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Chaining Behavior in Urban Tripmaking: Interim Report

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EXECUTIVE SUMMARY

Phase I of the "Chaining Behavior in Urban Trip Making" research project has focused on the achievement of three principal objectives:

1. Formulation of a theory of complex travel behavior based on a recognition of the full range of interdependencies associated with an individual's travel decisions in a constrained environment.
2. Development of an operational system of models based on that theory.
3. Initial empirical verification of the system of models developed.

The approach advanced in this study is based on a comprehensive theory of individual travel behavior that positions travel in a broader context than in single-trip methodologies. In this approach travel is viewed as input to a more basic process involving activity decisions. A fundamental tenet of this approach is that travel decisions are driven by the collection of activities that form an agenda for participation and, as such, cannot be analyzed on a link-by-link basis. Rather, the utility of any specific travel decision can be determined only within the context of the entire agenda.

A significant element in the development involves a theory of individual choice set formulation that includes both the effect of environmental/household constraints and that of individual limitations with respect to information processing and decision making. An alternate view of utility maximization and its relationship to decision making is presented in which the utility of a decision is comprised of two components: (1) the outcome of the decision and (2) the decision process itself.

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The Theory

A fundamental tenet of the theoretical framework is that travel decisions are subsidiary to activity participation decisions. At any particular time, an individual possesses a set of needs and desires that arise due to physiological, social and economic factors. The fulfillment of these needs/desires is achieved through participation in activities at specific locations and times. The activity locations and durations, as well as the actual activities, constitute an individual's activity program, which represents the demand for travel. For any specific activity program, an individual is faced with a set of decisions involving the scheduling of the activities (and, correspondingly, the travel linkages which connect the activities in the time-space continuum). Once implemented, these activity scheduling decisions transform an individual's activity program into an activity pattern--an ordered sequence of activities and travel accomplished during the time period.

The theory has been constructed to include the effects of both planned and unplanned activities on the travel decision process. In the theory, travel/activity decisions are viewed as determined principally by planned activites but influenced by the potential to participate in unplanned activities weighted by the likelihood of their occurrence. The theory centers about an individual's selection of the ordered collection of activities and travel linkages that comprise his/her daily activity pattern. The utility of any specific activity pattern consists of: 1) explicit utilities associated with each segment of the activity pattern,

represented as a triad of a) travel (if any) to the activity, b) waiting (if any) for the activity to commence and c) actual participation in the activity, and 2) implicit utilities associated with stochastic elements affecting implementation of the specific activity pattern, including the probability of occurrence of unplanned activities during the time period as well as the individual's limited knowledge of activity durations and travel times.

Within the theory, these elements are integrated in a manner consistent with identifying the tradeoffs among the components as well as with illustrating the complex nature of the dependency of individual decisions on those of other members of the household.

The Operational Model

Based on the theory, a comprehensive methodology has been developed to examine the formation of household travel/activity patterns utilizing a simulation approach in combination with techniques of pattern recognition, multiobjective optimization and disaggregate choice models. The model is comprised of six stages:

(1) Specification of individual activity programs from an examination of household activity programs and constraints, and the interactions between the household members given the existing supply environment.
(2) Generation of the set of feasible individual travel/activity patterns through a constrained combinatoric scheduling algorithm.
(3) Identification of distinct members of the set of feasible travel/activity patterns by means of pattern recognition techniques.
(4) Identification of a non-inferior (perceived) pattern set for individual choice utilizing a multi-objective programming approach.

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(5) Specification of a representative activity pattern set (if necessary), forming the choice set for each household member, utilizing pattern recognition and classification theory.

(6) Formulation of a pattern choice model, which specifies individual travel/activity pattern choice probabilities.

Each of these stages is operationalized within a series of computer modules written in ANSI FORTRAN (FORTRAN 77). These modules have been designed for ease of use and may be "plugged in or out" of the model system to alter the architecture of the model system to fit both the specific problem under analysis as well as the types of analysis to be performed. With the "component" framework, the model system can easily be updated, expanded or modified without extensive reprogramming.

In the first module (TROOPER), the interactive household forces affecting the formulation of individual activity/travel patterns are simulated internally to insure that the resultant patterns reflect household constraints.

Once the set of activity programs corresponding to each household member is specified, the set of feasible activity patterns, which contain the full range of possible scheduling and travel arrangements, is generated through a constrained, combinatoric scheduling algorithm (SNOOPER), the second module of the model system. The first of six basic elements of this module integrates the simulation of the activity program of a single household member into the supply environment presented by the activity/travel behavior of the remainder of the household. Combinatorics are introduced in the module's second element through a two-stage process. All tours are formulated as home-based, with the

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potential for insertion of intermediate in-home activities at each possible location of each activity ordering, generating all potential tour arrangements. The first sequencing stage produces the number of intermediate home inserts, while the second stage iteratively produces all permutations of the activities. In the third element of this module, modal choice combinatorics are introduced to the simulation procedure. The current version of the mnodel considers both private (e.g., auto, walk) and public (e.g., transit) modes, the latter requiring schedule and route information as input. Once an activity program has been ordered acceptably and assigned modes, the fourth element of the module determines feasible scheduling decisions constrained by the earliest and latest unconditional starting and ending times of the activities, the expected activity durations and travel time between locations. The actual simulation of the activity pattern occurs in the fifth element over the full range of potential activity start times and durations of the in-home activity inserts which define each tour composition. The sixth and final element of the second module outputs each simulated activity pattern in standard form.

The third module (GROOPER) of the model system has been developed and implemented to obtain an independent pattern set through the specification of representative activity patterns. The present formulation employs a multiple scale, scoring function classification technique to identify perceptually distinct members of the full set of feasible activity patterns generated in the constrained, combinatoric scheduling algorithm (SNOOPER). This reduces the rather large

opportunity set to a more manageable and theoretically consistent option set of representative patterns. The output of this module includes both tabular as well as graphical representations of the activity patterns.

In the fourth module (SMOOPER) the various utility measures arising from the theoretical development are computed for each representative activity pattern in the individual's option set. These utility values may either be input directly to the activity choice model module or, alternatively, serve as a basis for determining a choice set comprised only of non-inferior courses of action. In the latter option, the individual's choice of activity/travel pattern is viewed as a stochastic multi-objective decision problem in which only those opportunities (i.e., feasible, representative activity patterns) judged by the individual to be non-inferior based on his/her decision objectives are evaluated using a utility maximizing decision rule.

If desired, the size of the individual's option set may be reduced by activating the fifth module (REGROOPER) of the model system. Exercising this option produces a distinct choice set of any size mandated either by computational limitations or theoretical implications.

The choice set of representative activity patterns resulting from this five-stage process implicitly contains all activity program constraints in fully-specified, distinct activity patterns, with each pattern alternative defined along the same dimensions, forming an abstract choice problem. The sixth, and final, module (CHOOZER) is designed to utilize any one of a number of existing choice models (e.g., random utility (LOGIT) or non-compensatory (SEQUEL) choice structures) to establish pattern choice probabilities based on the specified choice set.

The model system has been developed in a manner that facilitates analysis of alternate transportation/land use policy options. For example, the potential impact of energy restrictive policies, such as fuel rationing, on the daily routines of various household types can be assessed simply by adjusting the travel contraints in the data input to the SNOOPER module; the output of the GROOPER and SMOOPER modules will produce a revised (relative to the pre-restrictive environment) option set which may be compared to the original option set to determine the nature of the impact of the policy on the choices available to the household; if an impact of the policy is the deletion of the current activity/travel pattern from the household's choice set, the CHOOZER module may be entered (in its predictive, rather than estimation, mode) to project the likely response of the household to implementation of the policy. In a similar manner, the model can be used to estimate the impacts of a range of policy options involving both temporal strategies (e.g., flextime, operating hours) as well as spatial strategies (e.g., trip chaining, ride sharing).

Preliminary Empirical Results

Prototype testing of the model system was accomplished using the data obtained in a 1980 home interview survey of over 600 households in the Windham, Connecticut Planning Region which included a comprehensive, single day, travel/activity diary for each member of each household in addition to a basic socio-economic profile and transportation supply inventory.

Prior to the modeling analysis the sample data were analyzed to uncover the basic features of the activity/travel behavior of the respondents to the Windham survey. This univariate analysis included aspects pertaining to:

1. activity frequency

2. mode choice

3. persons accompanying traveler

4. waiting time tolerated

5. schedule flexibility

6. location of activities

7. unplanned activities

8. respondent destination patterns by trip purpose

In addition to these univariate analyses, a more detailed analysis of activity duration was conducted across ten life-cycle groupings. The results of this analysis were used to determine the distribution of duration associated with the various activity types which, together with their frequency of occurrence, are used to estimate the probable nature of unplanned activities and the likelihood of their occurrence.

Another aspect in the to consideration of the impact of the provision for the occurrence of unplanned activities on choice of activity pattern involved destination choice modeling. The space-time prism defined by "pegs" in the planned activity pattern offers utility to the individual only in the potential destinations that might be chosen within the prism. Such choices are inherently tied both to the deviation (from the primary origin and destination points associated with the planned

activity.) time required to access the destination as well as to the temporal constraints imposed by the entire activity pattern vis a vis the expected duration of the unplanned activity.

As an initial step in developing a consistent procedure for examining destination choice issues within the context of the theory developed in this study, as disaggregate model of destination choice for the grocery shopping activity, specified in terms of the total activity pattern, was estimated. The sample used in the estimation was comprised of 122 individuals making a major grocery shopping trip between two fixed activities. The difference between the latest possible starting time of the activity succeeding grocery shopping and the earliest ending time of the preceding activity was used to define the "window" available for the grocery shopping trip. Destinations for which the travel time at each end plus the duration of the shopping activity exceeded this window were excluded from the individual's choice set. the model developed thus differs from the conventional in two important respects: a) the choice set is constrained based on spatial and temporal restrictions imposed by the activity pattern, and b) the travel time variable adopted measures the deviation from the line joining the spatially fixed end points of the activity sequence. In this particular empirical application, little difference was found between the activity pattern-based and conventional approaches. Both approaches led to an almost 90% correct choice prediction rate. It is concluded that, whatever the conceptual merits of the proposed hypotheses concerning the differences between the activity pattern-based and conventional approaches to destination choice modeling,

the ability to test those hypotheses is limited by the empirical environment--a high correlation between the activity pattern-based deviation measure of travel time and the conventional measure, and a high proportion of individuals with no constraints on their choice sets.

