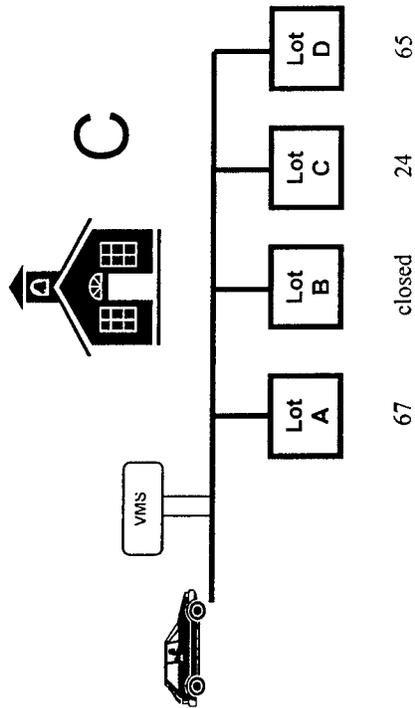
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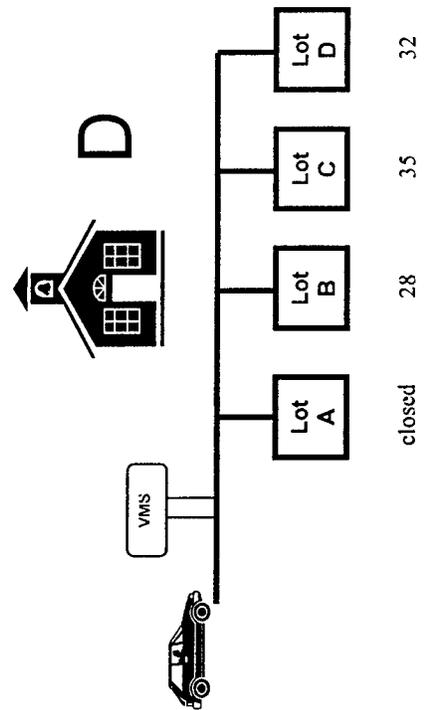
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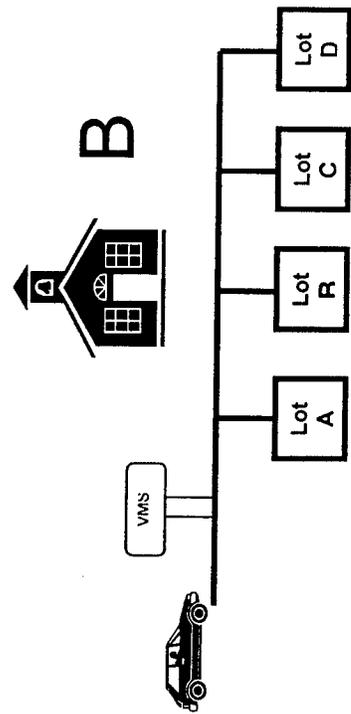
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(Fig. 13)

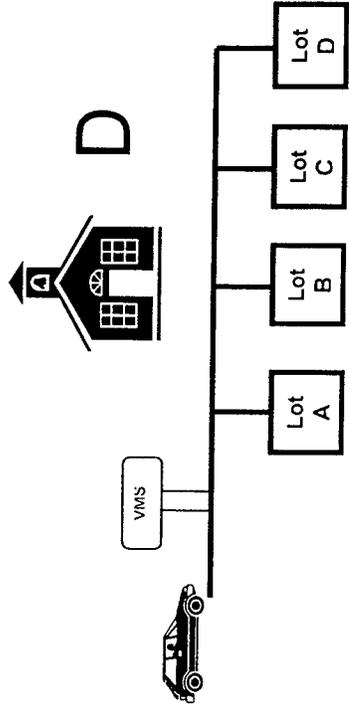


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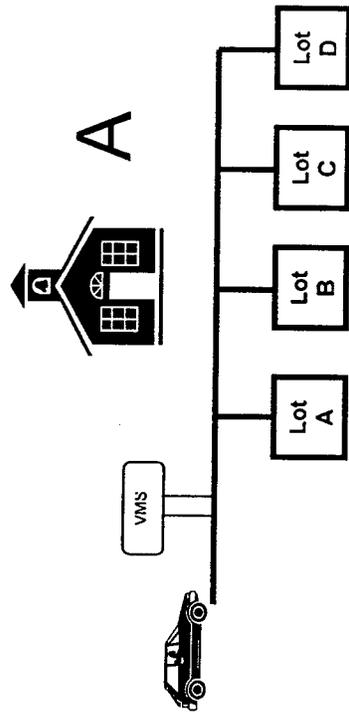
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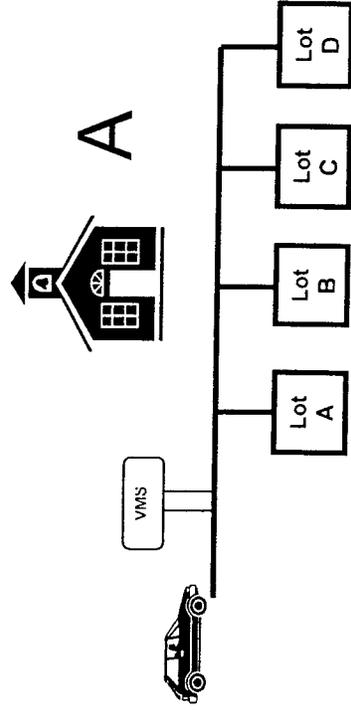
83 closed closed 51

(Fig. 18)



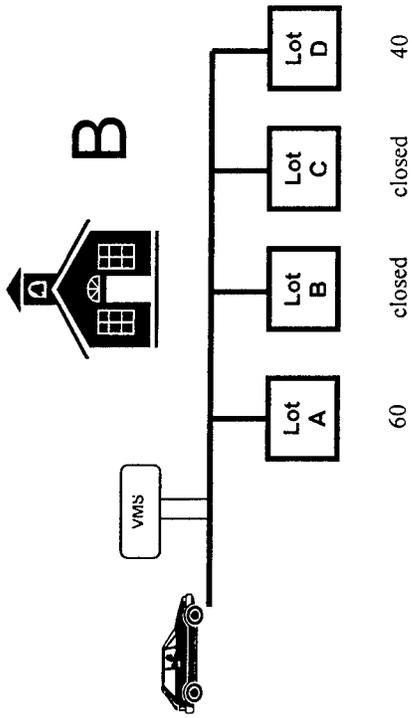
3 89 92 49

(Fig. 19)

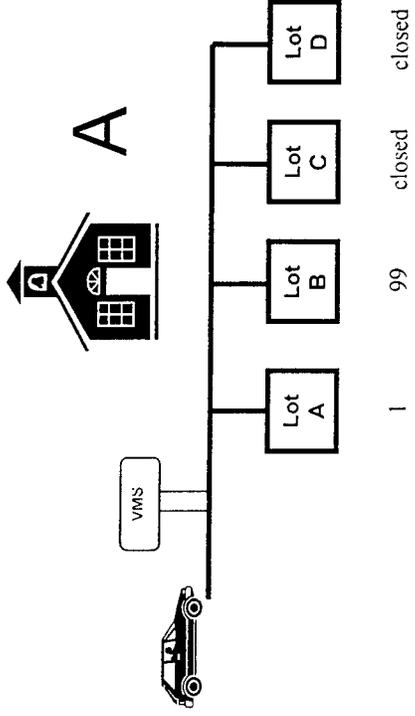


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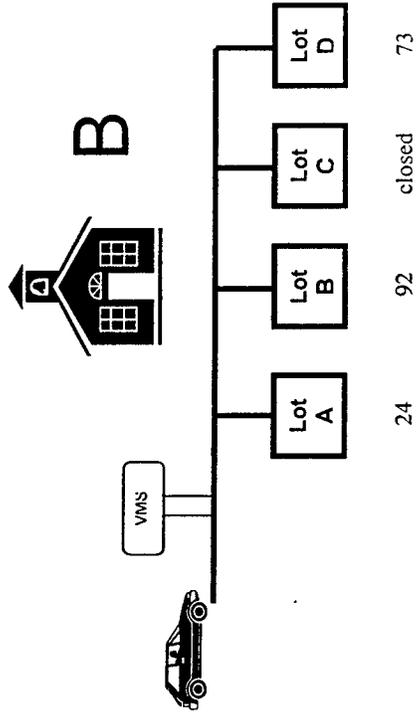
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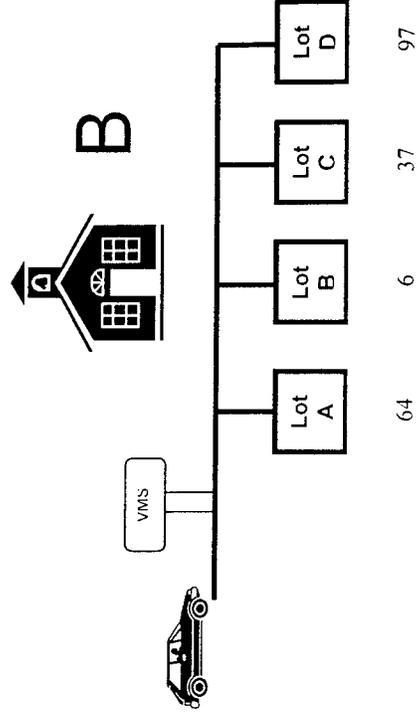
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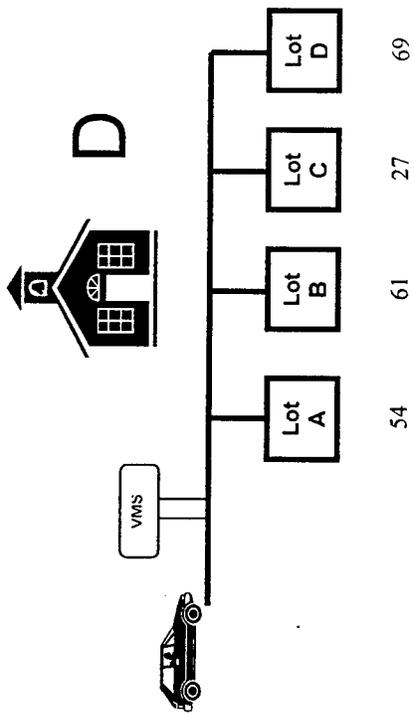
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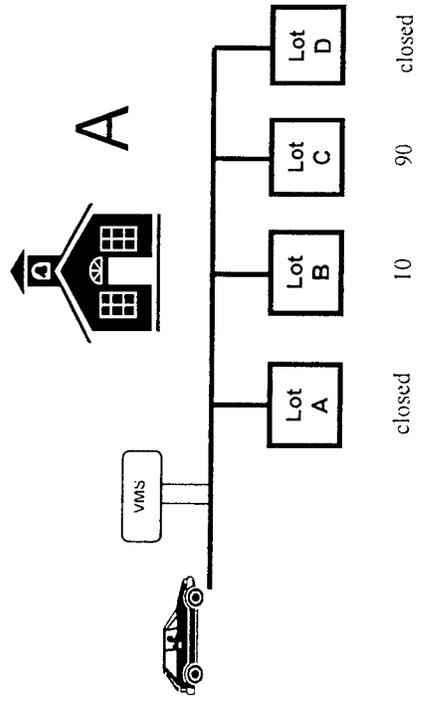
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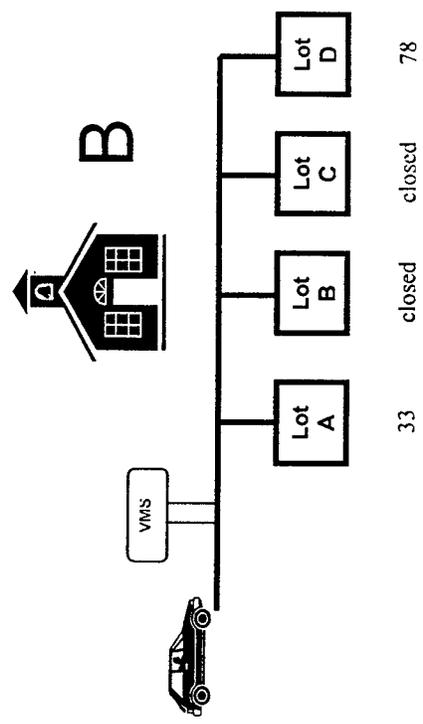
(Fig. 24)



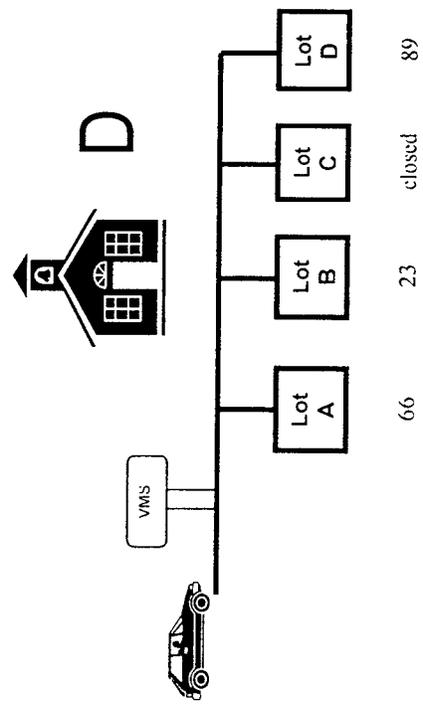
(Fig. 25)



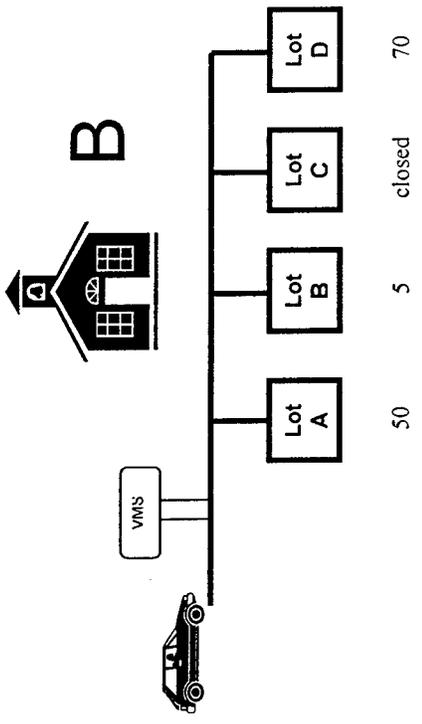
(Fig. 26)



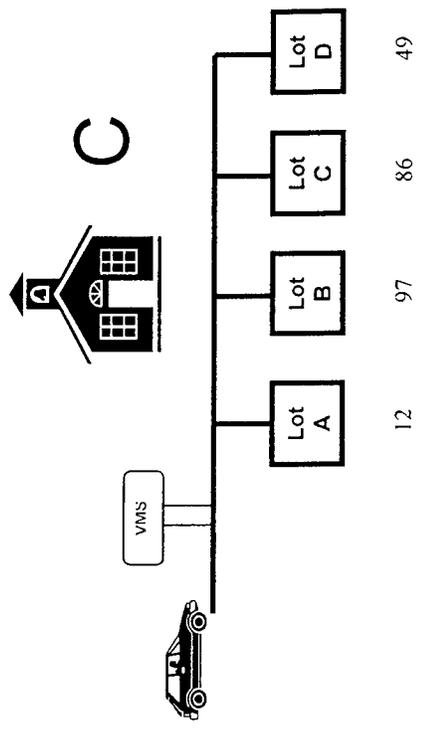
(Fig. 27)



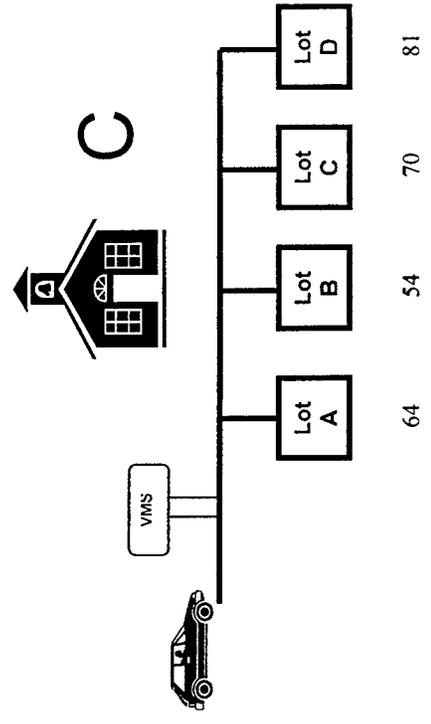
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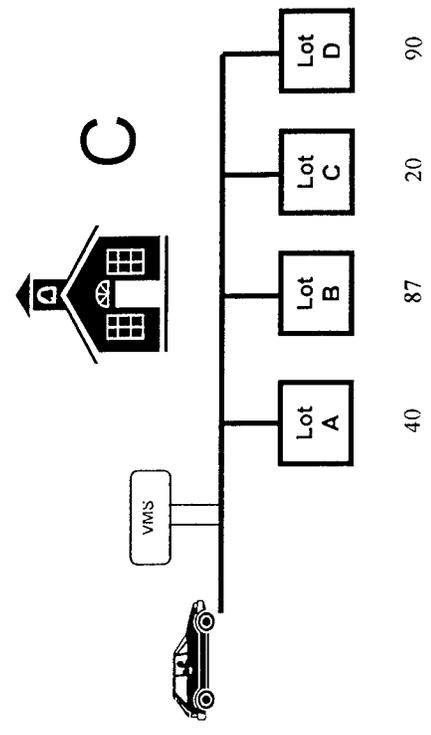
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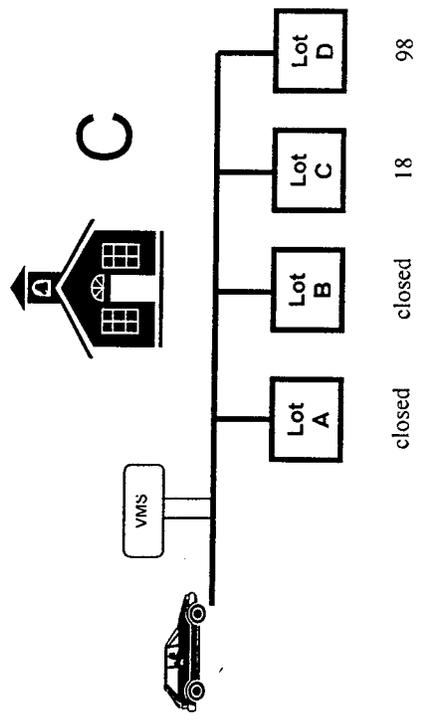
(Fig. 30)



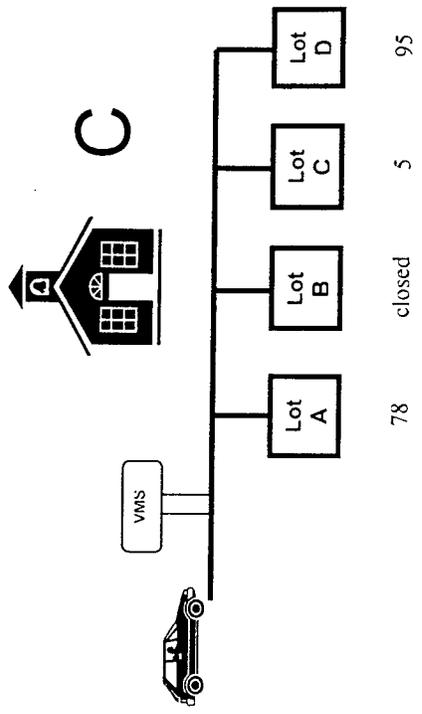
(Fig. 31)



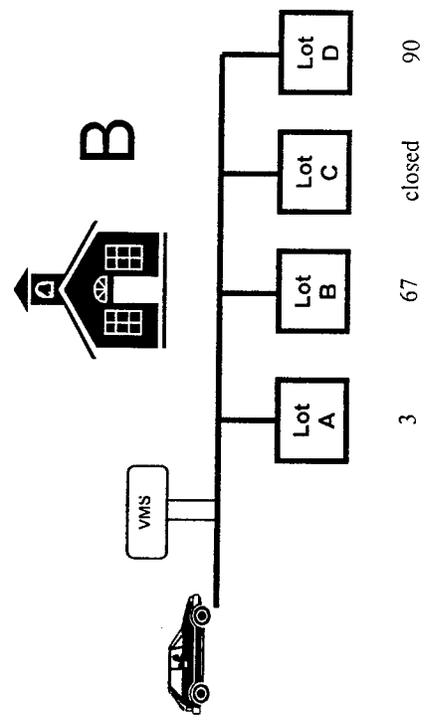
(Fig. 32)



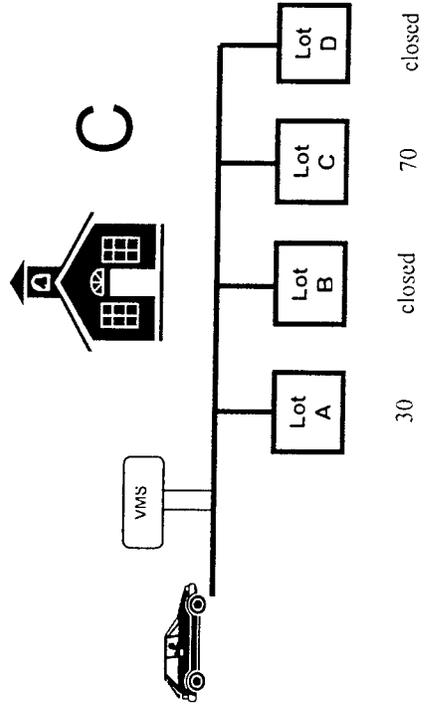
(Fig. 33)



(Fig. 34)



(Fig. 35)



(Fig. 36)

APPENDIX B
INSTRUCTIONS FOR EXPERIMENT 1

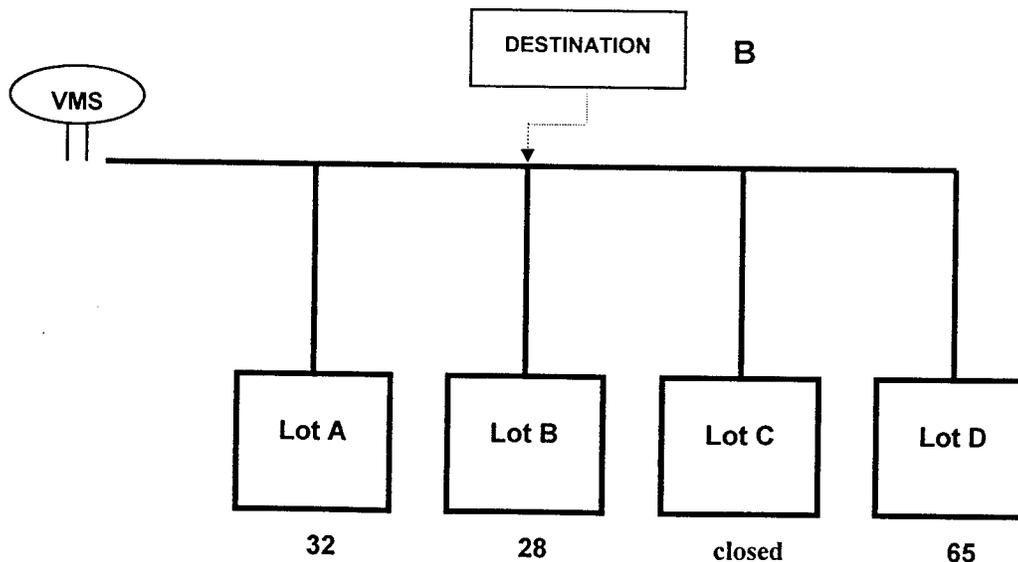
ADVANCED PARKING MANAGEMENT SYSTEMS
Parking Decision Survey

Project Description

Advanced Parking Management Systems (APMS) are being designed as part of the Intelligent Transportation Systems effort. APMS utilize variable message signboards (VMS) that give drivers up-to-the-minute information on the availability of parking at various alternative parking lots. The initial goal of this project is to identify which parking destination a driver will choose when given information on the number of available parking spaces at different parking lots.

Instructions

The following figures show 36 different parking scenarios. In each scenario, you must choose which parking lot *you* would park in based on the information given on the VMS signboard. Each scenario contains 4 parking lots (A, B, C, D), each having 100 spaces. Your starting position will always be at the VMS signboard. The position of your destination is indicated on the figure. Your destination may be at any of the 4 nodes on the example figure below. For example, if a “B” is displayed next to the building, then your destination is at the node indicated by the arrow (see figure).



The VMS signboard displays the number of parking spaces currently *empty* in each of the 4 lots. On the figure, the number of empty spaces in each lot is displayed below the corresponding lot. You do *not* know, however, how many cars may currently be ahead of you, but not yet in a parking space.

You have the following additional information. Each link in the road system takes 1 minute to drive and 3 minutes to walk. Thus, in the above example, if you decided to park in lot "A," it would take you 2 minutes to drive to the lot (2 links) and 6 minutes to walk to your destination (2 links). If a lot is full upon arrival, assume that you will wait 5 minutes for an available space. If a lot is "closed," you may not park in it.

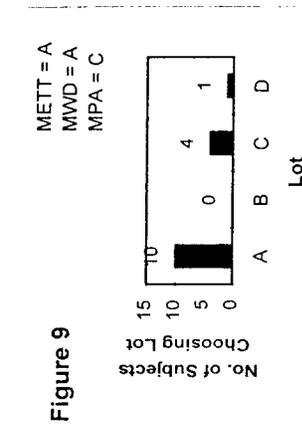
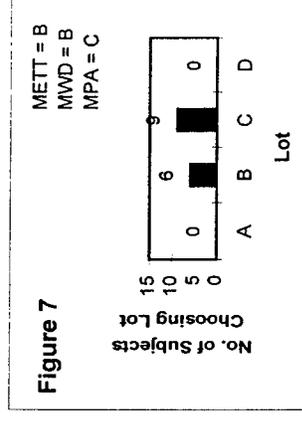
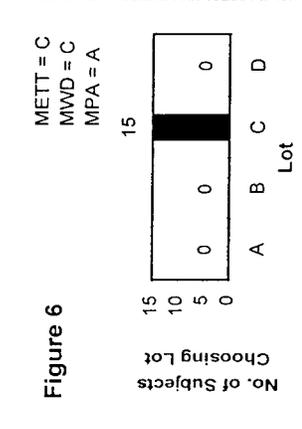
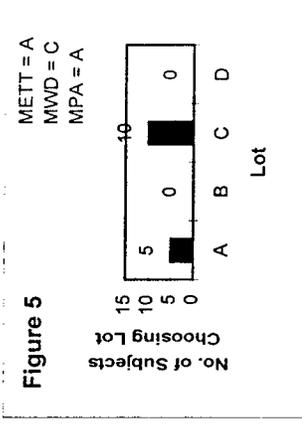
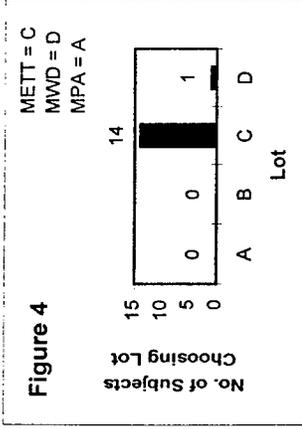
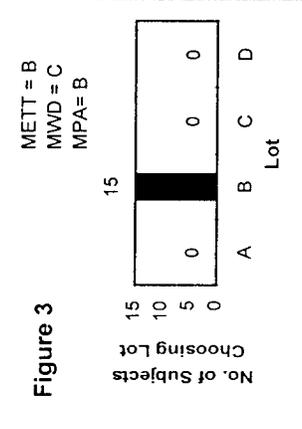
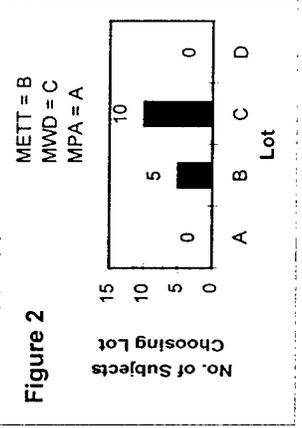
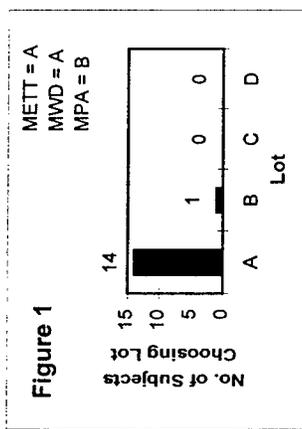
Given the above information, please review each of the following figures, and circle the parking lot that you would park in.

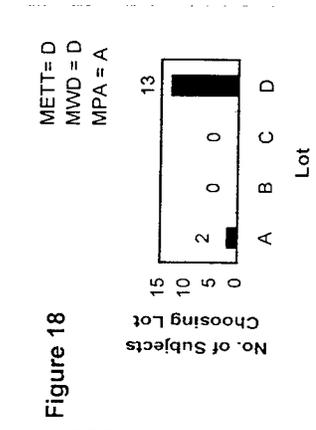
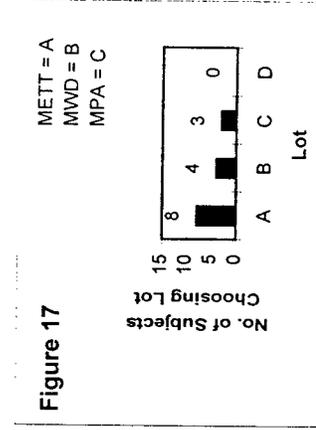
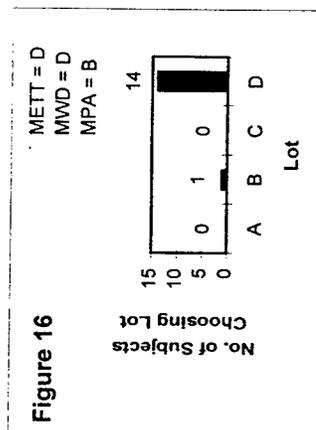
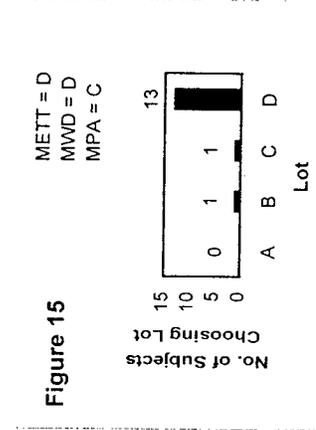
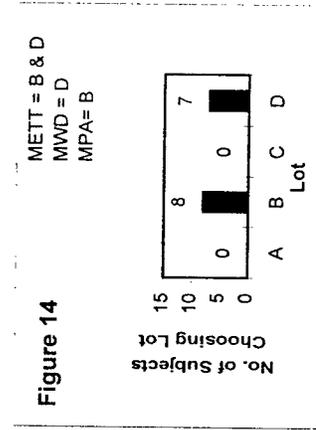
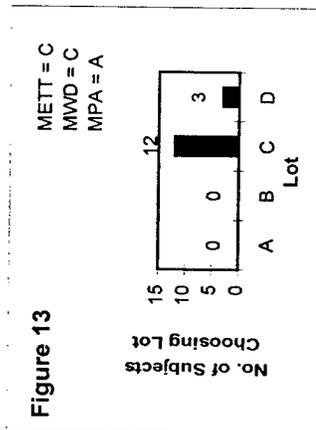
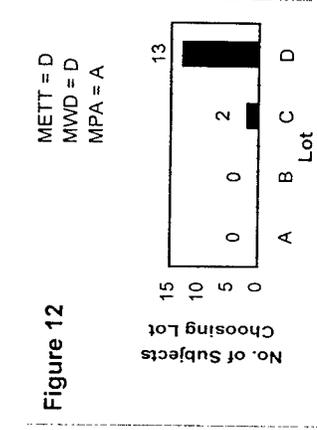
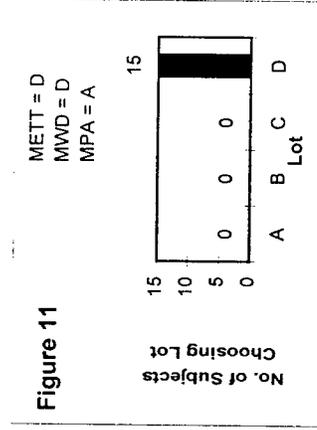
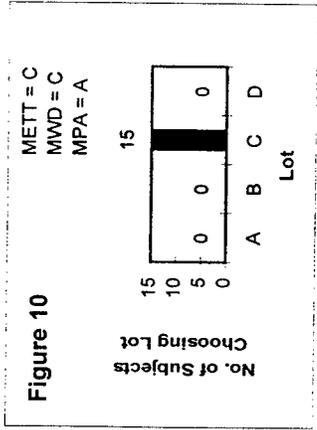
APPENDIX C
RAW DATA FOR EXPERIMENT 1