The major empirical effort during this first phase of the research study centered about the application of the theory and model to predict an individual's selection of activity/travel pattern (which also predicts mode usage, chaining behavior and activity scheduling as an inherent part of the pattern).

Preliminary testing of the model was accomplished on a sample of 79 residents of the Windham area, selected on the basis that their observed activity/travel pattern include no fewer than two, but no more than six, out-of-home activities. The activity programs and associated household and supply-side constraints of these individuals were input to the model system and all potential feasible activity/travel patterns generated for each individual. Depending on the nature of the constraints and the number of activities in the individual's program, the number of such patterns in each individual's feasible set varied from a few (e.g., 15-20) to several thousand. The pattern recognition element of the model system was applied to the potential feasible pattern set of each individual to identify the distinct elements of each set. This application resulted in a maximum of seven distinct representative feasible activity/travel patterns for any individual in the sample. The representative pattern closest to the observed pattern for each individual was designated as the "chosen" pattern for that individual.

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CHAPTER ONE

Introduction

1.1 Rationale

Empirical findings have documented that individuals employ a wide variety of strategies when faced with restrictions imposed by transportation policies (e.g. decreased transit service, gasoline restrictions). These strategies range from simple modal shifts to more complex adaptations involving trip consolidation (i.e., chaining), activity rescheduling and destination substitution. Conventional travel demand models, however, are unable to reflect (and hence, predict) these complex responses as a result of several theoretical shortcomings. In addition, estimation of the likely impacts of various activity system policies (e.g. flextime, extended hours for service facilities) is outside the realm of the present models. This study attempts to address these shortcomings by restructuring the prevailing microeconomic theory of travel behavior in a manner that facilitates an increased understanding of complex travel behavior and provides an additional capacity for analyzing policy impacts.

1.2 Why are Conventional Approaches Unsuitable?

Several authors (Heggie, 1978; Burnett, 1978; Hanson, 1980) have discussed in detail both the limitations of current disaggregate models as well as the basic underlying assumptions that give rise to these limitations; only a brief discussion of these is presented here. A

serious shortcoming of available theoretical frameworks is the use of individual trips as the basic unit of analysis. Despite the widespread acknowledgement that travel is a "derived" demand (i.e., the demand for travel is derived from a more basic need to participate in various activities at specific locations), most of the operational travel demand models have ignored the activities that give rise to the need for travel and have, instead, focused exclusively on travel itself. By ignoring the relationship between activities and travel, these models are unable to provide any meaningful information about how changes in the activities themselves affect individual's travel behavior. In addition, by focusing on individual trips (as opposed to a sequence of trips), the current models assume that the individuals' travel decisions are independent from any consideration of previous or future actions, thus implying a "memoryless" decision maker.

A second major problem associated with current models is their failure to incorporate explicitly the effect of constraints on individual travel behavior. Most of the models have focused on the explanation and prediction of the individual's observed choice without any consideration of how various constraints interact to restrict the range of choices available to the individual. Researchers at the Lund School of Geography in Sweden have demonstrated that the set of activity (and hence, travel) options available to an individual at a particular time is determined, in part, by his/her obligations to be at certain locations during specific times (e.g. work, home), the distribution (both spatial and temporal) of activity locations and the characteristics of the transportation system

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(e.g. availability, connectivity and speeds of various modes). Another set of constraints that has been ignored by current models is that which originates from the household as a result of the interaction among family members. Individuals do not exist in isolation, but instead are members of larger units (households) and, therefore, their decisions concerning travel and activities are influenced to some extent by the needs and constraints associated with other household members. As an example, consider a two-member household that owns one automobile. Any decision to utilize the automobile for a particular length of time by one member of the household will eliminate all of those activities that require the use of automobile from the set of potential alternatives available to the other member during that same time period.

The proper specification of the individual's choice set is another problem that is inherent to the current models. Although environmental and household constraints (when properly incorporated) delineate the set of feasible alternatives available to an individual, they fail to identify those alternatives that are actually considered by the individual. Many authors have speculated that the size of the latter set is much smaller than the former as a result of the individual's limited ability to process large amounts of information and make decisions. However, this concept has not yet been incorporated systematically in any mathematical model.

Finally, current disaggregate models assume that individuals make their decisions based strictly on the concept of utility maximization. Given a set of alternatives, an individual is viewed as determining the

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the MFPT provides information about indirect linkages through the number of "time periods" it takes an individual to travel from one state i (location, activity type, etc.) to another state j, this measure of time is actually just the number of multiplications of the transition matrix. Third, and probably most important, the probability of transition from state i to state j is dependent only on location i--not on any locations visited prior to i. It is this lack of influence of travel history on the individual's current decisions that gives the model its "memoryless" nature. Although there are serious shortcomings associated with modeling multiple-sojourn tours via a Markovian framework, the use of such models has provided some insight to the relative strength of various linkages.

2.3 Simulation Models

Several early research efforts concentrated on the development and testing of various simulation models. Theories (or partial theories) were formulated as explanations of certain observable properties of multiple-sojourn tours (e.g., number of sojourns per tour, types of establishments visited, etc.) and simulation models based on the theoretical constructs were then developed to test the validity of the theory. Nystuen (1967) saw travel behavior as the complement of spatial location (i.e., travel behavior both determines and is determined by the spatial distribution of facilities) and attempted to develop a general theory that would incorporate this interdependency. Two assumptions were crucial to the development of the model:

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(1) the location of a specific retail establishment relative to other establishments influences the individual's selection process, and

(2) home is a special location in the urban environment, the utility of which increases with time spent away from it.

A spatial association index of retail establishments was constructed together with a temporal probability function for tour continuance and these two components combined to form the simulation model. Given the first activity of the tour, the simulation model predicted whether the tour would terminate because of time and if not, where the next trip would go. The model resulted in an overestimation of total trips due to an overestimation of multiple-sojourn tours (at the expense of single-sojourn tours) but these results probably could be improved with the addition of activity duration into the model structure. Another stochastic model of multiple-sojourn tours was developed by Ginn (1969) with the aid of dynamic programming techniques. He assumed that the probability of making a link between two locations i and j, given that an arrival at location i took place on the previous link, was a function of (1) the utility of location j, (2) the transportation "cost" (both temporal and monetary) of travel between locations i and j and (3) the expected cumulative utility and cost for all of the other links on the tour beginning at location j. Due to the complexity of the phenomenon being modeled, Ginn did not seek true optimization in his model. Instead, probabilistic tour paths and expected frequencies of multiple-sojourn tours were estimated together with the expected

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cumulative utility and cost of the multiple-sojourn tours. Despite only limited empirical testing on hypothetical spatial arrangements, Ginn's recognition of the interdependent nature of the individual's travel decisions and his operationalization of this concept (through a dynamic "look-ahead" mechanism) is significant.

Another investigation of the relationship between retail location and consumer movement was conducted by Mackay (1971). He viewed individuals as "discriminating" between various establishments when making their decisions and modeled this "discrimination" as a sequential three-stage process involving the decisions (1) whether or not a shopping tour should be made at a particular time period, (2) how many establishments should be visited during the tour, and (3) which establishment type should be visited on each stop in the tour. Information concerning the household's composition, accessibility to retail establishments, attitudes about the "attractiveness" of retail establishments and general shopping habits (e.g., frequency, size of purchases, etc.) was used in the construction of discriminant (choice) functions and the individual choices were simulated by sampling the posterior probabilities of the discriminant functions with the aid of a Monte Carlo sampling procedure. Several consumer movement heuristics (e.g. total tour distance minimization, sequential trip distance minimization, etc.) were used to model the individual's final decision regarding the specific establishment to visit on each trip. Although discrepancies between simulated and observed multiple-sojourn shopping tours existed at the individual level, the simulated distributions of shopping tours by number of sojourns, day of

the week, distance traveled and establishment types are significantly close to the actual distributions.

Vidakovic (1974), in an attempt to model the relationship between the frequency of multiple-sojourn tours and tour length (i.e., number of sojourns), developed a harmonic series model. Statistical tests on the distribution of tours by number of sojourns failed to indicate any significant difference between the expected and observed distributions at the .05 level. Vidakovic (1977) also developed models of the relationships between tour length and the number of different activities combined on a given tour, the mixture of travel modes on a given tour and the distance traveled between activities. More important than the actual results are Vidakovic's recognition of the interrelationships that exist between individual's time-space decisions and his initial attempts to develop a methodological framework capable of analyzing all decisions as an integrated whole.

Westelius (1973) distinguished between activities that are fixed in time and space (e.g., work, school) and activities that are substitutable (i.e., activities that can occur at various times and locations) and with this dichotomy placed individual travel behavior into a "needs accumulation" context. The fundamental tenet of this approach is that individuals accumulate a desire (or need) to travel over time and travel does not take place until the need surpasses some minimum "threshold." Within this framework, multiple-sojourn tours occur as a result of one of two situations:

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(1) multiple travel needs exceeding the corresponding need thresholds at exactly the same time, or

(2) one travel need exceeding the need threshold, causing a trip to be made and then other thresholds being lowered below the current levels of need as a result of the original trip.

The individual need variables (although quite possibly related to the socioeconomic characteristics of the individual and/or household) were estimated heuristically with the aid of an iterative procedure. An initial set of values was specified for the need variables and input to the simulation model. Upon completion of the simulation, a comparison was made between the simulated and observed multiple-sojourn tours and the parameters were then adjusted prior to the next simulation. Results of the simulation showed that as the distance between the individual's home and the nearest retail center increases so does the mean number of sojourns per tour and the proportion of sojourns at substitutable activity locations made in connection with fixed activities. The substitutable activity locations visited in tours involving fixed activities are in close proximity to the fixed activity locations, indicating the effect that relative location has on destination choice.