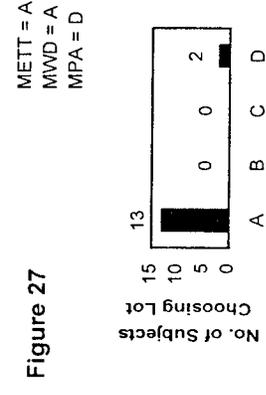
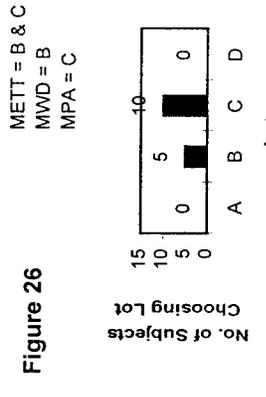
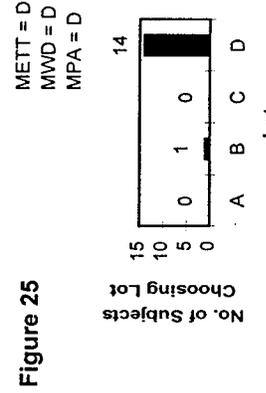
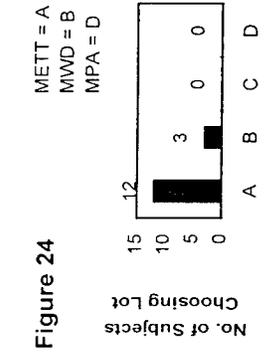
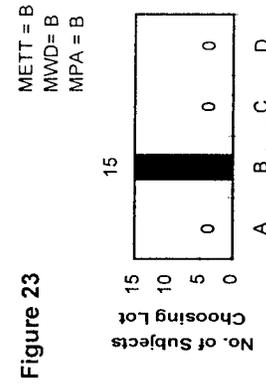
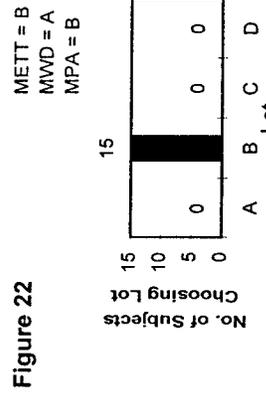
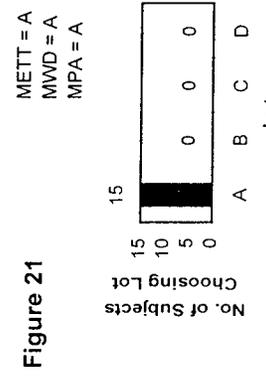
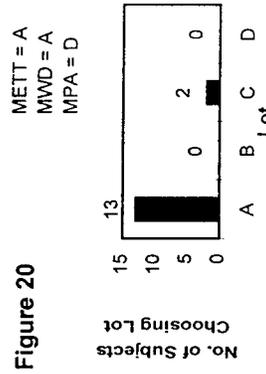
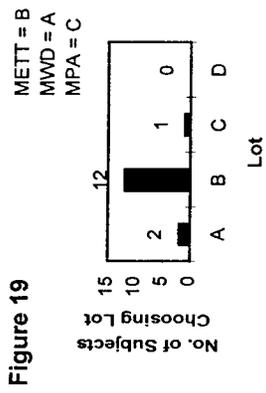
	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10	Subject 11	Subject 12	Subject 13	Subject 14	Subject 15	No. MWD	No. METT	No. MPA
Fig 1	B	A	A	A	A	A	A	A	A	A	A	A	A	A	A	14	14	1
Fig 2	B	C	C	C	C	C	C	B	C	C	C	B	C	C	B	10	5	0
Fig 3	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	0	15	15
Fig 4	C	C	C	C	C	C	C	C	D	C	C	C	C	C	C	1	14	0
Fig 5	A	A	A	A	A	A	A	A	C	C	C	C	C	C	C	10	5	5
Fig 6	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	15	15	0
Fig 7	C	C	C	C	C	C	C	C	B	C	C	B	C	C	C	7	7	8
Fig 8	B	C	C	C	C	C	C	B	C	C	C	C	C	C	C	13	15	2
Fig 9	C	A	C	A	A	A	C	C	A	A	A	A	A	A	A	11	11	4
Fig 10	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	15	15	0
Fig 11	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	15	15	0
Fig 12	C	D	D	D	D	D	D	C	D	D	D	D	D	D	D	13	13	0
Fig 13	D	C	C	C	C	C	C	C	C	C	C	C	C	C	C	12	12	0
Fig 14	B	D	D	D	D	B	B	B	D	4	2	B	D	D	B	7	15	8
Fig 15	D	D	C	D	D	D	B	D	D	D	D	D	D	D	D	13	13	1
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Fig 18	D	D	A	D	D	D	A	D	D	A	D	D	D	D	D	13	13	2
Fig 19	B	B	C	A	B	B	B	B	A	B	B	B	B	B	B	2	12	1
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Fig 22	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	0	15	15
Fig 23	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	15	15	15
Fig 24	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	3	12	0
Fig 25	B	D	D	D	D	D	D	D	D	D	D	D	D	D	D	14	14	14
Fig 26	C	B	C	B	B	C	C	C	B	C	B	C	B	C	C	7	15	8
Fig 27	D	A	A	A	A	A	A	D	A	A	A	A	A	A	A	13	13	2
Fig 28	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	15	15	15
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Fig 32	B	C	D	C	C	C	C	D	C	C	C	C	C	C	C	9	2	4
Fig 33	D	D	D	D	C	C	D	D	C	C	C	D	D	D	D	8	15	7
Fig 34	A	D	D	C	D	D	D	D	C	D	D	D	D	D	D	2	12	12
Fig 35	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	15	15	0
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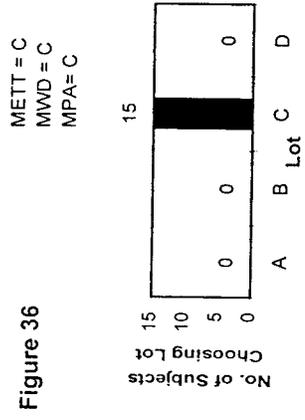
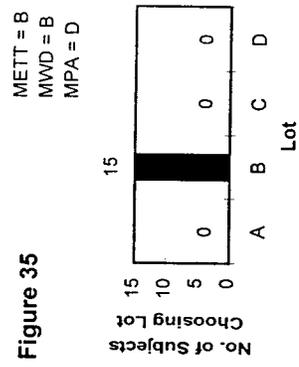
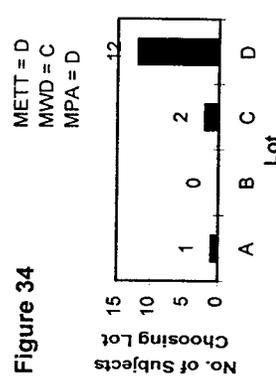
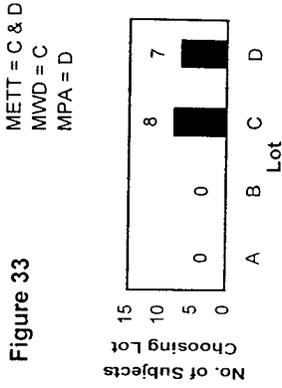
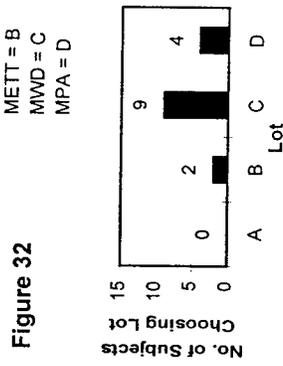
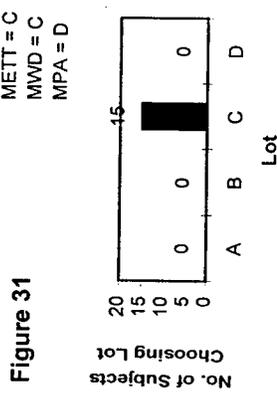
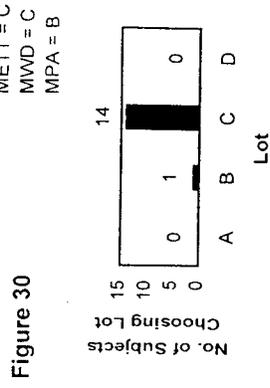
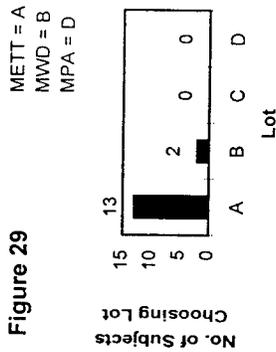
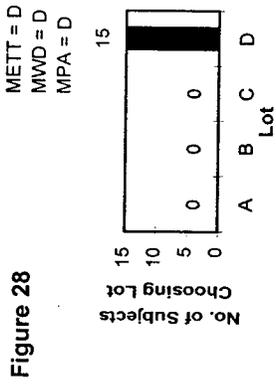
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	# MWD	22	28	23	24	30	28	25	24	23	28	28	31	27	28	28	67.22%	84.63%	32.22%
	# MPA	14	12	18	7	8	11	16	19	7	10	9	10	8	8	14			
	# other	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
te Scenarios	# METT	7	4	4	1	6	5	5	5	0	5	4	7	4	4	5			
	# MWD	0	2	1	6	1	2	2	0	7	2	3	0	3	3	0			
	# MPA	0	1	2	0	0	0	0	2	0	0	0	0	0	0	2			
	# other	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			

APPENDIX D
BAR GRAPH SUMMARIES FOR EXPERIMENT 1









APPENDIX E
INSTRUCTIONS FOR EXPERIMENT 2

Form 1: Description of Experiment

Participant,

Thank you for agreeing to participate in the following study. We estimate that this experiment should require no more than an hour of your time. You will be paid \$10 per hour for your participation. If at any time during this experiment you do not wish to continue, you may terminate your session by simply notifying the facilitator. You will be paid for your time even if you do not complete the entire session.

Project Description

Advanced Parking Management Systems (APMS) are being designed as part of the Intelligent Transportation Systems effort. APMS utilize variable message signboards (VMS) that give drivers up-to-the-minute information on the availability of parking at various alternative parking lots. The initial goal of this study is to identify which parking destinations a driver will choose when given information on the number of available parking spaces at different parking lots. Once the criteria which people use to decide where to park are known, the ways in which VMS signs might effect traffic flow in complicated parking scenarios can be fully evaluated.

Instructions

WHAT YOU WILL SEE

This study investigates drivers' choices of where to park using a driving simulator. You will be seated in a car, and in front of the car you will see a screen. The first image that will be presented on the screen is a scene of a road. The roadway will look similar to roadways that you drive on every day. The car will initially be stopped at a stop sign. You will see other vehicles on the road with you, however, you will only have control over your own vehicle. Additionally, you will see a sign which gives your destination. Your destination can be one of four buildings, labeled, simply A, B, C, or D. An aerial view is presented in Figure 1.

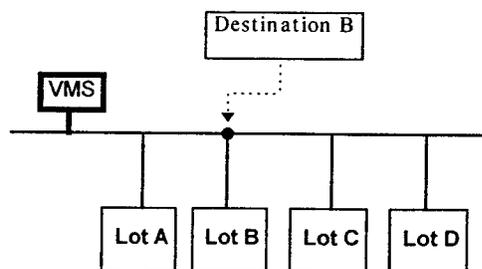


Figure 1

So, for example, the sign might read “Destination B,” which would mean that your destination is nearest Lot B (displayed as a dot in Figure 1). The same holds for other destinations (i.e. Building A is nearest Lot A, Building C is nearest Lot C, and so on).

Once you proceed past the stop sign you will see the VMS signboard. The VMS displays the number of open spaces (out of 100) available in each of the four (Figure 2).

Lot A	78	↑
Lot B	12	↑
Lot C	XX	↑
Lot D	49	↑

Figure 2

For example, in Lot B of Figure 2 there are 12 open spaces. The lot has a total of 100 spaces. Thus, 88 of the spaces are already taken. In some scenarios, certain lots may be closed. Closed lots will have a red “XX” to signify that you may not park in that particular lot. For example, in Lot C of Figure 2, there is a red “XX.” You may not park in that lot.

Once you travel past the VMS sign, you will find that the road continues for several miles (again, see the aerial view in figure 1). Note that traveling from left (the VMS sign) to right, you can exit the main road at any one of four lots. These lots will be signed, Lot A, Lot B, Lot C, and Lot D. When you turn onto a road marked with a lot, you will come to a stop sign. This second stop sign is located next to the lot in which you would normally park. However, in the interest of saving time, after breaking at the second stop sign you should continue driving forward. The roadway will combine with the original stretch of road, and another stop sign will appear. This final stop sign signifies the beginning of the next scenario.

WHAT YOU WILL DO

After reading the destination sign you should repeat it several times to yourself, and then say aloud to the facilitator, “My destination is Building X,” where X is either A, B, C, or D. Proceed past the first stop sign towards the VMS. You must scan the VMS and determine the parking lot in which you would like to park. In addition to the number of open spaces in each lot, you should also consider the following information (refer to Figure 1). Assume that each link in the road system takes 1 minute to drive and 3 minutes to walk. Thus, in Figure 1, if you decided to park in Lot A, it would take you two minutes to drive to the lot (2 links) and 6 minutes to walk to your destination (2 links). If a lot is full upon arrival, assume that you will wait 5 minutes for an available space.

The VMS signboards should be readable as you drive past them, however, you may stop and back up the car to re-read the VMS if you have trouble making out the information. You should then proceed to the parking lot of your choice.

After parking in the lot of your choice for the first scenario, you should continue past the stop sign. Continue driving forward until the road leads you back onto the original stretch of road, and to the next stop sign. This stop sign represents the beginning of the second scenario. The process will continue until all 36 different parking scenarios are completed.

Throughout this experiment you should drive as you would normally drive. It is important that you drive as “naturally” as possible. If you have any questions, please ask the facilitator before beginning the experiment. Thanks again for your participation!

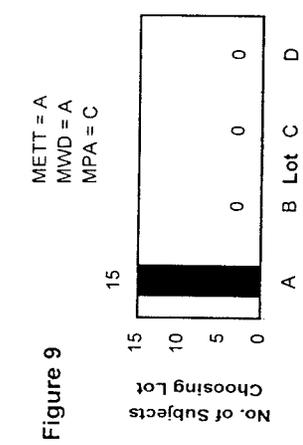
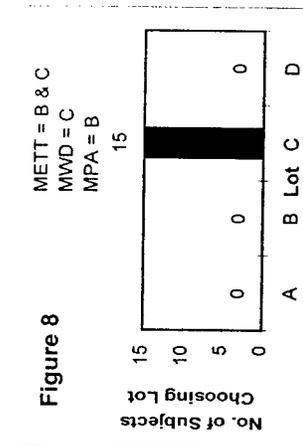
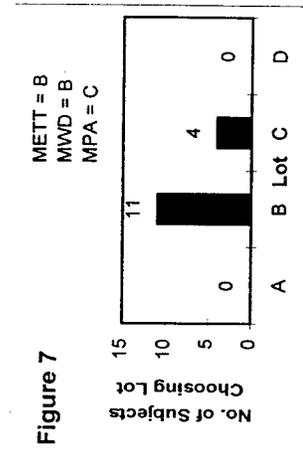
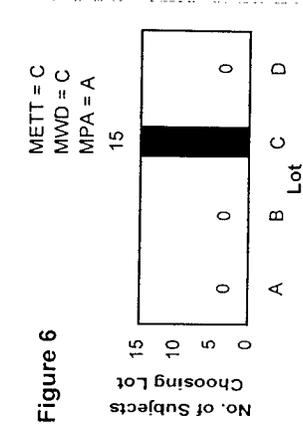
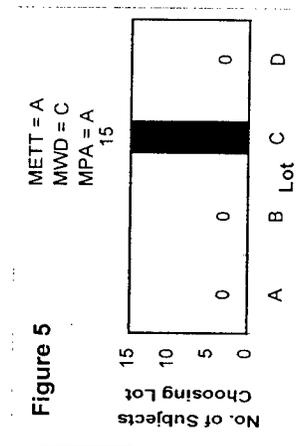
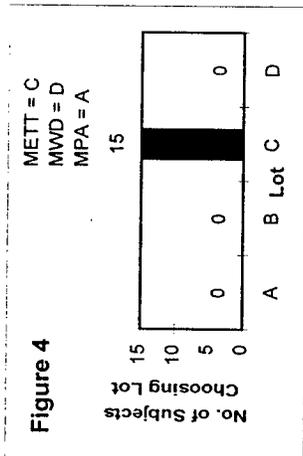
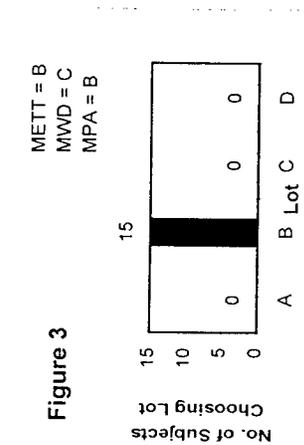
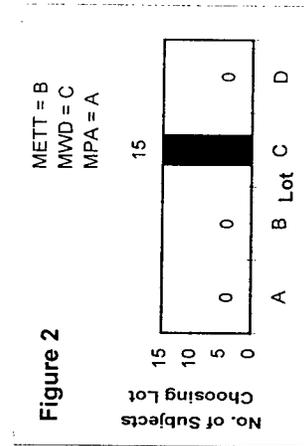
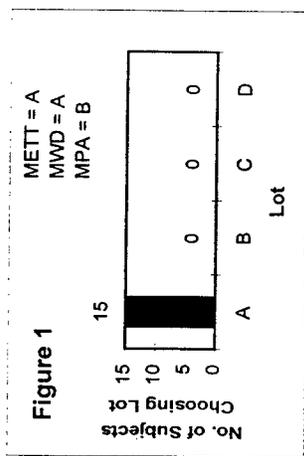
APPENDIX F
RAW DATA FOR EXPERIMENT 2

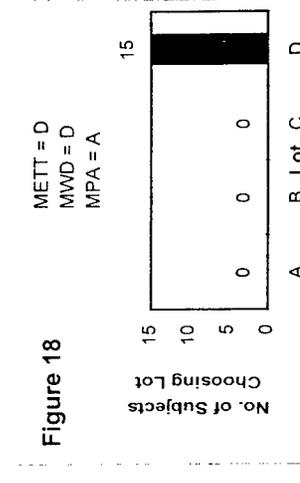
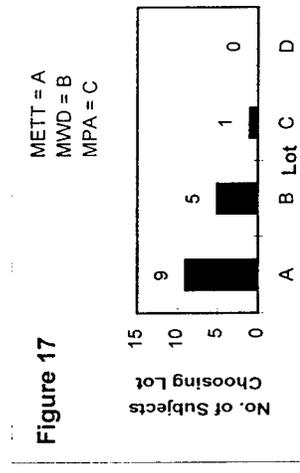
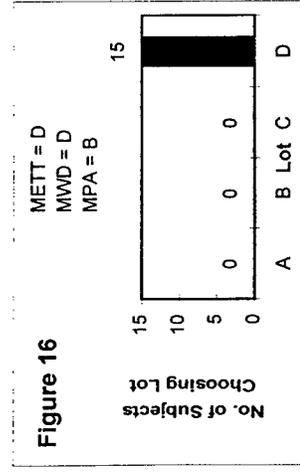
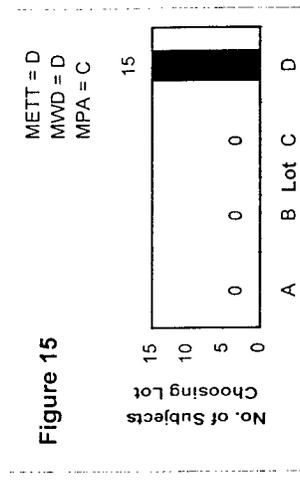
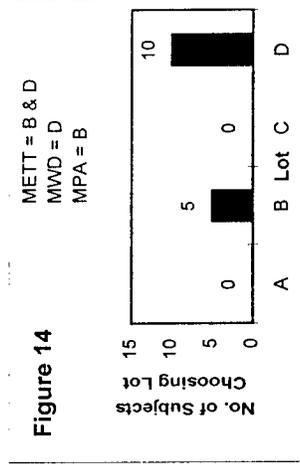
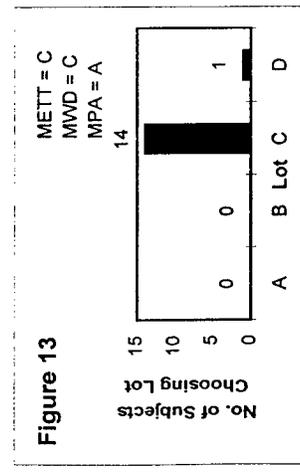
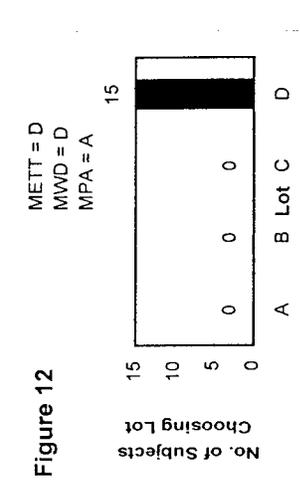
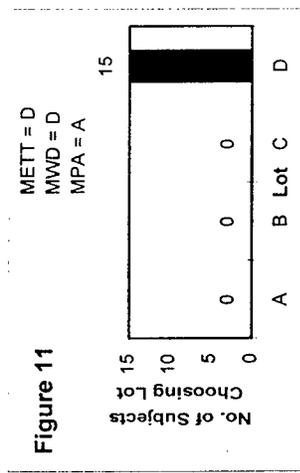
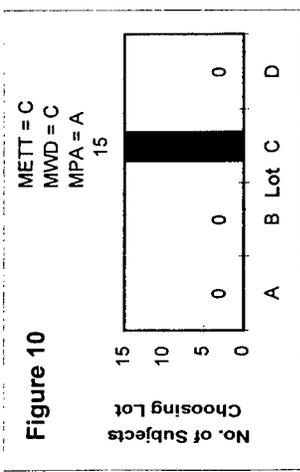
	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10	Subject 11	Subject 12	Subject 13	Subject 14	Subject 15	No. MWd	No. METT	No. MPA
Fig 1	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	15	15	0
Fig 2	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	15	0	0
Fig 3	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	0	15	15
Fig 4	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	0	15	0
Fig 5	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	15	0	0
Fig 6	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	15	15	0
Fig 7	C	B	B	B	B	B	B	B	B	B	C	C	C	C	3	15	0	
Fig 8	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	11	11	4
Fig 9	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	15	15	0
Fig 10	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	15	15	0
Fig 11	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	15	15	0
Fig 12	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	15	15	0
Fig 13	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	15	15	0
Fig 14	B	D	D	D	D	D	D	D	D	D	D	D	D	D	D	14	14	0
Fig 15	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	11	15	4
Fig 16	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	15	15	0
Fig 17	A	B	C	A	A	A	A	A	A	A	A	A	A	A	A	15	15	0
Fig 18	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	6	8	1
Fig 19	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	15	15	0
Fig 20	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	0	15	0
Fig 21	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	15	15	0
Fig 22	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	0	15	15
Fig 23	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	0	15	15
Fig 24	A	B	B	B	B	B	B	B	B	B	B	B	B	B	B	15	15	15
Fig 25	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	4	10	0
Fig 26	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	4	15	15
Fig 27	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	14	15	1
Fig 28	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	15	15	0
Fig 29	A	B	A	A	A	A	A	A	A	A	A	A	A	A	A	15	15	0
Fig 30	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	4	11	0
Fig 31	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	15	15	0
Fig 32	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	15	15	0
Fig 33	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	13	0	2
Fig 34	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	12	15	3
Fig 35	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	4	11	11
Fig 36	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	15	15	0
Fig 36	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	15	15	15