Almost all of the previous simulation models have been constructed under the general assumption of non-optimal behavior on the part of the individual. One notable exception to this is the optimization model developed by Kobayashi (1976). Created as a mathematical extension of the theoretical framework advanced by Chapin,[2] this model helped to relate the "latent mechanism" of travel patterns to the travel

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environment (as characterized by the transportation and activity systems). More specifically, serial queues were used to represent the transportation and activity systems and the maximum number of trips attainable by an individual in a given time period was estimated as a function of the amount of time required for travel and activity participation. A cost-effectiveness function was also developed based on both the maximum number of attainable trips and simple benefit-cost ratios for each individual trip.[3] The optimal travel pattern was then determined by maximizing the cost-effectiveness function subject to the constraint of total available time. Although the model was not tested on any real data, several hypothetical case studies were used to conduct a preliminary investigation of the model validity and, in general, the model produced realistic results.

Bentley, et al. (1977) acknowledged the multitude of factors that influence individual travel behavior and, as a result of the complexity at the disaggregate level, chose to model the distribution of return trips to home by stage in the tour. The two parameters of the distribution were estimated by comparing the observed distribution with the expected distribution and minimizing the chi-squared statistic.

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[2] Chapin's activity framework viewed trip motivation as arising from two sets of needs--fundamental and supplemental. An urban activity was defined as an interaction between human behavior and the environment and was seen as an evolutionary process of motivation-choice-activity in which both fundamental and supplemental needs are optimized (Chapin, 1968).

[3] The benefit per unit time of an activity was not defined; rather, it was assumed to be linearly proportional to the activity duration.

Although the authors offer possible behavioral interpretations of the parameters,[4] in actuality, they represent nothing more than the "best fitting" aggregate distribution of the observed number of multiple-sojourn tours. The authors do, however, present some supportive evidence that an analysis of tour continuation is a more appropriate analysis framework for urban travel behavior than an analysis of individual trips. Another attempt at modeling aggregate behavior was made by Burnett (1977). Using the widely acknowledged concept of distance decay (both with respect to information and destination usage) as a basis, Burnett hypothesized that the spatial distribution of the origins of all users of a specific destination could be described by a circular normal probability density function. Despite individuals' increasing levels of information over time, it was also hypothesized that the total amount of information obtained by individuals during a given time period would always decline with distance from the destination (i.e., circular normal probability density functions can be "fit" to data obtained over successive time periods, although the parameters of the distributions will vary with time). Goodness-of-fit tests showed that there were no statistically significant differences between the observed and estimated distributions, lending support not only to the original

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[4] The first parameter was seen as a measure of the proportion of initial trips that have the "potential to continue forward" (i.e., the potential to be linked with at least one additional trip in the same tour) while the second was interpreted as the proportion of the trips with the potential to continue that are actually continued forward to the next stage.

hypothesis but also to the further development of dynamic models of destination choice.

2.4 Spatial-Temporal Constraints

While all of the works cited previously recognize the complex nature of individual movement, it was the pioneering work of Hagerstrand and his University of Lund colleages that first provided a comprehensive and unified paradigm for the analysis of complex travel behavior. In his approach to understanding human behavior, an individual's choice of a specific activity "pattern" is viewed as being the solution to an allocation problem in which the individual simultaneously allocates limited resources of time and space to achieve some higher "quality of life." Hagerstrand approaches the problem of understanding individual behavior by analyzing the constraints imposed on an individual to determine how they limit possible behavioral alternatives. This view from "outside" represents a break from the more traditional "inside" viewpoint, in which individual behavior is described via observed actions. The constraints defined by Hagerstrand can be classified into one of three categories: capability, coupling or authority. Capability constraints are present due to the physical and physiological needs of the individual. Authority constraints are present whenever an individual is required to fulfill some obligation before participating in a particular action. Coupling constraints refer to items such as transportation technology, locational pattern of facilities and operating policies, which interact to determine where, when and how long an individual undertakes an activity.

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The means of illustration utilized by Hagerstrand was that of the three-dimensional space-time model, in which geographical space is represented by a two-dimensional plane and time is defined on the remaining, vertical, axis. The use of this representation allows definition of an individual's activity pattern in terms of a "path" through time and space. The location of activity sites, or "stations," together with the maximum speed an individual can travel in a given direction establishes the individuals's space-time "prism." The area (or volume) inside this prism represents the full range of possible locations which an individual can access (i.e. his/her physical "reach") or conversely, the outside depicts the entire set of locations that are inaccessible at any time. Once an individual travels to a specific location inside his/her "prism," the potential action space that remains for any subsequent activities will be reduced in size depending on the activity duration; hence, at no time is the individual able to visit the entire set of locations contained in the prism. In addition, the delineation of the reachable activity area is highly dependent on the mode of travel used because of the variation in travel speed across the different modes. Although this emphasis on potential rather than actual alternatives does not reveal explicitly the intrinsic character of the individual's choice mechanism, it does promote an understanding of the manner in which various types of constraints operate to restrict choice. Using these theoretical constructs, traditional atemporal home-based measures of accessibility can be replaced with measures that reflect the individual's accessibility with respect to current location in both time

and space. Consequently, an individual's accessibility to opportunities may, for example, be different if he/she is at work at 4:00 p.m. instead of at home at 12:00 p.m.

A host of other researchers have attempted to expand and refine the original theoretical foundation built by Hagerstrand. Cullen and Godson (1975) viewed individuals' lives as "containing highly organized episodes which give structure and pattern to the whole stream of behavior" and outlined a set of propositions which served as the basic framework for the analysis of the individual's activity/time /space decision process. The propositions focused on relationships between individual priorities, levels of activity commitment, flexibility of activities, number of participants and activity sequencing; it was felt that these "subjective" dimensions give rise to the highly organized episodes that act as "pegs" in the individual's scheduling process. A variety of statistical techniques (e.g. discriminant analysis, factor analysis, time series analysis, etc.) were used to investigate the validity of the proposed relationships and the following general conclusions were reached:

(1) Despite the lack of any direct constraints on sleeping, waking and eating, individuals tend to adhere to fairly rigid daily cycles for these activities.

(2) Work activities, routine non-work activities and activities arranged with other people are the most rigidly constrained in time and space and are also assigned the highest priorities by individuals. Consequently, these activities are the most important "structuring" episodes in the individual's day.

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(3) Activities constrained in space are more common than those constrained in time, but the temporal constraint is a much stronger "structuring" influence than the spatial constraint.

Stephens (1975) also postulated that the "level of activity commitment" is a crucial determinant of the individual's activity sequence in time-space and defined "level of commitment" in terms of an individual's perception regarding the degree to which an activity could be carried out at different locations and times. Using this definition, he constructed an activity flexibility measure which ranged from unexpected and unplanned to prearranged and routine. These subjective measures were combined with objective constraints imposed by the individual's environment and hypotheses concerning individual's space-time behavior were tested via simulation. Probability distributions (frequency of activity occurrence and duration by constraint, location, linkage and distance) were constructed as approximations to activity pattern structure and, using the "level of commitment" to determine the most fixed activity (or "peg"), a Monte Carlo procedure was employed to select activities, locations and durations which could be "fit" into a sequence centered around the peg. The simulation predicted the activity sequences in the neighborhood of fixed activities reasonably well, but was unable to reproduce those sequences involving activities of low commitment (i.e., high flexibility).

Tomlinson et al. (1973) utilized an aggregate approach in their simulation of complex travel behavior. Instead of focusing on the individual, they chose to model the distribution of individuals

(students) over different activities and locations throughout the day. Prior to the construction of the model, two basic assumptions were made regarding the aggregate behavior of the individuals. First, it was assumed that the amount of time spent in various activities (i.e. the time budget) remains constant for a particular socioeconomic group although it was allowed to vary across different groups. Second, it was assumed that the behavior of individuals is subject to a number of spatial and temporal constraints that determine the times and/or locations of activities. With these two assumptions, the problem of modeling complex travel behavior was seen as a problem of determining the most probable distribution of individuals over activities in time and space subject to the constraints that: (1) the proportion of time spent in different activities by the population groups must equal the observed time budgets and (2) activity availability restrictions cannot be violated. This distribution was obtained with the aid of a simulation model that incorporated both the theory of entropy maximation (used to generate the number of individuals engaged in a particular activity at a particular time) and the theory of distance decay (used to allocate the individuals to various activity locations). Although no attempt was made within the framework of the model to identify the sequence of activity and locational choices made by an individual, it was possible to examine the sensitivity of flows of people to various spatial and temporal distributions of activities and different levels of activity fixity. In general, the simulated distributions were reasonably close to those actually observed; however, additional improvements could be made by:

(1) removing the assumption that the distribution of individuals over activities at each time period is independent of preceeding distributions, (2) including additional factors in the submodel that distributes individuals to locations and (3) incorporating group time preferences with respect to activity participation.

Lenntorp (1976) also extended Hagerstrand's approach by developing a model that calculated the total number of space-time paths an individual could follow given a specific activity program (i.e., a set of desired activities and durations) and the urban "environment" (as defined by the transportation network and the spatial/temporal distribution of activities). Lenntorp's PESASP (Program Evaluating the Set of Alternative Sample Paths) model is especially noteworthy since it represented the first attempt to operationalize the theoretical framework advanced by Hagerstrand in a manner that would allow meaningful policy evaluation. One policy-oriented application of the model involved a sample of individuals from the city of Karlstad, Sweden (Lenntorp, 1976b). A set of feasible space-time paths was generated for each member of the sample under existing conditions and then compared to alternate sets of paths obtained by changing various public transit service characteristics (e.g., service frequency, travel speed, route configuration, etc.), repeating the simulation. Although Lenntorp's model yielded information about the effect of service changes on an individual's range of potential actions, it was unable to provide any information on the individual's most probable responses to the changes. This inability to predict individual reaction to change illustrates the

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major disadvantage of the model--a lack of any behavioral foundation. Despite this emphasis on potential rather _than actual alternatives, Lenntorp's approach does offer an understanding of how spatial and temporal constraints interact to restrict individual choice.

Constraints on individual behavior were also investigated by Burns (1978) through a methodological study of accessibility. In this study, Burns viewed accessibility as the freedom of individuals to participate in different activities and, with the aid of the space-time "prism" (which served as a diagrammatic representation of accessibility), investigated the dependence of accessibility on its transportation, temporal and spatial components. In addition, accessibility benefit measures were constructed based on different assumptions about how individuals value the opportunities available to them. These were used to analyze and compare the accessibility implications of a variety of transportation, temporal and spatial strategies. Two important results were obtained from this study:

(1) To produce equivalent marginal accessibility benefits, the percentage change in the individual's travel speed must be greater than that associated with the amount of time between fixed activities, and

(2) the less constrained an individual's freedom in space and time, the greater the attractiveness of a strategy that relaxes the time constraints compared to a strategy that increases the speed of travel.

Based on these results, Burns concluded that temporal strategies (i.e., those strategies that relax the time constraints of individuals) have the

potential to provide substantially greater increases in accessibility than velocity strategies.

The concept of space-time constraints and their effect on an individual's freedom of choice was also considered by Landau et al. (1980) in their study of shopping destination choice modeling. Recognizing that shopping activities are not performed in isolation from other activities, they developed a model to calculate the maximum amount of time an individual could spend at a retail establishment based on the following set of constraints: (1) the obligatory activities (i.e., work or school) contained in the individual's activity program, (2) the spatial distribution of retail establishments, (3) the temporal distribution of retail establishments and (4) the transportation system. Any stores that could not be reached by an individual were eliminated from the choice set. A demonstration of the model showed that the inclusion of spatial/temporal constraints in the destination choice set specification process yields improvements in destination choice prediction accuracy and facilitates the evaluation of temporal strategies (i.e., those strategies aimed at increasing the amount of time available to individuals for shopping). More important was the incorporation of activity program constraints into measures of individual accessibility. Results indicated that the accessibility of certain population sub-groups (i.e., workers, students) to shopping destinations is much slower than the accessibility of other groups as a result of the additional constraints imposed on them by obligatory activities (e.g. work or school). Finally, although the model considered only shopping activities, the

methodological framework is flexible enough to permit extensions to other activities.[5]

In acknowledgement that spatial/temporal constraints exert influence across many dimensions (not just destination choice), Landau et al (1981) also developed a trip generation model system that was sensitive to these constraints. Based on the assumption that household generation results from a two-stage, sequential decision process, the following models were developed:

(1) a household trip purpose (HTP) model that estimated the probability of a household making a trip for a particular purpose, and

(2) a household travel time period (HTTP) model that estimated the conditional probability that a trip for a particular purpose would be executed at a particular time period.

Since the latter model estimated only the probability of <u>any household member</u> executing a trip for a specific purpose at a particular time, an alternate model that estimated the probability of a <u>specific household member</u> executing a trip (HMTTP model) was also developed. The activities executed by households (i.e., the reasons for travel) were classified into three groups (subsistence, maintenance and leisure) based

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[5] One possible extension discussed by the authors involved a sequential procedure. It was assumed that activities could be classified according to priority (primary, secondary, tertiary, etc.) and the choice set for the primary activity constructed as previously defined. The specific choice of the primary activity would then impose additional constraints on the set of potential locations for the secondary activity. The location of the secondary activity would then be predicted, taking these new constraints into account.

on their degree of temporal flexibility and separate models were estimated for maintenance and leisure activities.[6] Results of the estimations showed that:

(1) the explanatory power of temporal constraints was more significant in the HMTTP model than in the HTTP model,

(2) temporal constraints were only significant in the models of leisure trips, and

(3) there was a significant influence on the HMTTP model due to the interaction variables (i.e., those variables which represented the activities of other household members).

Based on these results, the following behavioral implications were advanced by the authors:

(1) The individual, not the household, is the appropriate behavioral unit,

(2) maintenance trips, due to their essential nature, are usually performed at regular intervals and, once this interval is decided, the household will perform these trips regardless of any temporal constraints imposed on it, and

(3) an individual's decision to travel during a specific time period is influenced by both the amount of time available in different periods throughout the day and the activities performed by other household members.

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[6] No models were estimated for subsistence activities since they were assumed to occur on a daily basis at fixed locations and times.

Another study involving spatio-temporal constraints focused on the feasibility of various ridesharing strategies. Davis, et al. (1981), hypothesized the existence of a high potential for ridesharing (as a result of the inherent flexibility contained in individuals' activity patterns) and developed a methodology to investigate this potential. Various scenarios were constructed based on different assumptions regarding auto availability, fuel availability, the number of individuals per vehicle and the hours of operation of the ridesharing program. These assumptions were input to a simulation model to obtain estimates of the number of individuals who could utilize a ridesharing program. Although a simple maximum route deviation constraint was the only criterion used in the determination of whether or not an individual could utilize a ridesharing program, the examination of ridesharing for both work and non-work travel is significant.

2.5 Utility Maximization

A sizeable collection of complex travel behavior research efforts can be categorized as multivariate in scope. Borrowing heavily from the fields of operations research and econometrics, researchers have employed various methodologies, such as utility maximization, to develop models that explain how a set of "causal factors" affect individual behavior. A major emphasis of these models is the mathematical representation of the actual decision making process undertaken by the individual when evaluating alternate courses of action. Upon completion of the estimation of these models, many authors investigated the impacts of

changes in the transportation system, the activity system and the household.

In his thesis, Bain (1976) focused on activity duration (plus associated travel time) as the dependent variable and used the theoretical econometric approach of Tobin[7] to model the individual's two-fold choice of whether or not to participate and for how long. Although Bain included a variable "in-home activity supply" to account for the individual's trade-off between staying at home and traveling to non-home activities, he failed to account for the interdependence of activity durations and therefore was unable to explain particular activity sequences. Despite this shortcoming, Bain's work provided a foundation for subsequent research efforts. Jacobson (1978) extended the work of Bain with his investigation of the "simultaneity in intrahousehold task sharing." A simultaneous equation model was estimated and compared to single equation models for both the household head and spouse to test explicitly the hypothesis concerning joint allocation of activity time. Empirical results illustrated the need for additional research in the development of a behavioral theory that "recognizes the substitutability and complementarity of the household heads' activity time."

Horowitz (1976) used an ordinary least squares regression model to examine hypotheses regarding the effects of auto travel time and operating costs on the frequency of non-work travel and the demand for

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[7] Tobin, James (1958). "Estimation for Relationships for Limited Dependent Variables," Econometrica, Vol. 26, pp. 24-36.

multi-destination tours. Statistical tests revealed that only travel time had a significant effect on non-work auto travel frequency. In addition, reductions in travel frequency resulting from travel time increases were not compensated by increases in the average number of destinations visited per tour. Unfortunately, the hypothesis that increases in travel time cause reductions in trip length was not examined. In a second study, Horowitz (1978) developed a utility maximizing model for non-work travel demand that related tour frequency, sojourn frequency and destination choice to household characteristics, destination characteristics and transportation level of service. Horowitz hypothesized that households consider both past travel decisions and future travel plans when making current travel decisions due to limited travel resources (e.g., time, money, automobiles) and his incorporation of this concept into the model structure is significant. Model estimations showed that increases in household size and automobile ownership lead to increases in sojourn frequency. The average number of sojourns per tour was not, however, dependent on transportation level of service variables; this may be due to the failure to include travel times and costs between non-work destinations in the model structure. In another study, Horowitz (1980) employed a system of disaggregate travel demand models to estimate urban traveler responses to various gasoline allocation procedures. The allocation procedures considered were: (1) allocation by traditional rationing, (2) allocation by white-market coupons and (3) allocation by price increase (i.e., allowing the price to rise to a market clearing level). A wide range of potential responses

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was examined, including changes in mode, destinations, travel frequency, multi-destination tours and the price of gasoline. The results showed that reductions in non-work trip frequencies and trip lengths were the main sources of gasoline savings, irrespective of allocation procedure. Reductions in travel were considerably larger for low-income households than for high-income households when price-based allocation methods were used, while the distribution of effects is reversed in the case of non-price-based methods of allocation. Multi-destination travel increased only in the case of traditional rationing but this may have been due, in part, to the independent estimation of the work and non-work travel demand models which precluded any estimations of the potential for combining work and non-work travel. Sensitivity tests were also performed due to the age of the data set (1968 Washington, D.C. Household Interview Survey) and the indications were that the qualitative characteristics of travelers' responses to gasoline shortages were not highly sensitive to moderate changes in the travel environment.

Oster (1978a, 1978b) hypothesized that a principal incentive for visiting a non-work destination during a workplace-related trip (i.e., either a trip from home to work, a trip from work to home, or a tour that originates and terminates at the workplace) is to obtain a savings in the time and cost of travel, thereby lowering the total cost of the goods and services acquired via travel. Two alternate methods were used to obtain estimates of these savings. The first method (the fixed destination assumption) assumed that the household would have made a separate single destination trip to to the same destination for the same purpose. This

alternative represents the situation where the destination offers a highly specialized service (or product) of high value to the household and serves as an upper bound for the travel savings. The second method (the average destination assumption) assumed that a different destination would be visited for the same purpose via a single destination trip. This corresponds to the case where substitute services (or goods) are available at many locations in an urban area. Since the substitutability of activities varies across individuals and no information on this was available, the single destination trip used to visit this alternate destination was assumed to be equal to the average travel time and distance for all single destination trips made for the same purpose by households living in the same census tract. Results indicated that savings in travel resources on the order of 15% and 22% are obtained under the fixed and average destination assumptions. Oster also utilized ordinary least squares regression in an analysis of the relationships between the characteristics of household members and their use of workplace-related travel and found that the presence of a second worker in the household decreases the total number of non-work destinations visited but increases the number of non-work destinations visited via workplace-related travel.

Lerman (1979), in an important development, synthesized two different analysis methodologies, utility maximization and semi-Markov processes, to develop an operational, stochastic simulation model of non-work travel behavior. In this approach, probability distributions of dwell time at home and non-home locations were used to determine the departure times of

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the trips and multinomial logit models were estimated to predict the individual's joint choice of mode and destination.[8] (The actual simulation process consisted of alternating applications of the two methodologies throughout the day.) A lack of available data resulted in only limited testing of the model system. Despite the importance of this work several theoretical shortcomings in Lerman's approach can be identified. First, the individual's choice of departure time was assumed to be independent of any spatial effects (e.g., transportation level of service) or travel history (e.g., number of activity locations previously visited). Second, it was assumed that individuals choose their next mode/destination combination only after completion of their current activity. The assumed behavior thus precludes factors such as relative location from exerting an influence on individuals' choices. Finally, no consideration was given to the determinants of activity sequencing and therefore it was unclear how individuals decide the order in which they perform activities.