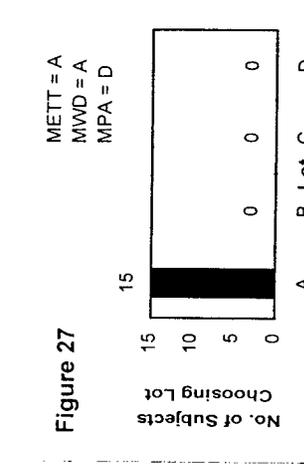
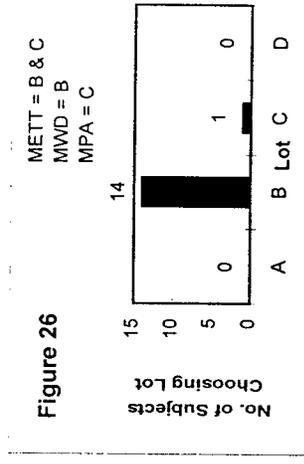
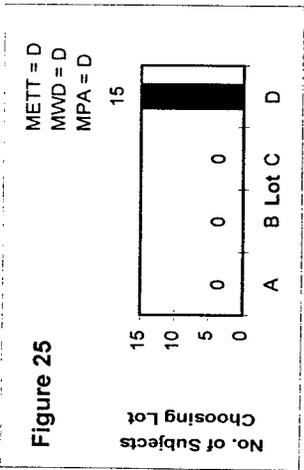
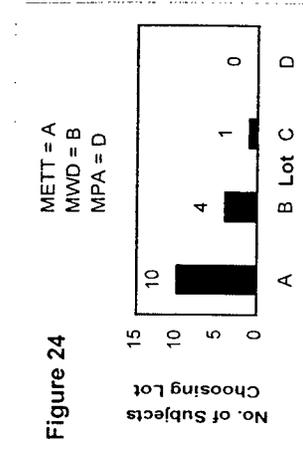
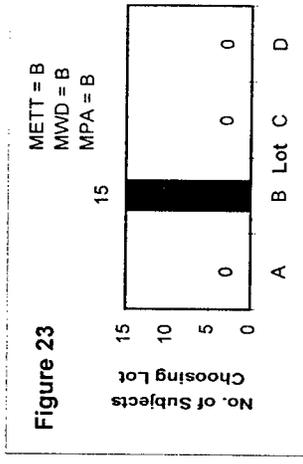
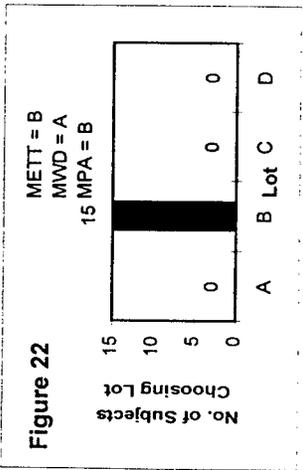
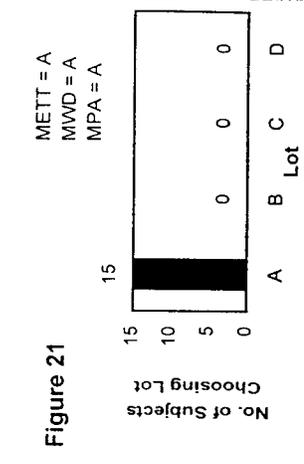
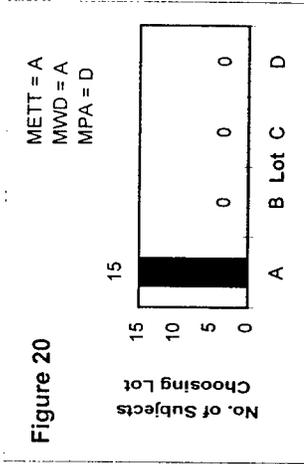
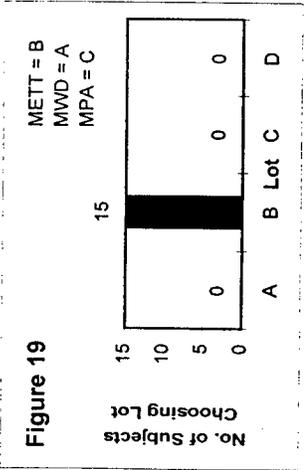
All Scenarios	# METT	# MWd	# MPA	# other	# METT	# MWd	# MPA	# other
	32	29	29	29	33	33	33	33
	25	32	32	32	28	28	28	28
	9	7	7	7	7	7	7	7
	0	0	0	0	0	0	0	0
	5	2	2	2	5	5	5	5
	2	5	5	5	2	2	2	2
	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0
	31	31	31	31	31	31	31	31
	26	26	26	26	26	26	26	26
	9	9	9	9	9	9	9	9
	1	1	1	1	1	1	1	1
	4	4	4	4	4	4	4	4
	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1
	423	470	470	470	423	423	423	423
	78.33%	87.04%	87.04%	87.04%	78.33%	78.33%	78.33%	78.33%
	24.26%	24.26%	24.26%	24.26%	24.26%	24.26%	24.26%	24.26%

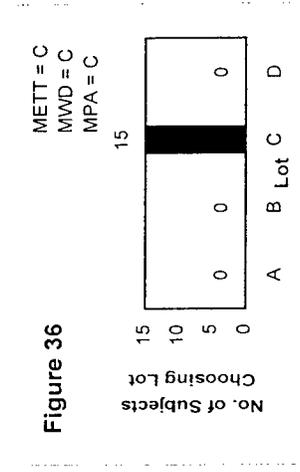
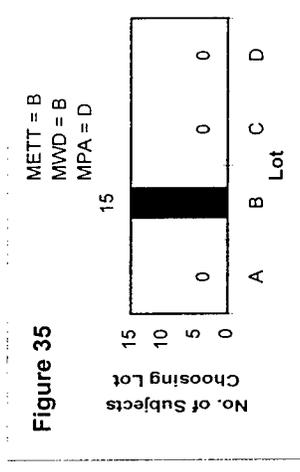
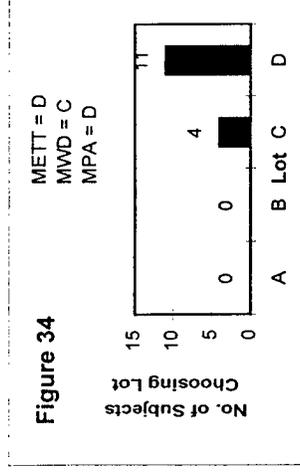
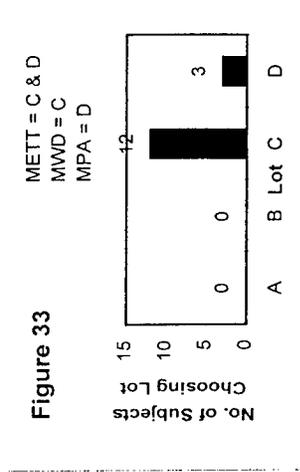
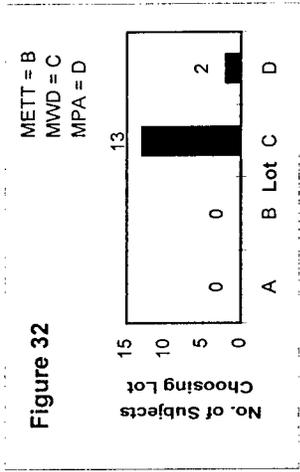
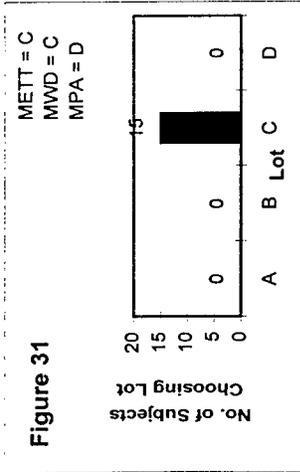
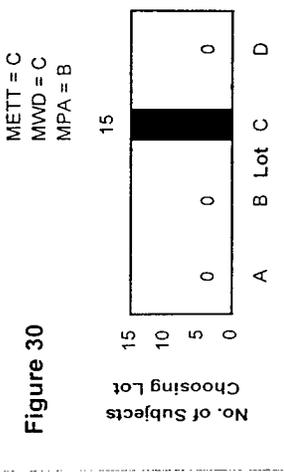
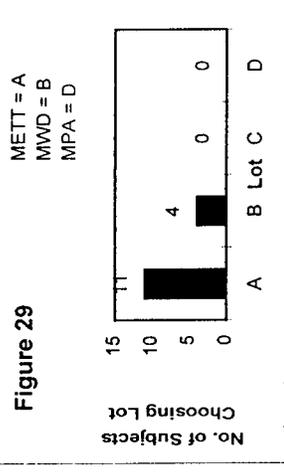
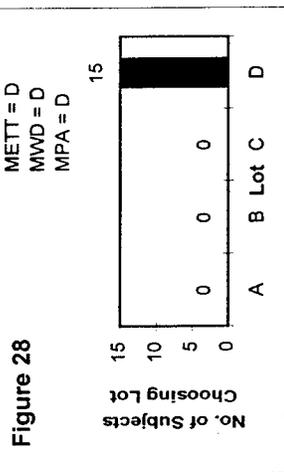
Jnlk Scenarios

APPENDIX G
BAR GRAPH SUMMARIES FOR EXPERIMENT 2









APPENDIX H
PARK PROGRAM

```

*****
C
C NAME:      PARK
C AUTHOR:    Amy Holton
C DATE:      2/1998
C
C DESCRIPTION:  Program PARK reads data concerning parking availability
C               in each of 4 lots (A-D) in a set of parking scenarios.  The program
C               then reads data concerning subjects' parking decisions in each of the
C               scenarios.  It is assumed that subjects make parking choices by
C               attempting to minimize their perceived total expected travel time.
C               It is further assumed that a subject's total expected travel time,
C               E(T), is given by,
C
C               E(T) = td + tw + Pfull(k,a,b)*tq
C
C               where td is the driving time, tw is the walking time, tq is the
C               queueing time if the lot is full upon arrival, and Pfull(k,a,b) is
C               the perceived probability that the lot will be full upon arrival.
C               Pfull is given by,
C
C               Pfull(k,a,b) =  $\frac{1}{2} \frac{1}{b} \frac{k-a}{k-a+b} - \frac{1}{2} \frac{1}{b} \frac{-(k-a)}{k-a+b}$ 
C
C               where k is the number of open spaces in the lot, and a and b are
C               adjustable parameters.
C
C               The PURPOSE of the program is to determine the set of parameters
C               {a,b} which best describes the subjects' choices, given the above
C               assumptions.  The program does this by stepping at user-defined
C               intervals through every possible {a,b} combination bounded by user-
C               defined maximum and minimum a and b values.  For each {a,b}
C               combination, the program computes using the above formulas the lot in
C               each scenario having the minimum E(T), and calculates the percentage
C               of subjects who chose minimum E(T) lots.
C
C INPUT:  Program PARK reads data from 3 input files, entitled
C         "filename_base.par", "filename_base.fig", and
C         "filename_base.pix".
C
C         The FILENAME_BASE.PAR file contains 3 rows of data, the first of
C         which contains two numbers and the 2nd and 3rd of which contain
C         three numbers each, with no punctuation:
C
C         Number of figures      Number of subjects
C         Minimum a              Maximum a              Step value for a
C         Minimum b              Maximum b              Step value for b
C

```

```

C   The FILENAME_BASE.FIG file contains 2 header lines (which are
C   ignored) followed by one row of numbers for each parking scenario.
C   The rows of numbers are arranged in 7 columns. The first 2 columns
C   contain code numbers which are ignored by the program. The next 4
C   columns contain the number of open spaces in lots A-D, respectively.
C   The last column contains a number between 1 and 4 identifying the
C   destination lot (A=1, B=2, C=3, D=4). The numbers are not separated
C   by any punctuation.
C
C   The FILENAME_BASE.PIX file contains 2 header lines (which are
C   ignored) followed by one row of numbers for each parking scenario.
C   The rows of numbers are arranged in s+2 columns, where s is the
C   number of subjects. The first 2 columns contain code numbers which
C   are ignored by the program. Each of the remaining s columns contains
C   a number between 1 and 4 indicating the lot chosen by a particular
C   subject in the given scenario (A=1, B=2, C=3, D=4). The numbers are
C   not separated by any punctuation.
C
C   OUTPUT: Program park writes 12 output files, entitled
C   "filename_base.tot", "filename_base.log", and "filename_base.abN",
C   where N ranges from 1 to 10.
C
C   The FILENAME_BASE.TOT file contains, for each scenario, the number of
C   subjects choosing each of lots A-D. An asterisk appears next to the
C   number in the column of the destination lot.
C
C   The FILENAME_BASE.LOG file contains, for each {a,b} combination
C   tested, the total percentage of subjects' choices consistent with
C   minimizing E(T). At the end of the file is a table of ten {a,b}
C   combinations with the highest % agreement.
C
C   Each of the FILENAME_BASE.ABN files contains, for each parking
C   scenario, the calculated expected travel times E(T) for each lot
C   A-D for the Nth best {a,b} combination. For example,
C   "filename_base.ab2" contains the calculated E(T)'s for the {a,b}
C   combination having the 2nd highest % agreement with subjects'
C   choices. For each parking scenario, an asterisk appears in the
C   column of the destination lot. For each scenario, the percentage of
C   subjects choosing the minimum E(T) lot appears in the last column.
C   A value of 999.99 for any E(T) indicates that the lot was CLOSED.
C *****

```

```

    program PARK

```

```

    implicit none

```

```

C   Constant Declarations

```

```

    integer k_fmax           ! Maximum number of figures
    parameter (k_fmax = 36)
    integer k_smax           ! Maximum number of subjects
    parameter (k_smax = 15)

```

```

C   Local Declarations

```

```

    integer n_open(k_fmax,5) ! Number of open spaces in each lot

```

```

integer choice(k_fmax,k_smax) ! -last column is MWD lot (1-4)
integer n_chosen(k_fmax,4) ! Lots chosen by subjects
real*8 ET_tab(k_fmax,5,10) ! Number of times each lot was chosen
real*8 temp_tab(k_fmax,5) ! Output tables for 10 sets {a,b}
! Temporary table containing all E(T)'s
! for a given set {a,b}
real*8 ab_tab(10,3) ! 10 best a, b, total % agreements
integer n_figs ! Number of figures
integer n_subj ! Number of subjects
integer num1, num2 ! Ignored integers in 1st 2 columns of
! input files
real*8 a_min ! Minimum value of alpha parameter
real*8 a_max ! Maximum value of alpha parameter
real*8 a_step ! Step value for alpha parameter
real*8 a ! Current value of alpha
real*8 b_min ! Minimum value of beta parameter
real*8 b_max ! Maximum value of beta parameter
real*8 b_step ! Step value for beta parameter
real*8 b ! Current value of beta
real*8 E_T_min ! Current minimum expected travel time
! for a scenario
integer n_hits ! Number of subjects choosing current METT
integer tot_hits ! Total no. choosing METT for a given
{a,b}
real*8 per_hits ! Total % choosing METT for a given {a,b}
integer i, j, m, n ! Counter variables
character*1 MWD_tic(k_fmax,5) ! Tic asterisk for destination lot
character*30 basename ! Base file name
character*40 filename ! File name

```

C Function Declarations

```

real*8 E_T ! E(T) function

```

C Main Program

```

C
C Get base file name from user and convert to expected file names.
C

```

```

write (*,*)
write (*,*) 'Enter filename base (\'?\' for help):'
read (*,'(a30)') basename
write (*,*)

if ((basename.EQ."?").OR.(basename.EQ."help")) then
    call Help
    goto 350
endif

```

```

C
C Open all of the files.
C

```

```

write (*,*) 'Reading input files...'

filename = basename(:index(basename,' ') - 1) // '.par'
open (unit=1, file=filename, status='old', err=10)

```

```

filename = basename(:index(basename,' ') - 1) // '.fig'
open (unit=2, file=filename, status='old', err=10)

filename = basename(:index(basename,' ') - 1) // '.pix'
open (unit=3, file=filename, status='old', err=10)

filename = basename(:index(basename,' ') - 1) // '.tot'
open (unit=4, file=filename, status='unknown', err=10)

filename = basename(:index(basename,' ') - 1) // '.ab1'
open (unit=7, file=filename, status='unknown', err=10)

filename = basename(:index(basename,' ') - 1) // '.ab2'
open (unit=8, file=filename, status='unknown', err=10)

filename = basename(:index(basename,' ') - 1) // '.ab3'
open (unit=9, file=filename, status='unknown', err=10)

filename = basename(:index(basename,' ') - 1) // '.ab4'
open (unit=10, file=filename, status='unknown', err=10)

filename = basename(:index(basename,' ') - 1) // '.ab5'
open (unit=11, file=filename, status='unknown', err=10)

filename = basename(:index(basename,' ') - 1) // '.ab6'
open (unit=12, file=filename, status='unknown', err=10)

filename = basename(:index(basename,' ') - 1) // '.ab7'
open (unit=13, file=filename, status='unknown', err=10)

filename = basename(:index(basename,' ') - 1) // '.ab8'
open (unit=14, file=filename, status='unknown', err=10)

filename = basename(:index(basename,' ') - 1) // '.ab9'
open (unit=15, file=filename, status='unknown', err=10)

filename = basename(:index(basename,' ') - 1) // '.ab10'
open (unit=16, file=filename, status='unknown', err=10)

filename = basename(:index(basename,' ') - 1) // '.log'
open (unit=17, file=filename, status='unknown', err=10)

goto 20

```

```

C
C Write error message if an error occurs while opening a file.
C
10 write (*,*) 'ERROR: Error opening file ' // filename
   write (*,*)
   goto 350
20 continue

C
C Read fitting parameters from "filename_base.par" file (file 1).
C
   read (1,*,end=30,err=30) n_figs, n_subj
   read (1,*,end=30,err=30) a_min, a_max, a_step

```

```

        read (1,*,end=30,err=30) b_min, b_max, b_step

C
C Read scenario information from "filename_base.fig" file (file 2).
C Read experimental data from "filename_base.pix" file (file 3).
C
    do i=1,2          ! Read 2 header lines at beginning of each file
        read (2,*,end=32,err=32)
        read (3,*,end=34,err=34)
    enddo
    do i=1,n_figs
        read (2,*,end=32,err=32) num1, num2, (n_open(i,j), j=1,5)
        read (3,*,end=34,err=34) num1, num2, (choice(i,j), j=1,n_subj)
    enddo
    write (*,*) 'Done.'
    write (*,*)
    goto 60

C
C Write error message if an error occurs while reading an input file.
C
30  filename = basename(:index(basename,' ') - 1) // '.par'
    goto 50
32  filename = basename(:index(basename,' ') - 1) // '.fig'
    goto 50
34  filename = basename(:index(basename,' ') - 1) // '.pix'
50  write (*,*) 'ERROR: Error reading file ' // filename
    write (*,*)
    goto 350
60  continue

C
C Perform the calculations...
C
    write (*,*) 'Performing calculations...'

C
C Initialize 5th column of MWD_tic table to all blanks.
C
    do i=1,n_figs
        MWD_tic(i,5) = ' '
    enddo

C
C Compute number of subjects who chose each lot in each scenario.
C Store totals in a table called n_chosen.
C
C Do the following loop once for each lot in every figure:
    do i=1,n_figs
        do j=1,4
C n_chosen(i,j) is the number of times lot j in figure i was chosen by
C subjects. Initially, set it to zero.
            n_chosen(i,j) = 0
C If the current lot is the destination lot, then assign a tic mark
C to it. Otherwise, assign a blank.
            if (j.EQ.n_open(i,5)) then
                MWD_tic(i,j) = '*'
            end if
        end do
    end do

```

```

        else
            MWD_tic(i,j) = ' '
        endif
C Do the following loop once for each subject:
        do m=1,n_subj
C If the subject chose lot j in figure i, add one to the number of
C times lot j in figure i was chosen.
            if (choice(i,m).EQ.j) n_chosen(i,j) = n_chosen(i,j) + 1
        enddo
        enddo
        enddo

        write (17,*) 'Alpha      Beta      % Agreement'
        write (17,*) '-----      ----      -----'

C
C START MAIN LOOP.
C
C Start a and b at their minimum values (a_min and b_min).
        a = a_min
        write (*,*) 'Alpha = ',a
        b = b_min

C Create a table (ab_tab) which will contain the 10 best {a,b} combinations,
C each with its % agreement.  Initially, fill the table with zeros.
        do i=1,10
            do j=1,3
                ab_tab(i,j) = 0.0
            enddo
        enddo

C The variable "tot_hits" will contain the total number of subject
C decisions consistent for METT for the current {a,b} set.  Initially,
C set it to zero.

80    tot_hits = 0

C Do the following loop once for each figure:

        do i=1,n_figs

C In a temporary table (temp_tab), store in the 1st column of the ith
C row (where i is the figure #) the E(T) for lot 1 (A).  E(T) is computed by
C passing to function E_T the lot we're interested in (1), the destination
C lot for figure i, the number of open spaces in lot A for figure i, and the
C current values of alpha and beta.

            temp_tab(i,1) = E_T(1,n_open(i,5),n_open(i,1),a,b)

C In a variable E_T_min, store the E(T) for figure i, lot A.  So far, this
C is the minimum E(T) for figure i.

            E_T_min = temp_tab(i,1)

C In a variable n_hits, store the number of subjects choosing lot A for
C figure i.

```

```

        n_hits = n_chosen(i,1)
C Do the following loop once for each of lots B-D (2-4):
        do j=2,4
C Store in the jth column of the ith row of the temporary table (temp_tab)
C the calculated E(T) for figure i, lot j.
                temp_tab(i,j) = E_T(j,n_open(i,5),n_open(i,j),a,b)
C Is this E(T) less than the current minimum E(T) for figure i? If so,
C replace the value in E_T_min with this (lower) value. Also, store in
C n_hits the number of subjects choosing this lot for figure i. But what
C if this E(T) is EQUAL to the current minimum E(T)? Then, add to the
C current value of n_hits the number of subjects choosing this lot. If
C this E(T) is greater than the current E_T_min, do nothing.
                if (temp_tab(i,j).LT.E_T_min) then
                        n_hits = n_chosen(i,j)
                        E_T_min = temp_tab(i,j)
                else if (temp_tab(i,j).EQ.E_T_min) then
                        n_hits = n_hits + n_chosen(i,j)
                endif
        enddo
C After computing the E(T) for each lot in figure i, determining the lot(s)
C with the lowest E(T), and calculating the number of subjects choosing the
C minimum E(T) lot(s), store in the 5th column of the temporary table the
C % agreement for figure i for the current {a,b} combination.
                temp_tab(i,5) = 100.0 * float(n_hits) / float(n_subj)
C Add the total number of hits for figure i to the total number of hits
C for all figures.
                tot_hits = tot_hits + n_hits
        enddo
C After computing the number of hits for each of the figures using the
C current {a,b} combination, compute the total % agreement for all
C figures combined. Write the results for this {a,b} set to the
C "filename_base.log" file (file 17).
                per_hits = 100.0 * float(tot_hits) / float(n_figs * n_subj)
                write (17,90) a, b, per_hits
90    format (f6.2,2x,f6.3,6x,f6.2)
C If the % agreement for the current {a,b} combination (per_hits) is
C among the top ten percentage agreements so far, the current a, b, and
C percentage agreement are stored in a table of the top ten {a,b} sets
C (ab_tab).
C In addition, the current temporary table of E(T) values (temp_tab) is
C stored in a stack of ten such tables (ET_tab) corresponding to the best {a,b}
C combinations. We need to compare per_hits to all of the % agreements
C currently in the ab_tab table.

```

```

C Do the following loop once for each {a,b} set currently in the ab_tab
C table:

    do i=1,10

C Is per_hits greater than or equal to the % agreement of the ith {a,b}
C set currently in the ab_tab table? If so, shift all of the {a,b}
C combinations in the ab_tab table down one row and put the current {a,b}
C combination above them. This keeps the table in order from best to
C worst {a,b} set.

        if (per_hits.GE.ab_tab(i,3)) then
C Shift worse {a,b} sets down to make a space for the new one...
            do j=10,i+1,-1
                do m=1,3
                    ab_tab(j,m) = ab_tab(j-1,m)
                enddo
            enddo
C Put the new a, b, and % agreement in the newly opened row of the table...
            ab_tab(i,1) = a
            ab_tab(i,2) = b
            ab_tab(i,3) = per_hits

C If we have inserted a new {a,b} set in the ab_tab table, then we also
C insert the temporary table of E(T) values (temp_tab) in the corresponding
C position in the stack of "top ten" E(T) tables (ET_tab). All E(T)
C tables corresponding to worse {a,b} sets must similarly be shifted down
C top keep the stack in order from best {a,b} set to worst {a,b} set.

C Shift E(T) tables corresponding to worse {a,b} sets down...
            do j=10,i+1,-1
                do m=1,n_figs
                    do n=1,5
                        ET_tab(m,n,j) = ET_tab(m,n,j-1)
                    enddo
                enddo
            enddo
C Insert the new E(T) table in the newly opened space in the stack...
            do j=1,n_figs
                do m=1,5
                    ET_tab(j,m,i) = temp_tab(j,m)
                enddo
            enddo

C If we have just inserted the current {a,b} into the "top ten" table,
C then we don't need to continue comparing it to {a,b}'s in the table, so
C we can go to line 100 and escape the loop. Otherwise, we need to
C continue checking the current per_hits against all 10 % agreement values
C in the top ten table.

            goto 100
        endif
    enddo
100 continue

C Advance to the next {a,b} combination by stepping beta up a step. If beta

```

C is at its maximum, then reset it to its minimum and step alpha up a step.
 C If both alpha and beta are at their maximum values, then we're done!

```

    if (b.LT.b_max) then
      b = b + b_step
      goto 80
    else
      if (a.LT.a_max) then
        a = a + a_step
        write (*,*) 'Alpha = ',a
        b = b_min
        goto 80
      endif
    endif
  endif
  write (*,*) 'Done.'
  write (*,*)

```

C
 C Write the ten best {a,b}, along with % total hits
 C Write this table on the screen, and also at the end of the
 C "filename_base.log" file (file #17)
 C

```

    write (17,*)
    write (*,*) 'The ten best {alpha,beta} combinations:'
    write (17,*) 'The ten best {alpha,beta} combinations:'
    write (*,*)
    write (17,*)
    write (*,*) '  Alpha      Beta      % Agreement'
    write (*,*) '  -----  -----  -----'
    write (17,*) '  Alpha      Beta      % Agreement'
    write (17,*) '  -----  -----  -----'
    do i=1,10
      write (*,120) (ab_tab(i,j), j=1,3)
      write (17,120) (ab_tab(i,j), j=1,3)
120     format (2x,f7.4,2x,f7.4,5x,f6.2,'%')
    enddo
    write (*,*)

```

C
 C Write file "filename_base.tot" containing table of lot choice
 C totals by figure. Place asterisks next to totals for MWD lots.
 C

```

    write (4,*) '                No. of Subjects Choosing Lot'
    write (4,*) 'Scenario          A      B      C      D'
    write (4,*) '-----          -      -      -      -'
    do i=1,n_figs
      write (4,200) i, (n_chosen(i,j),MWD_tic(i,j), j=1,4)
200     format(2x,i4,9x,i4,a1,3(2x,i4,a1))
    enddo

```

C
 C Write 10 files containing E(T) and % hits for best 10 {a,b} sets.
 C

```

  do i=1,10
    j = i + 6
    write (j,*) 'Alpha = ',ab_tab(i,1)
    write (j,*) 'Beta = ',ab_tab(i,2)

```

```

        write (j,*)
        write (j,*) 'Scenario          A          B          C          D',
&      '          % METT'
&      write (j,*) '-----          -----          -----          -----',
&      '          -----'
        do m=1,n_figs
            write (j,250) m, (ET_tab(m,n,i),MWD_tic(m,n), n=1,5)
250          format(2x,i4,7x,f6.2,a1,3(2x,f6.2,a1),4x,f6.2,'% ',a1)
            enddo
            write (j,*)
            write (j,260) ab_tab(i,3)
260          format (3lx,'TOTAL % AGREEMENT = ',f6.2,'%')
        enddo

```

```

C
C Close all files and end program.
C

```

```

        close (unit=1, status='keep')
        close (unit=2, status='keep')
        close (unit=3, status='keep')
        close (unit=4, status='keep')
        close (unit=7, status='keep')
        close (unit=8, status='keep')
        close (unit=9, status='keep')
        close (unit=10, status='keep')
        close (unit=11, status='keep')
        close (unit=12, status='keep')
        close (unit=13, status='keep')
        close (unit=14, status='keep')
        close (unit=15, status='keep')
        close (unit=16, status='keep')
        close (unit=17, status='keep')

```

```

350 end

```

```

C *****
C
C FUNCTION E_T
C
C PURPOSE: Compute the expected travel time E(T) using the equation,
C
C           $E(T) = t_d + t_w + P_{full} * t_q$ 
C
C The following values are passed to function E_T from the main
C program:
C
C          c_lot      - the lot for which we are computing E(T)
C          d_lot      - the destination lot
C          k          - the number of open spaces in the lot for which we
C                    are computing E(T)
C          a          - the alpha parameter
C          b          - the beta parameter
C
C Given these values, t_d and t_w are calculated as follows:
C
C           $t_d = 1 + c\_lot$ 
C           $t_w = 3 + 3 * |d\_lot - c\_lot|$ 
C

```

```

C
C The function returns the expected travel time E(T) to the main
C program.
C
C NOTE: If k=0, indicating that the lot is closed, the E(T) is
C arbitrarily assigned a high value of 999.99.
C
C *****
C real*8 function E_T(c_lot,d_lot,k,a,b)
C implicit none
C
C Constant Declarations
C
C real*8 t_q ! Queueing time
C parameter (t_q = 5.0)
C
C Local Declarations
C
C integer c_lot ! Chosen lot
C integer d_lot ! Destination lot
C integer k ! No. of open spaces
C real*8 t_d ! Driving time
C real*8 t_w ! Walking time
C real*8 a ! Alpha parameter
C real*8 b ! Beta parameter
C
C Function Declarations
C
C real*8 P_full ! Probability function
C
C Code
C
C Compute t_d and t_w.
C t_d = 1.0 + float(c_lot)
C t_w = 3.0 + 3.0*abs(float(d_lot - c_lot))
C If the lot isn't closed, compute E(T). If it is closed (k=0),
C assign E(T) an arbitrary large value of 999.99.
C if (k.GT.0) then
C E_T = t_d + t_w + P_full(k,a,b)*t_q
C else
C E_T = 999.99
C endif
C
C Return the value of E(T) (or "E_T") to the main program.
C return
C end
C *****
C
C FUNCTION P_full
C
C PURPOSE: Compute the perceived probability that a lot will be full
C upon arrival using the ogival power probability function.
C
C The following values are passed to function P_full from function E_T:
C
C k_i - number of open spaces in the lot