Most of the prior research, although recognizing the complicated nature of an individual's travel behavior, chose to simplify the problem by either ignoring one or more dimensions of choice (e.g., mode, destination, departure time, tour length, etc.) or assuming independence

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[8] Lerman estimated two distributions of departure time from home (one for the first departure and one for all subsequent departures) in recognition that the observed distribution of first departures from home is significantly different from the distributions of succeeding departures. In addition, two multinomial logit models were estimated (a home based model and a non-home based model) so that home was only considered as a potential destination when the individual was at a non-home location.

among the various dimensions. An attempt to model the full complexity of individual travel behavior (i.e., to explicitly incorporate the interdependent nature of the individual's choices) was made by Adler (1976). The basic underlying hypothesis of Adler's theoretical model is that households develop needs for non-home activities and make trade-offs between the desire to meet each need as it arises and the transportation expenditures required for travel. Households were assumed to choose a complete daily travel pattern based on its attractiveness (or utility) relative to other possible travel patterns. This attractiveness was expressed as a function of the attributes of the destinations selected for non-work activities, the total time spent performing non-home activities, the remaining household income after travel expenses and the households' socioeconomic characteristics. In addition, a variable--"scheduling convenience"--was developed to measure the "degree to which a travel pattern fits the schedule of household activities." Scheduling convenience was divided into two main components: (1) the allocation of household activities among activity sites (as measured by the total number of sojourns contained in the pattern) and (2) the allocation of sojourns among tours (as measured by the number of sojourns per tour). This latter component allowed Adler to incorporate explictly the households' trade-offs between single and multiple sojourn travel. The effects of a variety of transportation policies on an aggregate sample were predicted using an empirical model (a multinomial logit model) developed in accordance with the theory and the forecasts indicated that the average number of sojourns per tour decreased from the

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base value for each of the policies tested. This resulted from either an increase in the number of tours (in the case of travel incentive policies) or a decrease in the number of sojourns (in the case of travel disincentive policies). For transit-oriented policies, shifts in the use of multiple-sojourn tours were not significant enough to result in major changes in the relative proportion of home and non-home based trip links. In the case of the auto-oriented policies, however, the number of non-home based links decreased at a substantially higher rate than home-based trip links. Although Adler's use of individual travel patterns as the primary unit of travel demand is significant, several questions were left unanswered:

(1) How many alternate daily travel patterns does a household consider when making its decision?

(2) How does the temporal distribution of activities affect "scheduling convenience"?

(3) How does household interaction affect the choice of travel pattern?

2.6 Fully Integrated Pattern Approaches

The need to examine the entire collection of choices made by an individual was also recognized by Recker et al. (1980) in their empirical analysis of household activity patterns. In this study, an analysis framework was developed whereby the impacts of various transportation policies on individual's current daily behavior (i.e., activity patterns) could be assessed quantitatively. Individual activity patterns were

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transformed using pattern recognition techniques (a Walsh-Hadamard[9] transformation) and the resulting pattern coefficients were cluster analyzed using a k-means clustering algorithm. The pattern centroids were then inverted using associated inversion formulae to produce representative activity patterns which depicted the mean response pattern of all the individuals associated with a particular group. These representative activity patterns can be thought of as distinct market segments, in which all the members of a specific segment exhibit similar travel/activity behavior (i.e., choice of activities, activity time allocations, sequencing of activities, etc.) Upon completion of the classification phase, multiple discriminant analysis was used to determine the relative influence of various household and urban form characteristics on the representative activity patterns. Results based on a sample of 665 individuals in Orange County, California showed that the activity patterns of the sample population could be classified into nine representative patterns. In addition, it was found that employment status, role in the household, residential housing density and employment density were the dimensions that best discriminated the representative patterns. To illustrate the advantage of activity pattern analysis over conventional trip-oriented methodologies with respect to policy impact estimation, various daily restrictions on total vehicle miles traveled and gasoline purchases were imposed on the sample and tabulations of the total number of people unable to execute their observed activity patterns

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[9] Welchel, J.E. and D.F. Guinn (1968). "The Fast Fourier-Hadamard Transform and Its Use in Signal Representation and Classification," EASCON 1968 Record, pp. 561-573.

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were performed. The effectiveness of trip-chaining in counteracting the travel restrictions was also assessed via simulation. In the first simulation, a "chained" activity pattern was constructed by: (1) removing intermediate trips to and from home and (2) linking successive non-home activities. This procedure was carried out subject to the following constraints:

(1) The original non-home activity locations were fixed, and

(2) The original temporal sequence of the non-home activities was fixed.

The second simulation relaxed the constraint regarding original temporal sequence but imposed additional constraints on the timing of certain non-home activities. Results showed that a larger number of individuals were able to execute their activity pattern under travel restrictions by trip chaining and rearranging their activity sequence than simply by trip chaining. In addition, it was demonstrated that the impacts of travel restraint and the benefits of trip chaining and activity re-sequencing are not uniform across the population.

A second attempt at identifying general categories of urban travel behavior and the salient characteristics that give rise to this behavior was undertaken by Pas (1981). Although the entire activity pattern was once again chosen as the basic analysis unit, the methodologies employed to classify the behavior were quite different from those of Recker et al.

In the first step of the approach, Pas developed an index to measure the degree of similarity between pairs of activity patterns and used this to construct a similarity matrix. This similarity matrix was then

transformed, using the method of principal coordinates,[10] into a set of coordinates in Euclidean space. Finally, Ward's clustering algorithm[11] was used to group those patterns that were closest to each other in the Euclidean space (i.e., those patterns that were most similar). In addition, an investigation into the relationships between various demographic variables (e.g., age, marital status, employment status) and the activity pattern types was performed with the aid of the likelihood ratio chi-squared statistic. The empirical results indicated that a population's activity/travel behavior could be grouped into a small number (6-12) of categories without a significant loss in information and that certain demographic characteristics such as sex and number of children under twelve years of age influence the group membership. These results are similar to those obtained by Recker et al. despite the use of two different sets of analysis techniques.

Another research effort directed at developing an adequate framework for the analysis of complex travel behavior was undertaken by Kitamura et al. (1980). Unlike the two studies mentioned previously that considered the quantification and categorization of entire patterns of human behavior, this study attempted to develop a set of fundamental properties concerning an individual's spatio-temporal behavior (as depicted by

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[10] Gower, J.C. (1966). "Some Distance Properties of Latent Root and Vector Methods Used in Multivariate Analysis," Biometrika, Vol. 53, pp. 325-338.

[11] Ward, Jr., J.H. (1963). "Hierarchical Grouping to Optimize an Ojective Function," Journal of American Statistics Association, Vol. 58, No. 301, pp. 236-244.

various characteristics of their space-time paths). It was postulated that these properties, once empirically tested, would then serve as an appropriate foundation for the construction of a comprehensive theoretical framework. A simple stochastic-process model, integrating the concepts of the space-time prism and the intervening opportunities approach to trip distribution, was used to explore some of the basic relationships between tour size (i.e., number of sojourns), sojourn duration, sojourn location and time of day. Statistical tests resulted in the verification of the following set of spatio-temporal properties:

(1) The probability of returning home (i.e., completing a tour) is an increasing function of both time and distance from home.

(2) The average sojourn duration decreases as the number of sojourns in the tour increases.

(3) The average trip length to sojourn locations decreases as the number of sojourns in the tour increases.

(4) The number of tours performed by an individual increases with the number of available autos and the number of children in the household.

There are several important behavioral implications associated with these spatio-temporal properties. First, the dependence of the spatial distribution of sojourn locations on the number of sojourns, the interrelationship between sojourn duration and the number of sojourns and the interrelationships between tour continuance, time of day and distance from home all imply that the time-homogeneity and history-independence assumptions contained in the Markovian approach are inappropriate for the

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analysis of individual travel behavior. Second, the negative correlations between the number of sojourns and both the average sojourn duration and the average trip length suggest trade-offs between competing objectives--a feature that could be incorporated in a mathematical model of the individual decision process. Third, the strong correlation between the number of tours and the composition of the household (i.e., the number and ages of children in the household) indicates that the presence of children in the household place additional demands and constraints on the other family members which often results in a larger number of tours. This last hypothesis illustrates the need to include the effect of inter-personal household linkages in the theoretical framework.

2.7 Activity-based Approaches

Although it has been widely acknowledged that travel is a "derived demand," only recently has there been a shift in research emphasis from trip-based analysis frameworks to activity-based analysis frameworks. A pioneer in the area of activity-based approaches to complex travel behavior has been the Transport Studies Unit (TSU) in Oxford, England. Using the information obtained via in-depth interviews, the researchers at TSU developed a theoretical framework that placed individual travel behavior within the context of household activity scheduling behavior. More specifically, individual travel patterns were seen as resulting from a complex household interaction process which occurs as a consequence of both the interdependent nature of household members' activity schedules

and the presence of environmental constraints. Jones (1977) and his TSU colleagues attempted to gain some insight regarding the household interaction process with the aid of their Household Activity Travel Simulator (HATS). This interactive gaming device involves the use of visual display equipment in an in-depth, group interview situation. Each household member is first asked to construct his/her current activity schedule by placing a series of different colored blocks on a time line that represents the twenty-four hour day. The length of each block is proportional to the duration of the activity which it represents and a separate color is used for each different activity type (including travel). After being informed of a specific policy change, the household members are asked to rearrange their activity schedules. In addition to the information on the specific adaptations made by the individual household members (as provided by the "new" activity schedules), the interviewer is also able to obtain information about the actual household interaction process (e.g., priorities, preferences, etc.). Results from actual applications of HATS in West Oxfordshire (school hour revisions) and Basildon (alterations in bus service) indicate that the reallocation of activities among household members often takes place after changes are made in the transportation or activity system. Although this technique is extremely useful in small scale exploratory studies, it is clearly inappropriate for large scale studies involving a wide range of policy options.