```

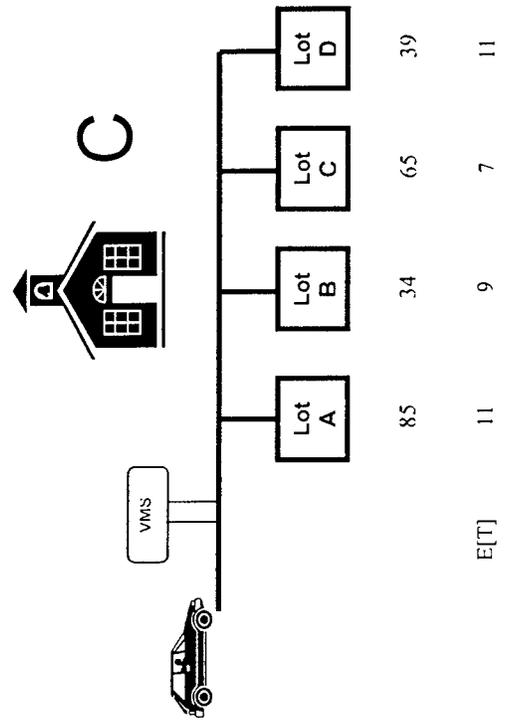
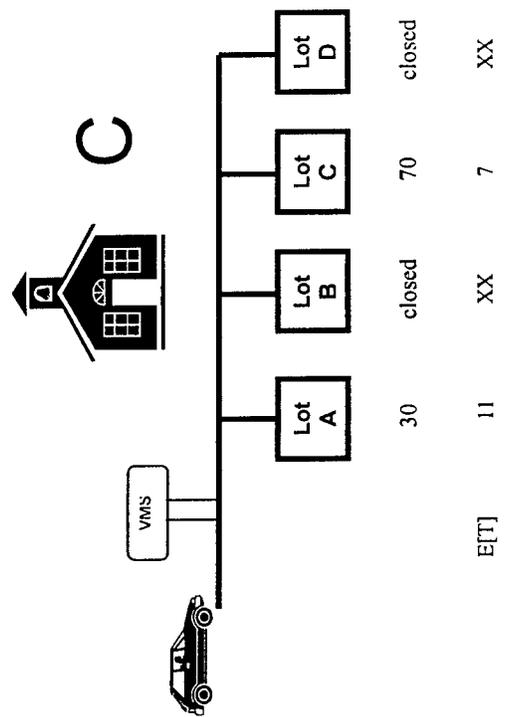
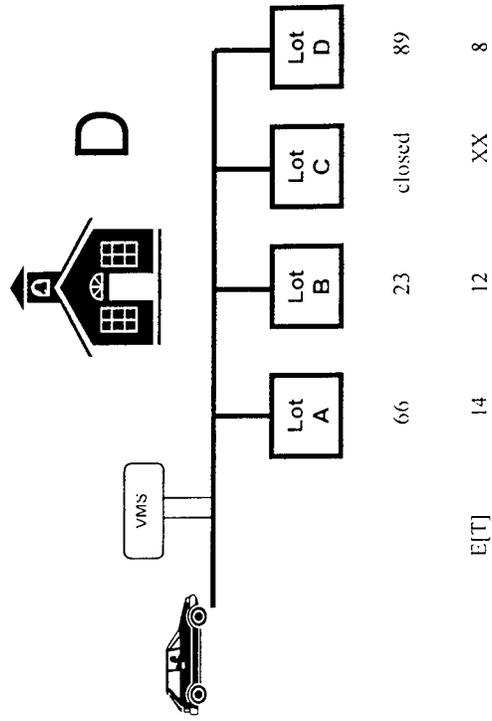
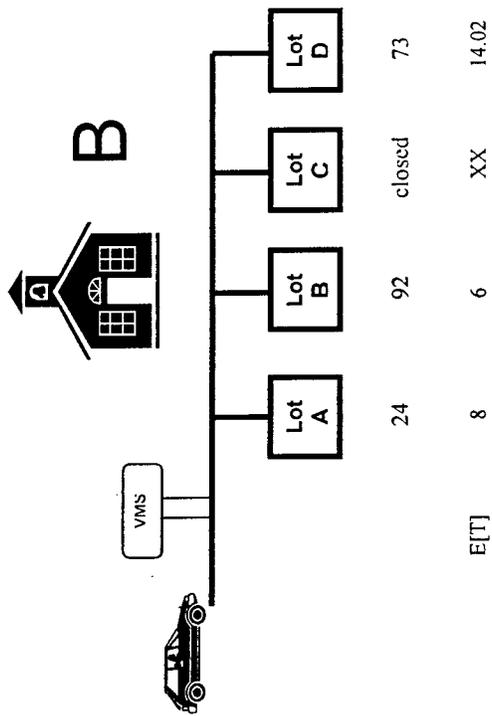
```

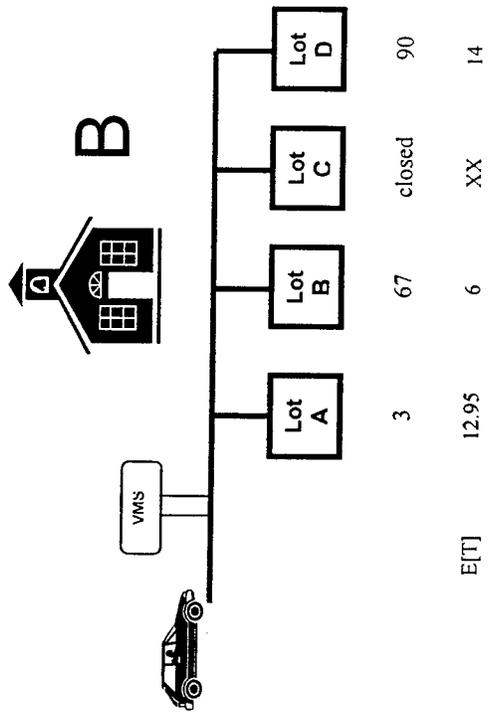
C          a          - alpha parameter          *
C          b          - beta parameter          *
C
C The function P_full returns to function E_T the perceived probability, *
C P_full, that the lot will be full upon arrival. *
C
C *****
C          real*8 function P_full(k_i,a,b)
C          implicit none
C
C Local Declarations
C
C          integer k_i          ! No. of open spaces in lot
C          real*8 k          ! Real value of k_i
C          real*8 a          ! Alpha parameter
C          real*8 b          ! Beta parameter
C
C Code
C
C Convert the integer number of spaces in the lot (k_i) to a real
C number (k) for the purpose of the calculation to follow.
C          k = float(k_i)
C
C          P_full = 0.5 - 0.5*((b**(k-a) - b**(-(k-a))) /
C          & (b**(k-a) + b**(-(k-a))))
C
C Return the value of P_full to function E_T.
C          return
C          end
C *****
C
C SUBROUTINE Help          *
C
C PURPOSE: Write some useful information on the screen for the user. *
C
C *****
C          subroutine Help
C
C          write (*,*) 'Help...'
C          write (*,*)
C          write (*,*) 'This program determines the values of the alpha and'
C          write (*,*) 'beta parameters in the ogival probability function,'
C          write (*,*) 'such that the expected travel times computed'
C          write (*,*) 'result in maximal agreement with an experimental'
C          write (*,*) 'data set, under the assumption that subjects make'
C          write (*,*) 'parking decisions so as to minimize their total'
C          write (*,*) 'expected travel time.'
C          write (*,*)
C          write (*,*) 'Expected file names are:'
C          write (*,*) ' filename_base.par - fitting parameters (INPUT)'
C          write (*,*) ' filename_base.fig - # open spaces in lots, ',
C          & 'destination lots (INPUT)'
C          write (*,*) ' filename_base.pix - lots chosen by subjects ',
C          & '(INPUT)'
C          write (*,*) ' filename_base.tot - lot choice totals (OUTPUT)'
C          write (*,*) ' filename_base.abN - table of E(T) for the Nth ',

```

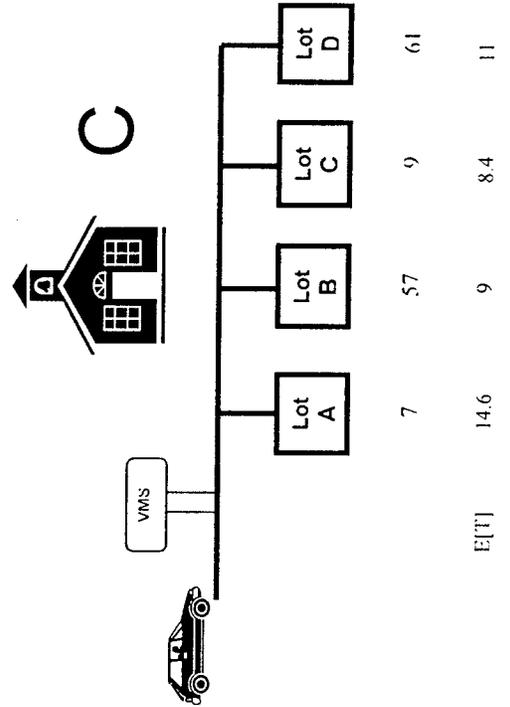
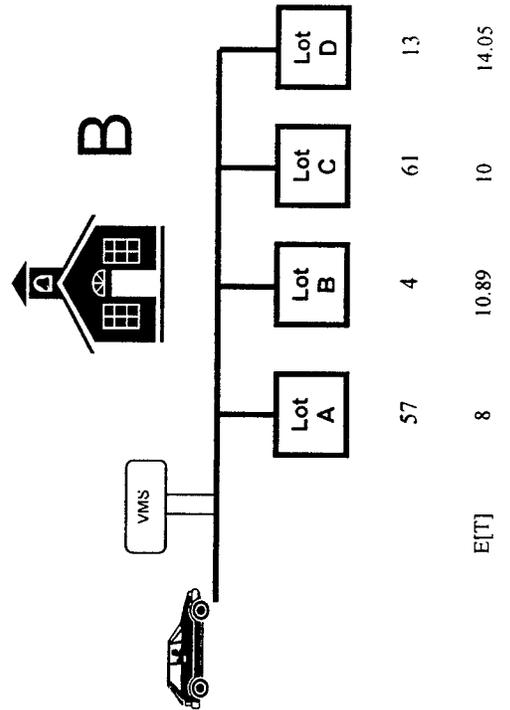
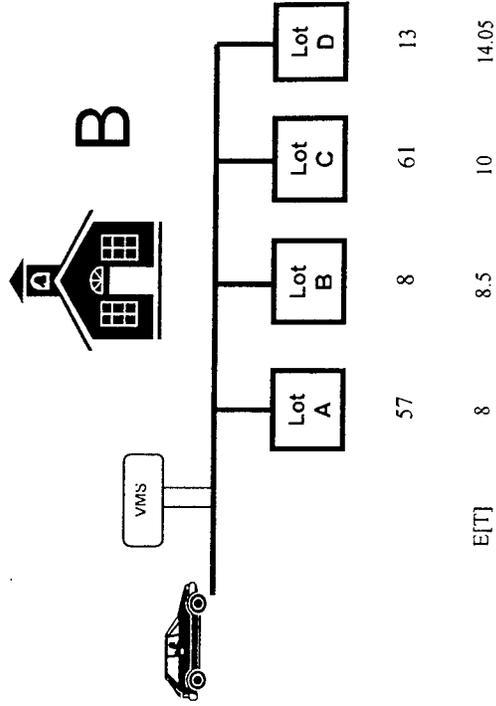
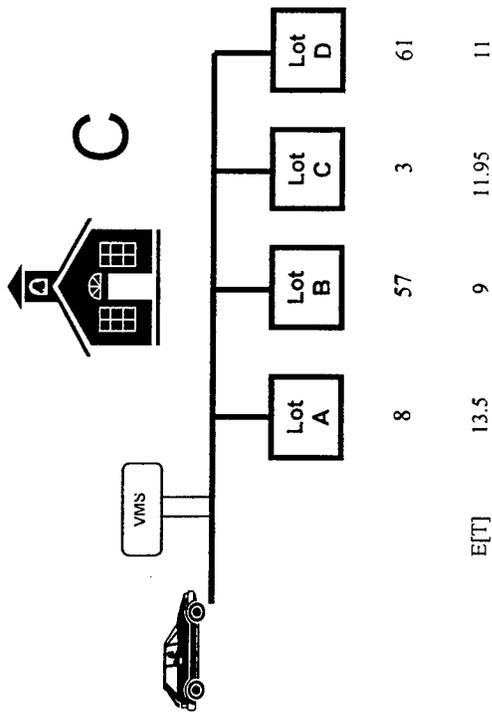
```
& 'best {a,b} (OUTPUT)'  
write (*,*) ' filename_base.log - % agreement for all {a,b} ',  
& 'combinations (OUTPUT)'  
write (*,*)  
  
return  
end
```

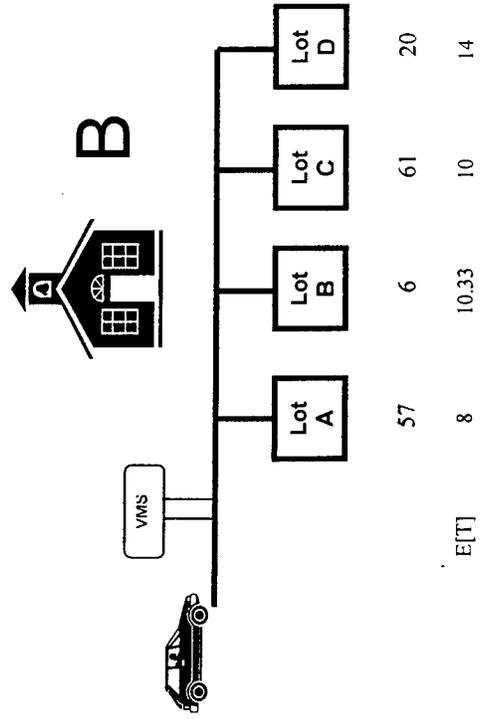
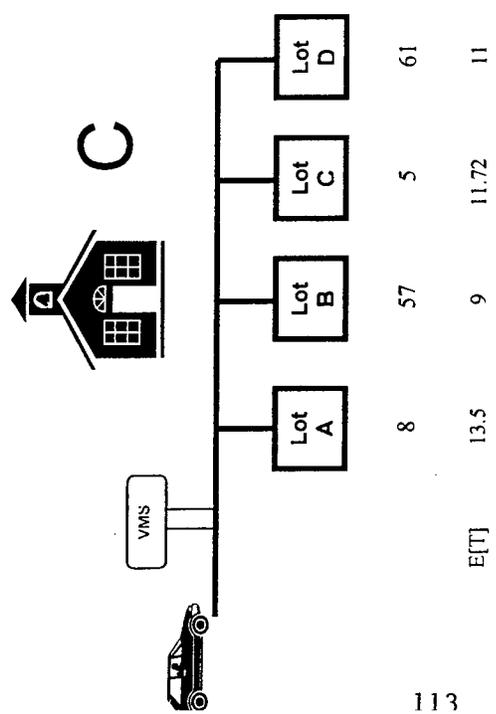
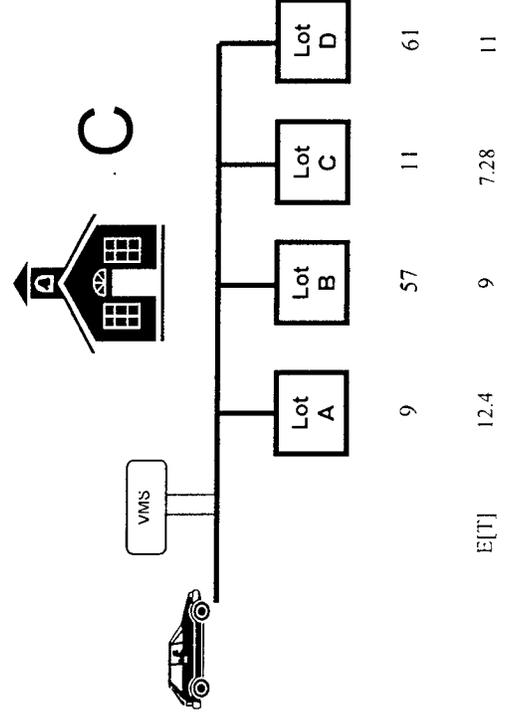
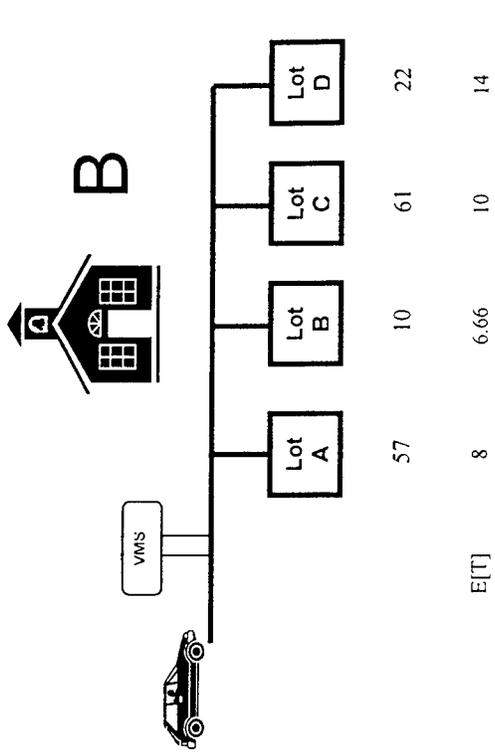
APPENDIX I
NAÏVE SCENARIOS FOR EXPERIMENT 3

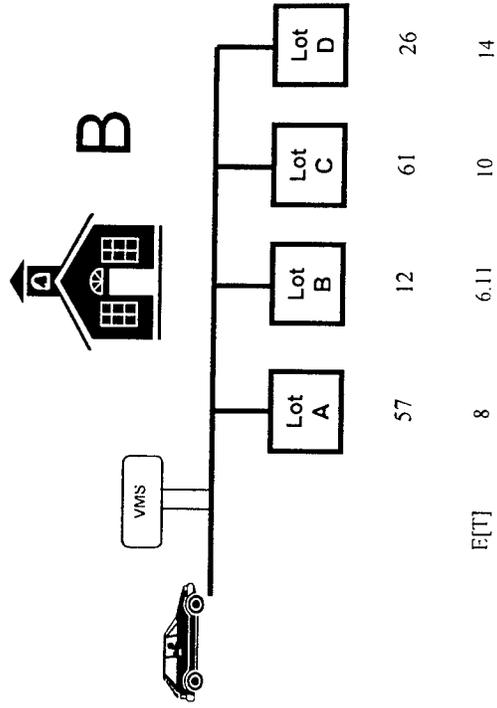
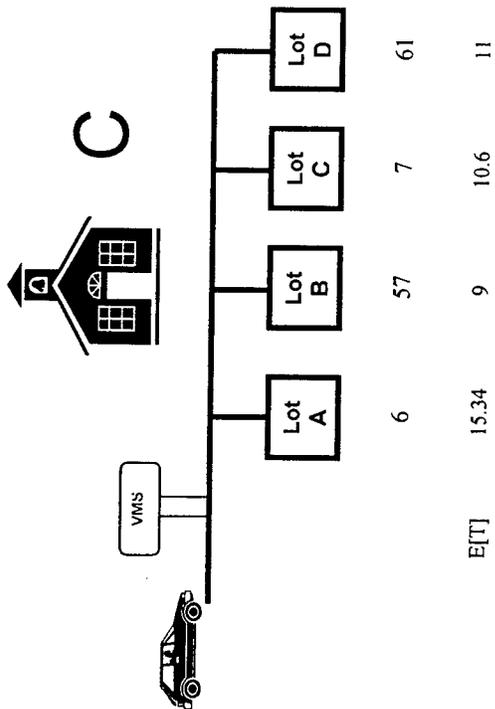




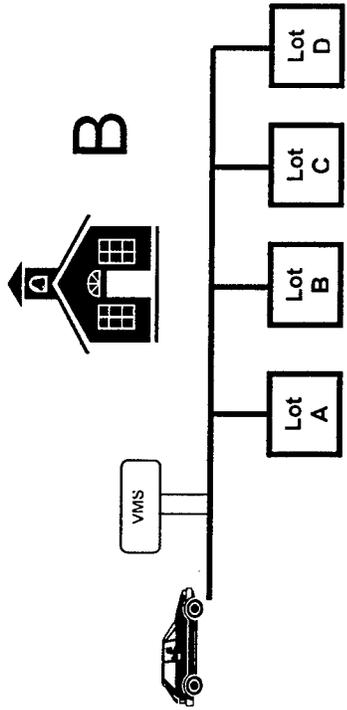
APPENDIX J
CRITERION SCENARIOS (CS) FOR EXPERIMENT 3