Several researchers have attempted to incorporate the TSU framework into mathematical models of activity scheduling behavior. Damm (1979)

chose to view activity scheduling behavior as a series of non-home activity participation decisions. Following the recommendations of Jones (1977) and Heggie (1977),[12] Damm divided the twenty-four hour day into five time periods: (1) the time prior to the trip to work, (2) the time during the trip from home to work, (3) the time at work, (4) the time during the trip from work to home and (5) the time after the trip to home. The individual was assumed to choose between participating or not participating in a non-home activity during each of the five time periods. A decision not to participate was seen as an implicit decision to maintain one's current location (during time periods 1, 3 and 5) or travel destination (during time periods 2 and 4). It was also assumed that the individual's choice regarding length of participation in non-home activities was conditional on his/her choice of whether or not to participate and a separate model was estimated for activity duration. Embodied in this framework is a recognition that certain in-home activities are discretionary in nature and compete with out-of-home activites for a "place" in the individual's activity schedule. This competition was incorporated in the model with the introduction of a variable representing the time allocated to discretionary activities in time periods other than that being evaluated. Estimation of the models revealed that the variable, "time spent in other periods," was significant (i.e., interrelationships exist among the various temporal

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[12] Both Jones and Heggie agree that the twenty-four hour day should not be treated as a continuous block of time but instead should be divided into a progression of discrete time periods to better understand the interdependence of an individual's time/space decisions.

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and spatial decisions made by an individual throughout the day) although its effect was not uniform across all time periods (i.e., certain time periods are planned more separately than others). The effects of socioeconomic variables were also not uniform across the time periods as individuals were influenced more by household characteristics in time periods involving the home (periods 1 and 5) than by those involving the work site (periods 2, 3 and 4). Two variables that served as surrogate measures of the effect of household competition for automobiles (i.e., workers per auto in period 1 and auto accessibility for non-workers in periods 2, 3 and 4) also proved significant, indicating the interdependence that exists among individual household members. Despite of the compromises made during the construction of various proxy variables, Damm's efforts have provided much insight not only into the relative influence of various factors but also into the interrelationships among these factors. Several issues, however, were not addressed in the methodology, including:

(1) How can the choice of mode be integrated into the model framework?

(2) How does an individual decide on a particular non-home activity sequence during a given time period?

(3) What are the time periods associated with non-working individuals?

Van der Hoorn (1981) also modeled individual travel behavior as a subset of the total activity pattern using a disaggregate model/simulation system. Multinomial logit models, developed for both

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choices of activity and location, were incorporated in a simulation system that generated the individual's activity pattern. The simulation system was similar to that developed by Tomlinson et al. (1973), with the exception that the fixed "apriori probabilities" used by Tomlinson et al. were replaced by those estimated from the logit models. Since the simulation system addressed aggregate behavior, the logit models were aggregated using a three-stage process. First, the population was classified into 21 subgroups based on car ownership and urbanization levels. Second, the average values of the explanatory variables were calculated and included in the logit models. Third, the average subgroup choice probabilities generated in the second step were weighted by the proportion of the subgroup contained in the total population to yield total aggregate shares. Although Van der Hoorn's model, like that developed earlier by Damm, accounts explicitly for the trade-offs between staying at home and traveling to non-home destinations, only two non-home locations (in town and outside town) were included in the model. In addition, mean travel times were employed in the model under the assumption that they were representative of the travel by any individual in a particular subgroup. Finally, all locations with travel times greater than their corresponding durations were eliminated from the individual's choice set, which resulted in the exclusion of several observed choices.

In general, much of the recent research has provided insight to the degree of choice available to individuals (or households) when making their decisions. Unfortunately, almost all of this research suffers

from the same limitation--an inability to provide any information on the specific set of alternatives (i.e., the choice set) considered by an individual during the decision process. Although many authors have speculated that the number of alternatives actually considered by an individual is much less than the total number of potential alternatives, they have as yet been unable to systematically incorporate this premise into a theoretical framework. An exception to this is the work of Clarke and Dix (1980). As a preliminary step in the development of a mathematical model of choice set formulation, a combinatorial algorithm (CARLA[13]) was used to generate all of the feasible permutations of a given set of activities (i.e., alternative activity schedules). In recognition of the need to maximize computational efficiency, constraints on the timing of activities were introduced into the model prior to the generation of the permutations. These constraints consist of two basic types:

(1) supply side constraints (e.g., stores are only open during certain hours) and

(2) institutional constraints (e.g., meal times can only be shifted by 45 minutes either way).

The input required by the model included a list of the activities to be scheduled, their corresponding durations, and the temporal constraints. The output of the model consisted of all the "feasible" permutations of the activities (i.e., all those permutations that did not violate the

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[13] Combinatorial Algorithm for Rescheduling Lists of Activities

constraints). Activity data obtained from a study of school hours changes in Burford, England (both "before" and "after" data) was used to test the model and the results showed that in 65% of the cases, the chosen activity schedule was generated as one of the alternatives in the choice set. Although the authors point to the need for further development of the model (e.g., the incorporation of inter-personal linkages, and travel times between activity locations, the estimation of a choice mechanism), preliminary results have demonstrated the feasibility of using a combinatorial approach to the choice set problem.

2.8. Research Directions

In the myriad of behavioral hypotheses presented throughout this review, it is possible to identify three basic concepts which hold particular promise for the development of a comprehensive theory of complex travel behavior. The first involves the role of travel in individual daily life. Demand for travel is derived from the need to participate in various activities at specific locations and, therefore, individuals' travel choices should be viewed as arising from a more fundamental set of activity participation choices. The second concept concerns the environment in which activity participation decisions are made. Choices regarding activity participation are not unlimited, but are instead subject to a variety of constraints such as the spatial/temporal distribution of activity locations, the spatial/temporal obligations of the individual (e.g., the need for employed individuals to spend a fixed amount of time at a fixed location) and the transportation modes available for use by the individual. Much of the prior research

that has focused exclusively on observed choice has been unable to explain the more "complex" aspects of travel behavior (e.g., trip chaining) due to an inability to distinguish between those choices that are available to an individual and those that are not. An explicit recognition of the manner by which various constraints act to limit the choices available to an individual will not only eliminate infeasible courses of action from consideration but also allow a much wider range of policies (e.g., flextime, changes in the operating hours of service facilities, ridesharing) to be analyzed. A third concept (and one that is closely associated with the second) relates to the interdependent nature of an individual's activity participation decisions. At any point in time, an individual's current decision is influenced both by previous actions as well as by future intentions, and all of these are influenced by the decisions of other household members. These interdependencies result from:

(1) Individuals can only be at one location at any given time.

(2) Individuals can only change their location by consuming time (and this is a limited quantity).

(3) Different activity locations are not available at all times and/or at all locations.

(4) Certain activities require the participation of more than one individual (household member).

As a result of these interdependencies, there exists a need to analyze the entire set of individual activity participation decisions as a whole, instead of analyzing each individual decision in isolation from the others.

CHAPTER THREE

Theoretical Development

3.1 Introduction

In this chapter a comprehensive theory of complex travel behavior is presented that places travel in a broader context than in single-trip methodologies. In this theory travel is viewed as an input to a more basic process involving activity participation decisions. A significant portion of the theoretical development involves the formulation of a theory of individual choice set generation that incorporates the effects of both environmental and household constraints as well as individual limitations with respect to information processing and decision making.

3.2 The Relationship Between Travel and Activity Scheduling

A fundamental tenet of the theoretical framework advanced is that travel decisions are subsidiary to activity participation decisions. This approach is consistent with the accepted notion that travel is a derived demand, that is, individuals travel to participate in activities that take place at spatially separated locations. At any particular time an individual possesses a set of needs and desires that arise due to physiological, social and economic factors. The fulfillment of these needs is achieved through participation in activities at specific locations and times. The activity locations and durations, as well as the actual activities themselves, scheduled for completion during a specified time interval constitute the individual's activity program.

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This activity program represents the demand for travel during that time interval and can be represented as,

$$P = \{(a_1, \ell_1, \tau_1), (a_2, \ell_2, \tau_2), \ldots, (a_j, \ell_j, \tau_j), \ldots, (a_N, \ell_N, \tau_N)\} \qquad (3.1)$$

where: P = the activity program associated with a particular individual

a_j = the jth activity $(j=1,2,\ldots,N)$

ℓ_j = the location of the jth activity

τ_j = the duration of the jth activity

For any specific activity program, P, individuals are faced with a set of decisions involving the scheduling (and, correspondingly, the travel linkages which connect the activities in the time-space continuum) of the activities contained in P. Once implemented, these activity scheduling decisions transform the individual's activity program into an activity pattern--an ordered sequence of activities and travel accomplished during some time period, termed the <u>action period</u>. This sequence can be represented as,

$$AP = \{(a_1, \ell_1, \tau_1, t_1), (a_2, \ell_2, \tau_2, t_2), \ldots, (a_j, \ell_j, \tau_j, t_j), \ldots, (a_N, \ell_N, \tau_N, t_N)\}; \qquad (3.2)$$
$$t_1 < t_2 < t_3, \ldots, < t_j, \ldots, < t_N$$

where: AP = the activity pattern associated with a particular individual

t_j = the starting time of the jth activity

a_j, ℓ_j, τ_j are as previously defined

and the transformation process can be represented as,

$$AP = d \circ P ; \quad d \in D \qquad (3.3)$$

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where: d = the set of activity scheduling decisions made by a
            particular individual

        D = the total collection of feasible activity scheduling
            decision sets available to a particular individual

        AP,P are as previously defined.

Therefore, implicit in an individual's selection and implementation of a
specific activity pattern is the selection and implementation of an
entire set of decisions concerning the scheduling of activities. Within
this context, travel is seen as the mechanism that allows an individual
to schedule activities in a particular manner and consequently, complex
travel behavior is the resultant of complex activity scheduling behavior.