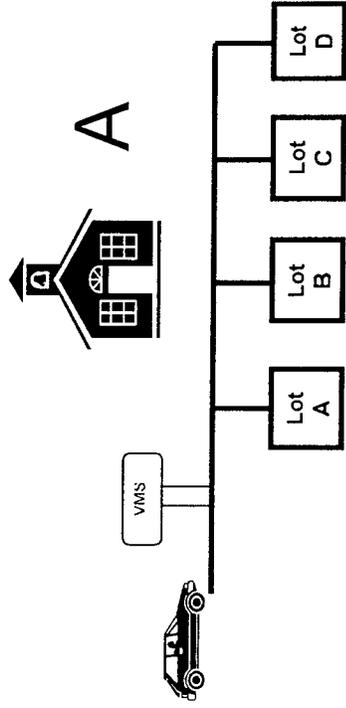




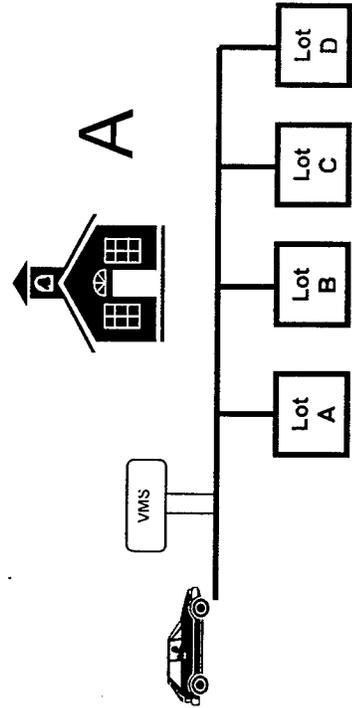
APPENDIX K
LVM SCENARIOS FOR EXPERIMENT 3



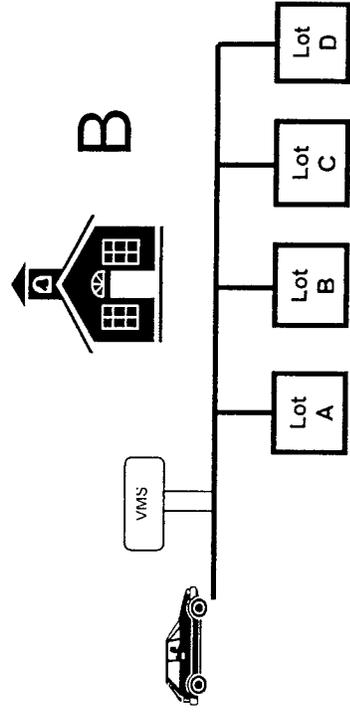
closed 2 closed 50
E[T] XX 10.98 XX 14



2 closed 15 25
E[T] 9.98 XX 13.01 17

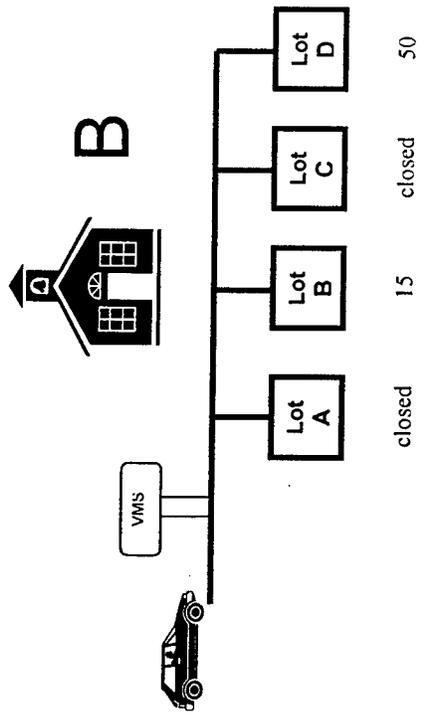


1 closed 64 10
E[T] 9.99 XX 13 17.66

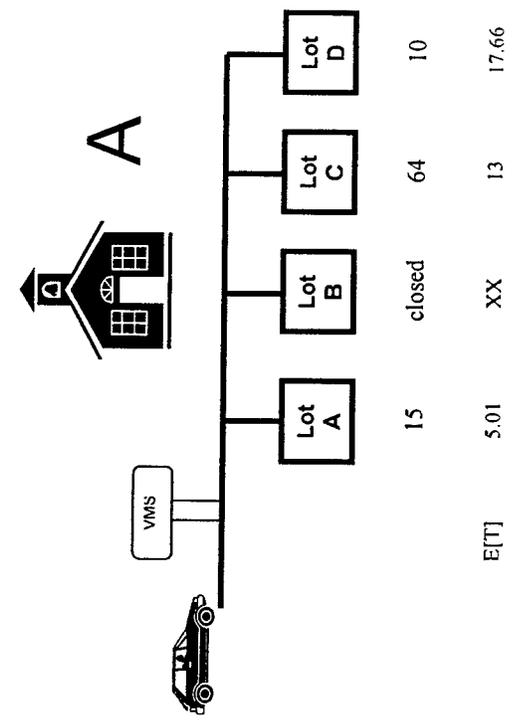


closed 1 closed 72
E[T] XX 10.99 XX 14

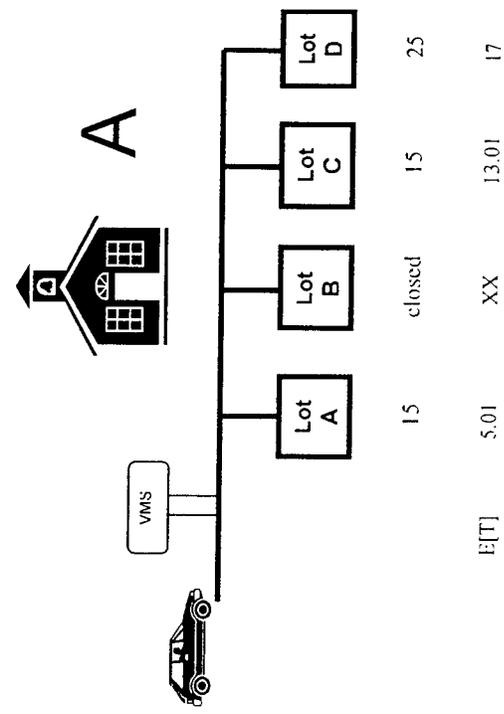
APPENDIX L
COUNTERBALANCING (CB) SCENARIOS FOR EXPERIMENT 3



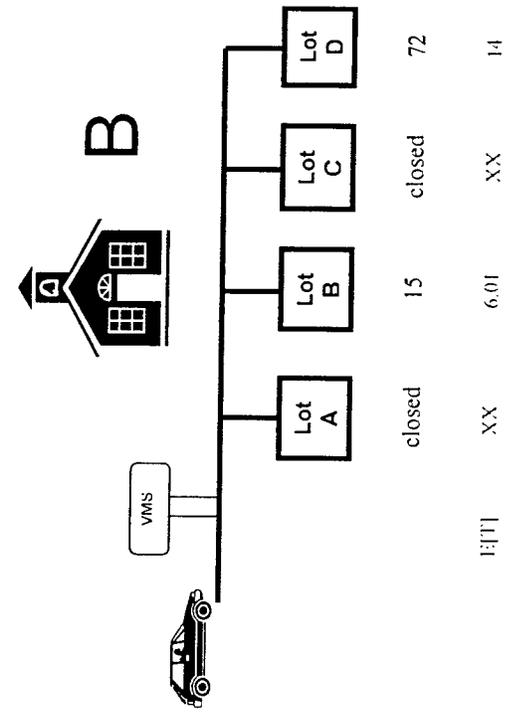
E[T] XX 6.01 XX 14



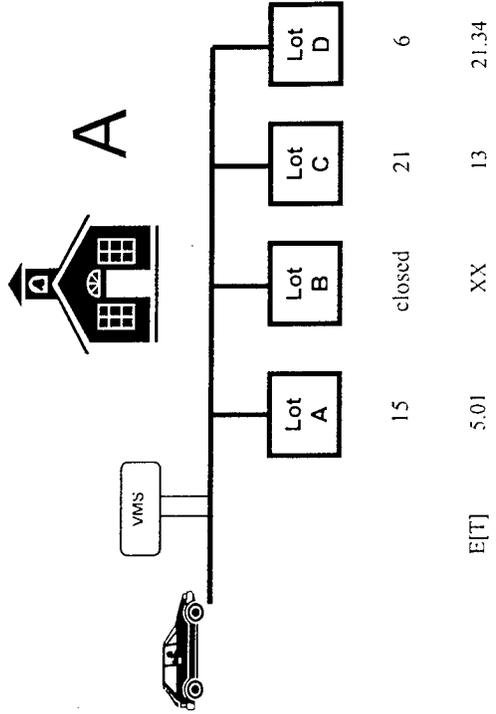
E[T] 5.01 XX 13 17.66



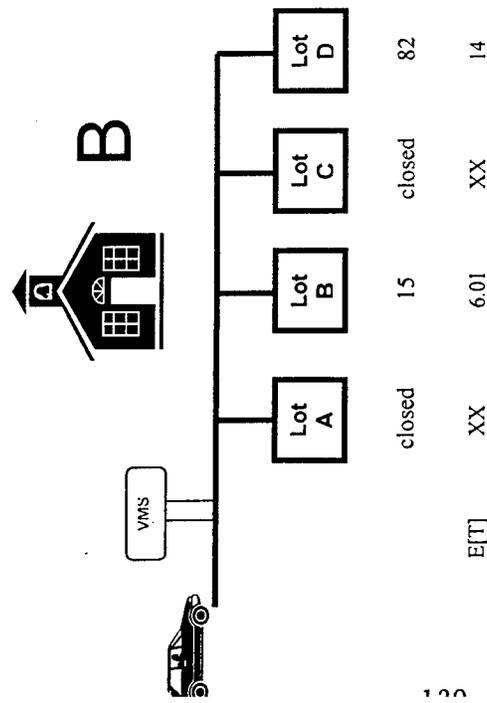
E[T] 5.01 XX 13.01 17



E[T] XX 6.01 XX 14

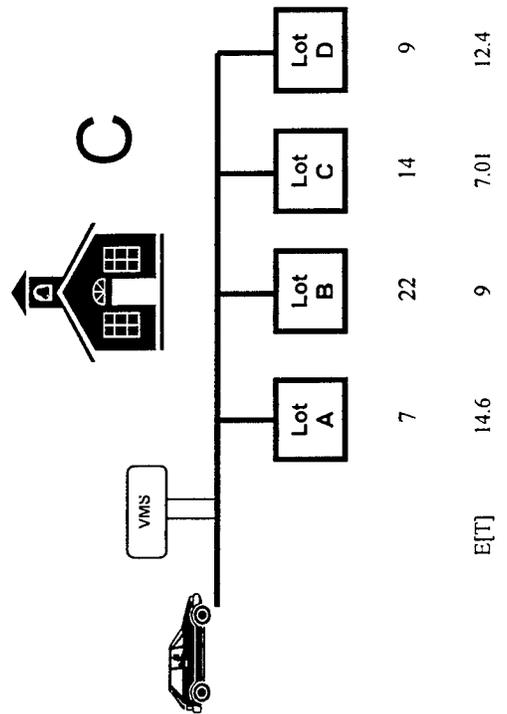
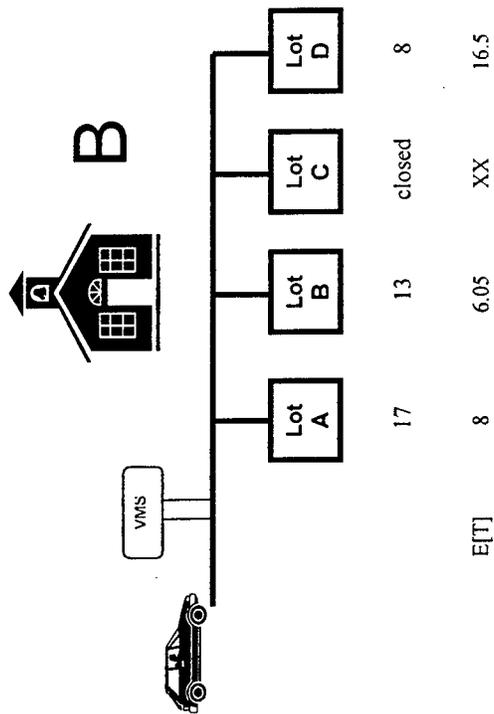
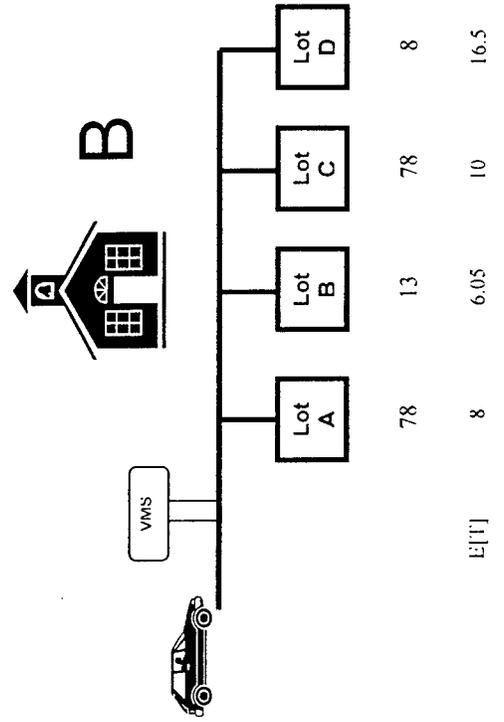
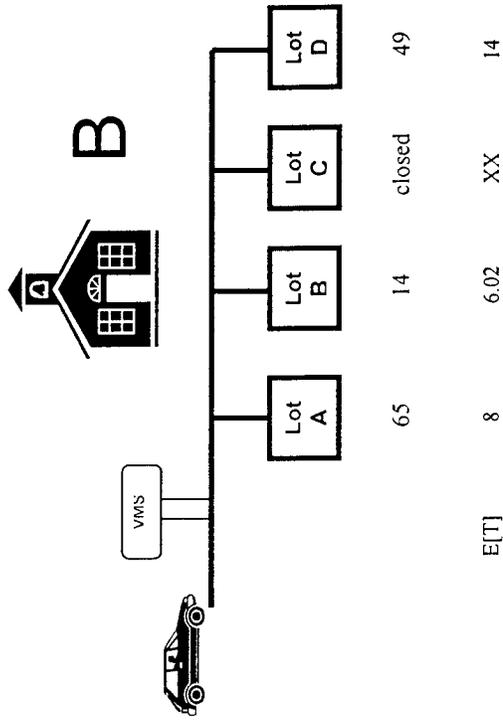


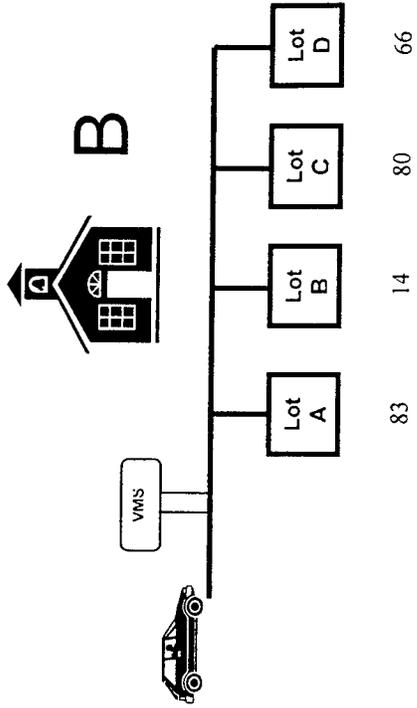
15 closed 21 6
 E[T] 5.01 XX 13 21.34



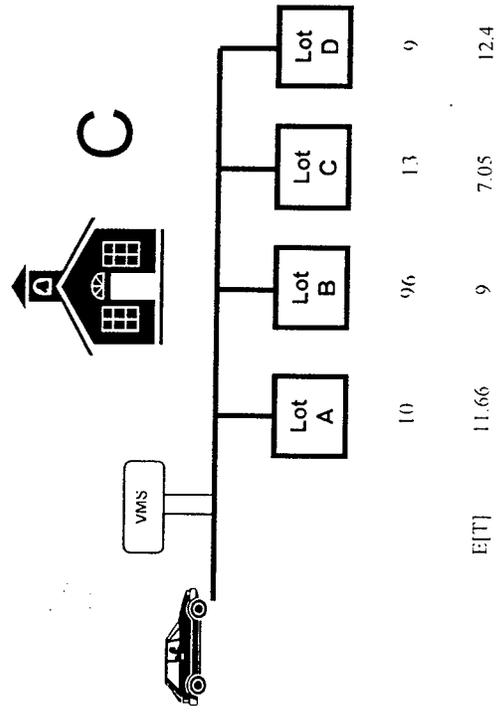
closed 15 closed 82
 E[T] XX 6.01 XX 14

APPENDIX M
ALTERNATIVE LOT SCENARIOS (ALS) FOR EXPERIMENT 3

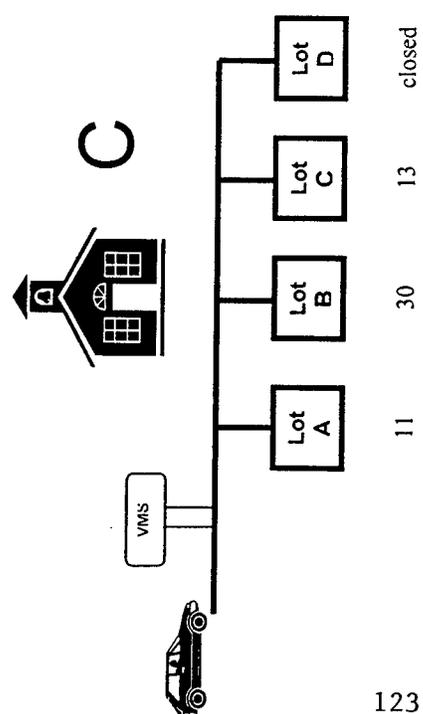




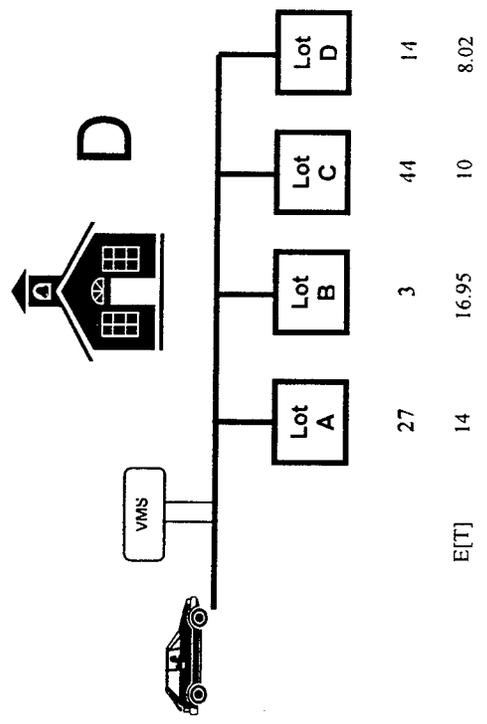
E[T] 8 6.02 10 12



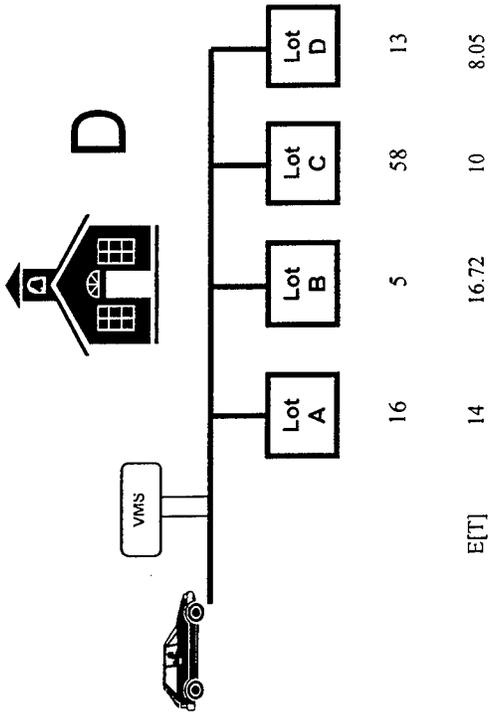
E[T] 11.66 9 7.05 12.4



E[T] 11.28 9 7.05 XX



E[T] 14 16.95 10 8.02



$E\{T\}$

APPENDIX N
INSTRUCTIONS FOR EXPERIMENT 3

DESCRIPTION OF EXPERIMENT

Participant,

Thank you for agreeing to participate in the following study. We estimate that this experiment should require no more than an hour of your time. You will be paid \$10 for your participation. If at any time during this experiment you do not wish to continue, you may terminate your session by simply notifying the facilitator.