3.3 Formulation of the Individual's Choice Set

Prior to the examination of the set of activity scheduling decisions
made by the individual (i.e., the observed activity pattern), those sets
of activity scheduling decisions that could be implemented by the
individual (i.e., the feasible activity patterns) must be identified.
Although individuals may face a variety of constraints that limit the
number of feasible activity patterns, the constraints that are of primary
interest here exist because individuals cannot:

   •   occupy more than one location at a given time,

   •   participate in activities at all locations or at all times of
        the day,

   •   travel between activity locations instantaneously (i.e.,
        individuals must consume time to change their location) and,

   •   travel to all locations by all modes at all times of the day.

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The specific constraints imposed on an individual are determined by the nature of his/her transportation supply environment, while the actual opportunities available to the individual are the result of the interaction between this environment and the individual's activity program. The process by which an individual's transportation supply environment and activity program are formulated is illustrated in Figure 1. Associated with each household is a household transportation supply environment that consists of the following:

- the set of modes available to the household
- the spatial distribution of activity locations
- the times during which the activity locations are available, and
- the spatial connectivity of activity locations by modes.

In addition, each household also has associated with it an activity demand environment which is composed of the desired activities of each individual member of the household. The individuals in the household are viewed as making decisions regarding the allocation of activities and automobiles based on a complex household interaction process which includes the specific nature of the activities, the household roles associated with each individual member and the characteristics of the supply environment. Although the actual relationship between the two allocation decisions is unknown, three possible relationships can be posited:

(1) activities are distributed among individual household members and then automobiles are allocated to individuals based on the nature of their activities, .

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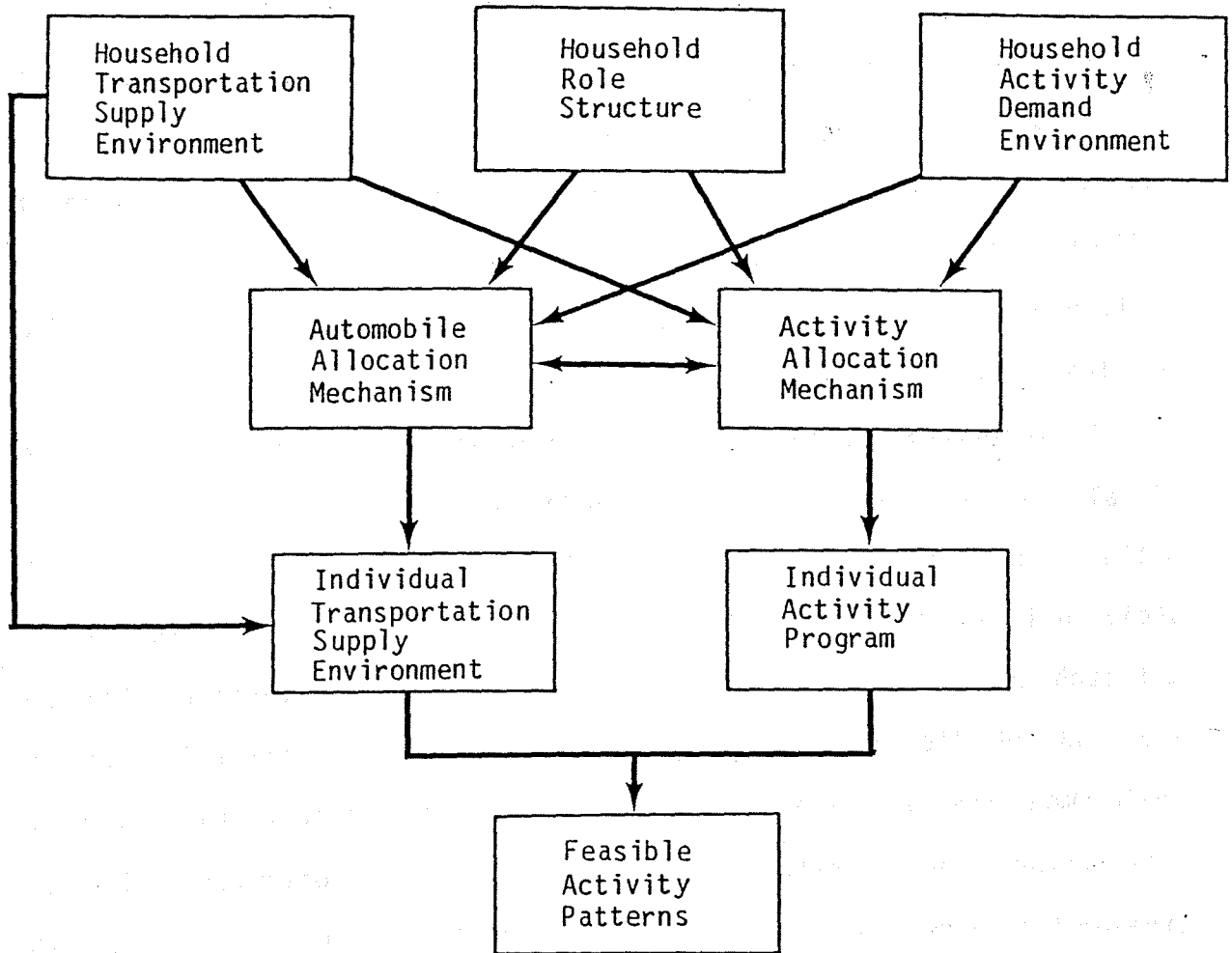
Figure 3.1.   Feasible Activity Pattern Generation Process

(2) automobiles are allocated to individual household members and then activities are distributed among individuals based on their "share" of the household automobiles, or

(3) activities and automobiles are allocated simultaneously.

The outcome of this complex interaction process is the creation of both an individual transportation supply environment and an individual activity program. The individual transportation supply environment differs from the household transportation supply environment in that it contains those specific times when the individual has an automobile available for his/her use.

The opportunities theoretically available to the individual consist of all of the feasible activity patterns (i.e., all those activity patterns that do not violate any of the constraints imposed on the individual by his/her transportation supply environment). Let the set of all such opportunities be denoted F. Although the interaction between the individual's activity program and his/her transportation supply environment restricts the number of available options that can be chosen, that number, in general, will be quite large--a consequence that is problematic from both operational and behavioral points of view. With respect to the former, the application of utility maximizing choice models to choice sets involving large numbers of alternatives results in extremely small choice probabilities for all of the alternatives contained in the set. This property has resulted in the use of various random sampling techniques to reduce the size of the choice set prior to the estimation of the choice probabilities. With respect to the latter,

empirical evidence obtained from various studies in experimental psychology has shown that individuals are limited with respect to the number of alternatives that they can consider when making a choice.

In addition, there is no guarantee that the feasible activity patterns that result from the interaction between the individual's activity program and transportation supply environment are perceived by the individuals as distinct options. Certain activity patterns, because of their similarity with respect to a large number of dimensions, may be perceived by the individual as being indistinguishable and therefore not treated as separate alternatives. Consequently, the actual choice set can be represented as,

$$C = \psi \text{ o } F \tag{3.4}$$

where: C = the actual choice set available to a particular individual

F = the opportunity set available to a particular individual

ψ = a classification reduction process that operates on the opportunity set in such a manner that distinct elements are produced.

The output of this classification procedure consists of a smaller set of distinct activity patterns that comprise the individual's choice set. This resultant choice set can be characterized by the following properties:

(1) The number of alternatives contained in the choice set is smaller than the total number of opportunities available to the individual.

(2) The choice set is composed of distinct alternatives.

(3) The alternatives reflect the effects of both environmental and household constraints.

(4) The choice set varies across individuals (as a result of the variation in constraints).

3.4 Representation of the Activity Program

In general, the activity program of an individual can include both planned and unplanned activities,[1] i.e.,

$$A = \{C,X\} \tag{3.5}$$

where:

A = set of activities $(a_1, a_2, \ldots, a_j, \ldots, a_n)$ included in the activity program.

C = set of planned activities $(c_1, c_2, \ldots, c_j, \ldots, c_m)$

X = set of unplanned activities $(x_1, x_2, \ldots, x_j, \ldots, x_r)$

and

$$a_j \in C \quad \text{if } P_{t_0}(a_j) = 1$$

$$a_j \in X \quad \text{if } P_{t_0}(a_j) < 1$$

where: $P_{t_0}(a_j)$ = the probability that at the commencement, t_0, of the action period a need will exist for activity j to be performed by the individual.

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[1] In the context of its use in this development the term "unplanned" refers to activities for which the scheduling process occurs during the action period, while "planned" refers to those activities for which the scheduling process occurs prior to the action period. Both types of activities occur, of course, during the action period.

The corresponding activity program for an individual can now be represented as:

$$P = \{(c_1,\ell_1,\eta_1),(c_2,\ell_2,\eta_2),\ldots,(c_j,\ell_j,\eta_j),\ldots,(c_m,\ell_m,\eta_m);$$

$$(x_1,\ell_1^*,\eta_1^*),(x_2,\ell_2^*,\eta_2^*),\ldots(x_j,\ell_j^*,\eta_j^*),\ldots,(x_r,\ell_r^*,\eta_r^*)\} \qquad (3.6)$$

where: P = an individual's activity program

c_j = the jth planned activity

ℓ_j = the required location of the jth planned activity

η_j = the required duration of the jth planned activity

x_j = the jth unplanned activity

ℓ_j^* = the required location of the jth unplanned activity

η_j^* = the required duration of the jth unplanned activity

and where it is assumed that, prior to the action period, ℓ_j and η_j are known by the individual while ℓ_j^* and η_j^* are unknown.

3.5 The Components of Time

In the development that follows, it is convenient to visualize the action period, $t_0 \leq t \leq t_1$, as comprised of time segments of three basic types: travel, wait and participation. The total time associated with any activity j of type m, Q_j^m, is given as:

$$Q_j^m = D_j^m + T_j^m + W_j^m$$

where:

D_j^m = time spent participating in the jth activity of type m

T_j^m = time spent traveling to the jth activity of type m

W_j^m = time spent waiting to participate in the jth activity of type m

Q_j^m = total time associated with the jth activity of type m

and

$$\sum_{\forall j \varepsilon P} Q_j = t_1 - t_0 \qquad (3.7)$$

3.6 The Utility of an Activity Pattern

The utility of any specific activity pattern to an individual is comprised of the utilities of each of its component parts. Each activity segment of an activity pattern can be represented as a triad consisting of: 1) travel (if any) to the activity, 2) waiting (if any) for the activity to commence and 3) actual participation in the activity.[2]

The utility corresponding to each component of the triad associated with any activity j can be designated as:

$U(D_j^m)$ = the utility of time spent participating in the jth activity
of type m

$U(T_j^m)$ = the utility of time spent traveling to the jth
activity of type m

$U(W_j^m)$ = the utility of time spent waiting to participate
in the jth activity of type m

In addition to their inherent attributes, activities have two functional classifications of importance to this study. The first such classification (already identified) involves whether or not the knowledge

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[2]Any waiting time following a particular activity is viewed as waiting time for the next activity.

that the activity would be performed preceded the action period during which it is performed (i.e., planned vs. unplanned). The second classification relates to whether or not the location of the activity is the home location (i.e., in-home vs. away-from-home).