Project Description

Advanced Parking Management Systems (APMS) are being designed as part of the Intelligent Transportation Systems effort. APMS utilize variable message signs (VMS) that give drivers up-to-the-minute information on the availability of parking at various alternative parking lots. The goal of this study is to identify which parking destination a driver will choose when given information on the number of available parking spaces at four different parking lots. Once the criteria which people use to decide where to park are known, the ways in which APMS might effect traffic flow in complicated parking situations can be fully evaluated.

Instructions

This study investigates drivers' choices of where to park using a driving simulator. You will encounter a total of 36 different parking scenarios in the simulation, which will be presented to you in 3 sets of 12 trials. A short break will be given at the end of each set. Each of the parking scenarios will consist of a destination sign, a VMS, and 4 parking lots labeled Lot A, Lot B, Lot C, and Lot D. Your task is to indicate for each scenario which parking lot you would choose to park in based on the information provided in the VMS.

The simulation will begin with your vehicle positioned behind a stop sign. Two other vehicles will be positioned in front of your car. At no time during the simulation should you ever attempt to pass these vehicles. Just past the stop sign you will see a brown a white sign indicating to which of the 4 parking lots your final destination is nearest for the particular scenario. For example, "Destination B" implies that your final destination is closest to parking Lot B. Once you proceed past the destination sign you will see the VMS, which displays the number of open spaces (out of 100) available in each of the 4 parking lots. *Figure 1* displays a sample VMS. Notice that in this case Lot B has 12 open spaces indicating that 88 of the spaces are already taken. In some scenarios, certain lots may be closed. Closed lots display a red "XX" where the number of open spaces would have been to signify that the lot is not available for parking.

Lot A	78	↑
Lot B	12	↑
Lot C		↑
Lot D	49	↑

Figure 1: Sample VMS

Before proceeding past the stop sign you should read the destination sign and then say aloud to the facilitator, “My destination is building X,” where X is either A, B, C or D. You may then proceed toward the VMS at a rate of 15 mph. After reviewing the information contained in the VMS you should indicate to the facilitator the parking lot you would choose to park in, and then proceed to the next parking scenario. You will not actually park in the parking lot you choose. You will simply state your choice to the facilitator and continue to the next scenario. You may travel at a speed of up to 25 mph when moving from the VMS to the stop sign in the next scenario.

In addition to the number of open spaces in each lot, you should also consider the following information (refer to *Figure 2*). Assume that each segment of the road system takes 1 minute to drive and 3 minutes to walk. Thus, in *Figure 2*, if you decided to park in Lot C, it would take you 4 minutes to drive from the VMS to the lot (4 segments @ 1 minute/segment), and 6 minutes to walk from the lot to your final destination (2 segments @ 3 minutes/segment). If a lot is full upon arrival, assume that you will wait 5 minutes for an available space.

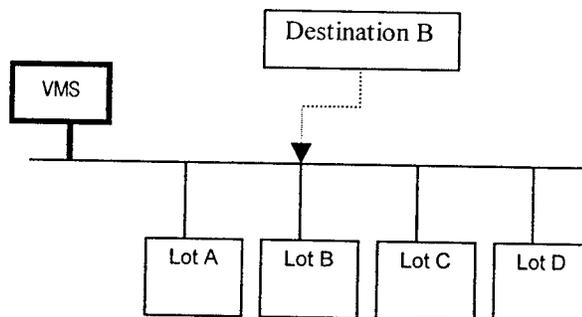


Figure 2

Throughout this experiment you should drive as you would normally drive. It is important that you drive as “naturally” as possible. You will be given a practice session for you to become familiar with maneuvering the simulator and with the simulation itself. The facilitator will now go over these instructions with you verbally. If you have any questions, please ask the facilitator before beginning the experiment. Thanks again for your participation!

APPENDIX O
RAW DATA FOR EXPERIMENT 3

Figure Number	Pilot 1	Pilot 2	Pilot 3	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10	Subject 11	Subject 12	Subject 13	Subject 14	Subject 15	Subject 16	Subject 17	
1	4	3	2	3	3	3	2	3	4	2	3	3	3	2	2	2	3	2	2	3	2
2	3	3	3	3	3	3	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3
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APPENDIX P

BAR GRAPH SUMMARIES FOR EXPERIMENT 3

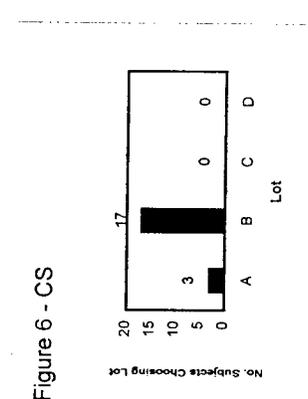
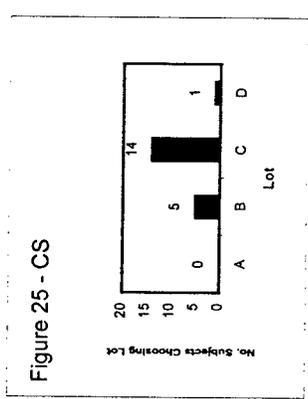
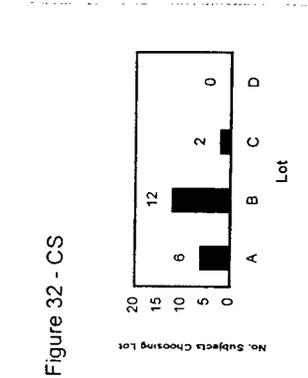
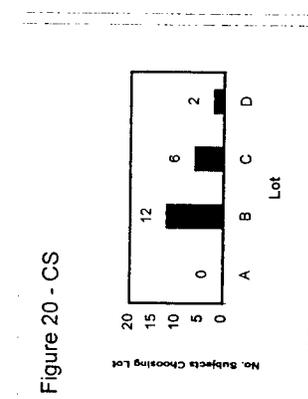
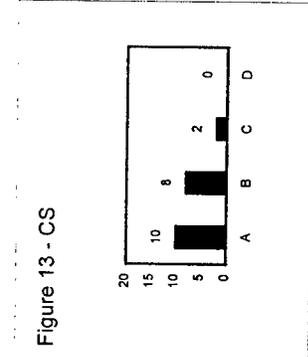
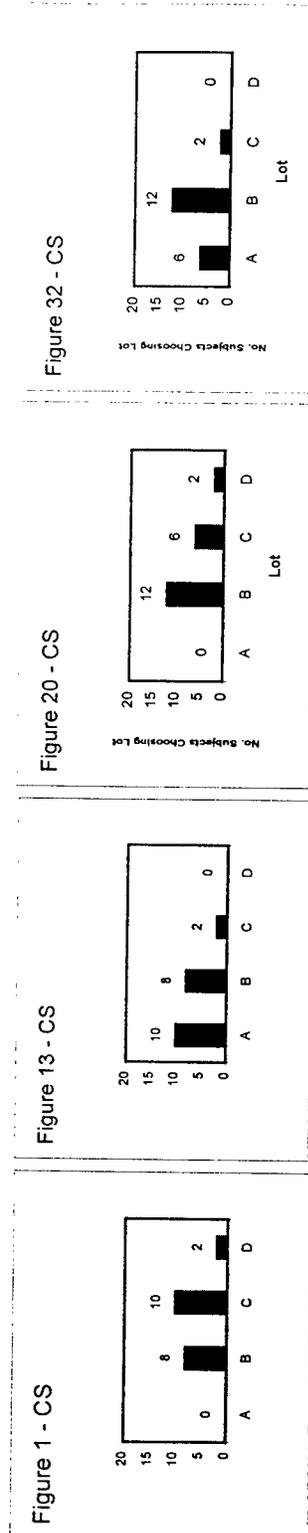
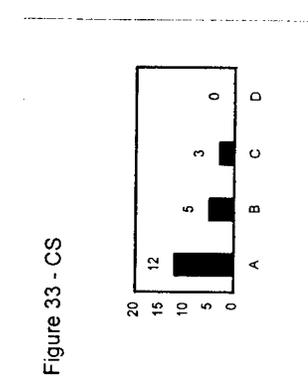
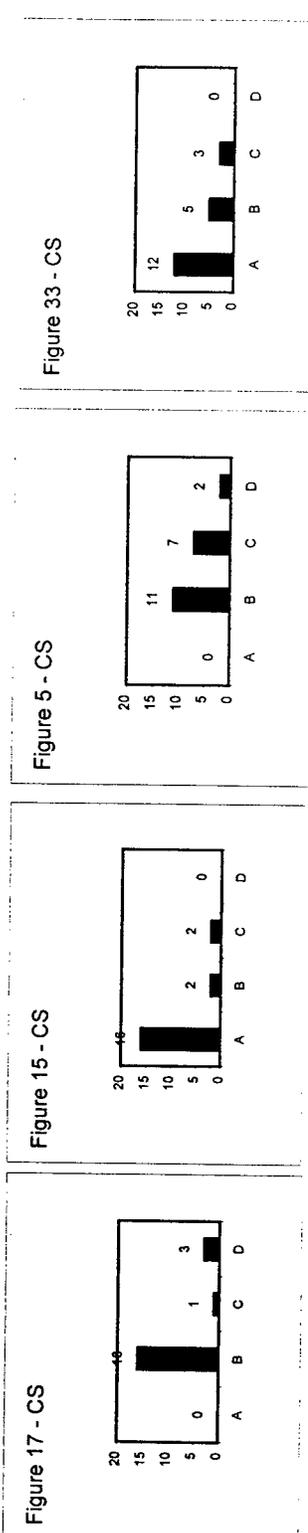


Figure 35 - LVM

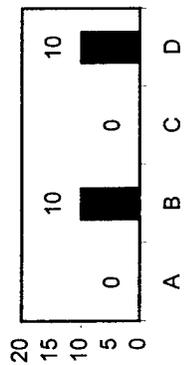


Figure 9 - LVM

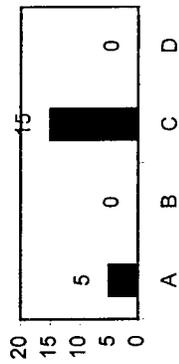


Figure 21 - LVM

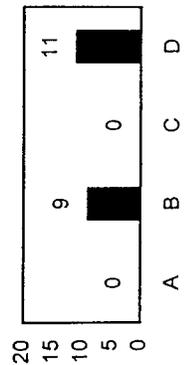


Figure 22 - LVM

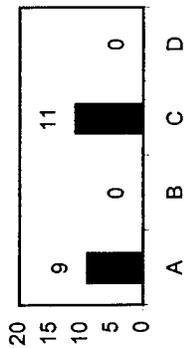


Figure 29 - LVM

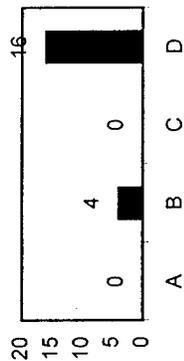


Figure 4 - LVM

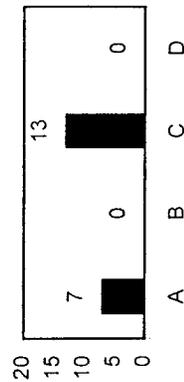


Figure 3 - CB

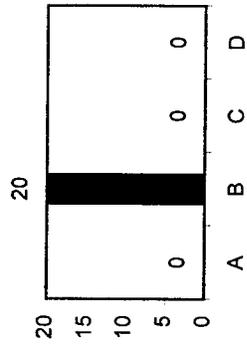


Figure 34 - CB

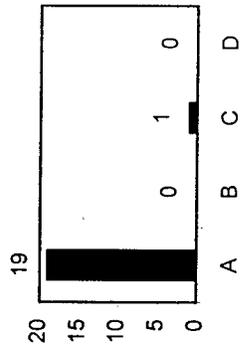


Figure 7 - CB

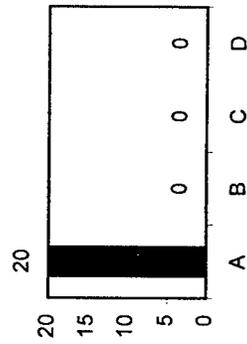


Figure 16 - CB

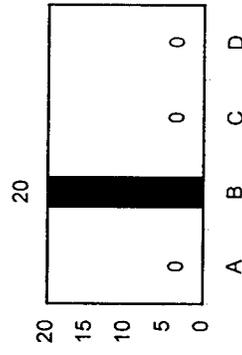


Figure 27 - CB

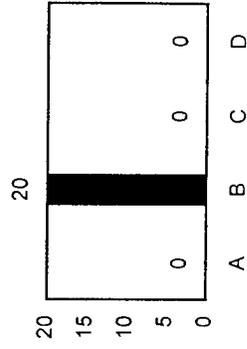


Figure 19 - CB



Figure 14 - ALS

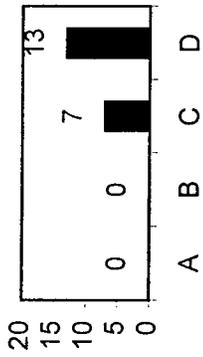


Figure 10 - ALS

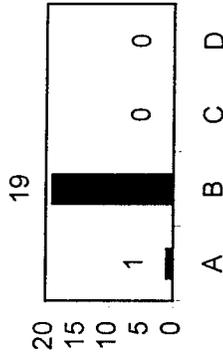


Figure 31 - ALS

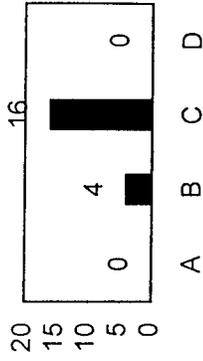


Figure 36 - ALS

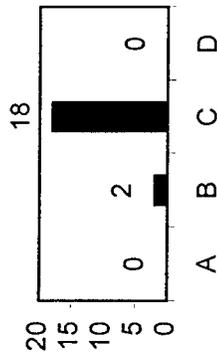


Figure 18 - ALS

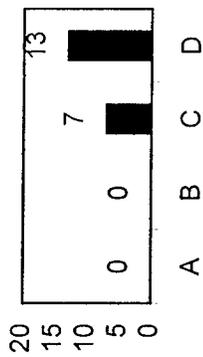


Figure 23 - ALS

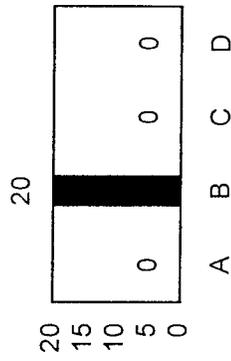


Figure 28 - ALS

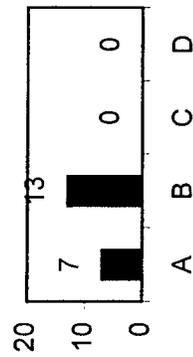


Figure 8 - ALS

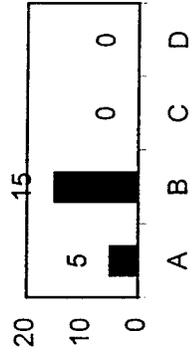


Figure 12 - ALS

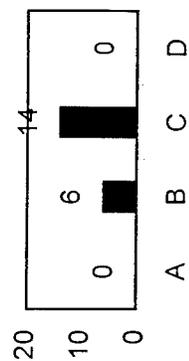


Figure 30 - NM

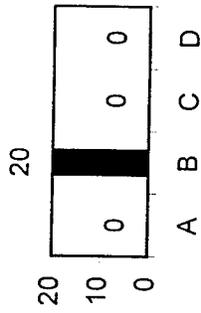


Figure 11 - NM

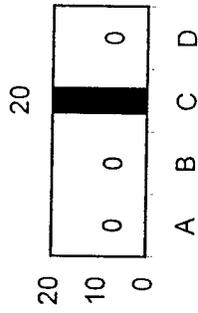


Figure 26 - NM

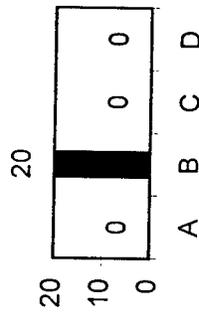


Figure 2 - NM

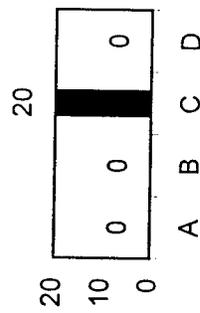


Figure 24 - NM