Planned activities are functionally different from their unplanned counterparts in that the latter must be inserted into an existing activity pattern which may already contain commitments with varying degrees of rigidity. Indeed, the probability that unplanned activities may arise during the action period can be expected to influence the amount of flexibility built into the "planned" executable activity pattern on an individual's agenda at t_0.

That the home is an activity location of special significance need not be argued. It is the location that simultaneously offers the maximum amount of privacy from non-household members and the maximum potential for interaction among household members. More importantly, it represents the base for staging an individual's activity pattern. Furthermore, the value of time spent at this location is as much determined by the activity schedules of other members of the household as by the inherent characteristics of the location itself.

The discussion that follows is organized according to these functional classifications.

3.6.1 The Utility of Participation in Planned Activities

Participation in planned activities is predicated on the availability, within the individual's activity pattern, of a segment of

time greater than or equal to the time required to complete the activity. Since both the actual travel times to activity locations as well as the activity durations themselves are stochastic in nature, the individual will possess incomplete information regarding the availability of time in his/her planned activity pattern. Because of the cumulative effect of these stochastic events, the individual can reasonably be expected to have more confidence in his/her estimates of scheduling requirements associated with trips/activities that occur early in complex tours than with those that occur late in such tours and also more with simple tours than with complex tours. Given that the utility of participating in an activity is only realized if the participation actually takes place and there exists a non-zero probability that participation will not take place, individuals are assumed to consider the expected utility of participation in planned activities.

Let:

$E\{U(D_j{}^C)\}$ = the expected utility of time spent participating

in planned activity j

then:

$$E\{U(D_j{}^C)\} = U(D_j{}^C) \cdot P_j \qquad (3.8)$$

where

P_j = the probability that sufficient time will be available to complete the planned activity associated with the jth position in the activity pattern.

Let:

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$E\{T_j\}$ = the expected value of time spent traveling to activity j

ϵ_j = the random component of time spent traveling to activity j

$E\{D_j\}$ = the expected value of time spent participating in activity j

θ_j = the random component of time spent participating in activity j

Then:

$$T_j = E\{T_j\} + \epsilon_j \qquad (3.9a)$$

$$D_j = E\{D_j\} + \theta_j \qquad (3.9b)$$

and the corresponding value of P_j can be shown to be given by

$$P_j = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} \prod_{k=1}^{j-1} f_k(t_k)dt \prod_{k=1}^{j} g_k(u_k)du_k .$$

$$F_j(t_j^f - t_j^d - E\{T_j\} - E\{D_j\} - \sum_{k=1}^{j-1} t_k - \sum_{k=1}^{j} u_k) \quad (3.10)$$

where

t_j^d = the departure time of the trip to activity j

t_j^c = the ending time of participation in activity j

t_j^f = the ending time of the temporal availability of activity j

$f_j(t)$ = the density function for ϵ_j

$F_j(t)$ = the distribution function for ϵ_j

$g_j(t)$ = the density function for θ_j

$G_j(t)$ = the distribution function for θ_j

and where all distributions are assumed to be independent.

If it is assumed that the the utility of time spent participating in planned activity j is invariant with respect to the actual time over which participation takes places, given that participation takes place during time period $[t_0, t_1]$ i.e.,

$$U_t(D_j{}^c) = \mu_j \quad \text{for} \quad t_0 \le t \le t_1 \tag{3.11}$$

where: $U_t(D_j{}^c)$ = the utility of time spent participating in planned activity j when participation takes place during time interval $[t_0, t_1]$

μ_j = an activity specific constant,

then,

$$E\{U_t(D_j{}^c)\} = \mu_j \cdot P_j \quad \text{for} \quad t_0 \le t \le t_1, \tag{3.12}$$

3.6.2   The Utility of Time Spent Waiting to Participate in Planned Activities

Participation in certain activities may be dictated by schedules inherent to the activity (e.g., theater, physician visits). Arrival at a location prior to the scheduled start of an activity will, in such cases, result in a period of time spent by the individual waiting for commencement. It is assumed in this research that individuals derive no direct utility from time spent waiting to participate in planned activities, i.e.,

$$U(W_j{}^c) = 0 \; ; \; \forall c_j \tag{3.13}$$

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3.6.3 The Utility of Travel to Planned Activities

As stated previously, travel has utility only within the context of the access it provides to a desired or needed activity. Arguments relative to the disutility of travel are well documented and will not be repeated here. Rather than attempt to select a precise functional form, it will suffice for this study to assume that the utility of time spent traveling to planned activity j is inversely related to the amount of time spent traveling and directly related to activity importance, i.e.,

$$U(T_j^c) = f(-T_j^c, m_j) \tag{3.14}$$

where the negative sign is used merely to designate that an inverse relationship exists between the dependent variable and the corresponding independent variable. Since

$$T_j = E\{T_j\} + \epsilon_j,$$

therefore:

$$U(T_j^c) = f(-E\{T_j^c\}, m_j) \tag{3.15}$$

3.6.4 The Utility of Participation in Unplanned Activities

As a result of the possibility that unplanned activities may arise during time period $[t_0, t_1]$, there exists some utility associated with reserving, within the planned activity pattern, the potential to participate in unplanned activities, i.e., the flexibility to meet unforseen needs. This potential is, in the most general sense, a function of the number of activity locations that an individual can

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access within a time sufficient to participate in the activity, i.e.,

$$V_j^X = f(Y_j) \tag{3.16}$$

where

V_j^X = the potential to participate in unplanned activity j

Y_j = the number of activity locations that an individual

can travel to and participate in unplanned activity j

The number of activity locations, Y_j, is itself a function of the volume of the space-time prism, the spatial and temporal distributions of activity j locations, and the time required to complete the activity, i.e.,

$$V_j^X = f'(\nu, \rho_j, \lambda_j, \eta_j^*) \tag{3.17}$$

where

ν = volume of the space-time prism

ρ_j = spatial distribution of activity j

λ_j = temporal distribution of activity j

The space-time prism, $\wp$, is defined as the set of all points (k,t) in space-time such that,

$$t \geq t_{\ell_i} + T_{\ell_{i,k}} \tag{3.18a}$$

$$t \leq t_{\ell_{i+1}} - T_{\ell_{k,i+1}} \tag{3.18b}$$

i.e., $\quad \wp = \{(k,t) \mid t_{\ell_i} + T_{\ell_{i,k}} \leq t \leq t_{\ell_{i+1}} - T_{\ell_{k,i+1}} \} \tag{3.19}$

where

t_{ℓ_i} = time an individual is free to leave location i

$t_{\ell_{i+1}}$ = time an individual must arrive at location $i+1$

$T_{\ell_{i,k}}$ = the travel time from location i to location k

$T_{\ell_{k,i+1}}$ = the travel time from location k to location $i+1$

Furthermore, the geographical region, R, encompassing all the locations that the individual can reach and still satisfy the coupling constraints he/she confronts is defined by all locations k such that,

$$T_{\ell_k} \leq (t_{\ell_{i+1}} - t_{\ell_i})$$

(3.20)

i.e.,

$$R = \{k \mid T_{\ell_k} \leq (t_{\ell_{i+1}} - t_{\ell_i})\}$$

(3.21)

where

T_{ℓ_k} = the travel time from location i to location $i+1$

through location k (i.e., $T_{\ell_k} = T_{\ell_{i,k}} + T_{\ell_{k,i+1}}$) .

Let

Γ_k^* = the constrained maximum duration of time spent

at location k .

Then:

$$\Gamma_k^* = (t_{\ell_{i+1}} - t_{\ell_i}) - T_{\ell_k}$$

(3.22)

Also, let

τ_k^* = the set of all possible durations contained in the

segment of time Γ_k^*

The potential opportunities associated with each location $k \in R$ can now be characterized by both the set of activities that can be performed at

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location k and the set of durations contained in the segment of time defined by the constrained maximum duration of time spent at location k, i.e.,

$$\Omega = \left\{ (\underset{\sim}{A}_k, \tau_k^*)_{k \in R} \right\} \tag{3.23}$$

where

Ω = the set of total potential opportunities

$\underset{\sim}{A}_k$ = the subset of activities that can be performed at location k

Although Γ_k^* represents the maximum duration that an individual could spend at location k given the coupling constraints $(t_{\ell_i}, t_{\ell_{i+1}})$, more important is the maximum amount of time an individual can spend participating in activities at location k given these same constraints.

Let: $t_{j,k}^s$ = the starting time of the temporal availability of activity j at location k

$t_{j,k}^f$ = the ending time of the temporal availability of activity j at location k

Then the unconstrained maximum participation duration for activity j at location k, $\Gamma_{j,h}$, is given by

$$\Gamma_{j,k} = t_{j,k}^f - t_{j,k}^s . \tag{3.24}$$

Denote by $\tau_{j,k}$ and $\tau_{j,k}^*$ the set of possible durations contained in the segment of time $\Gamma_{j,k}$ and $\Gamma_{j,k}^*$, respectively, where the latter time segment corresponds to the constrained maximum participation duration for activity j at location k (i.e., determined

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$$U(T_j^c) = f(-T_j^c, m_j) \qquad (3.14)$$

where the negative sign is used merely to designate that an inverse relationship exists between the dependent variable and the corresponding independent variable. Since

$$T_j = E\{T_j\} + \epsilon_j,$$

therefore:

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As a result of the possibility that unplanned activities may arise during time period $[t_0, t_1]$, there exists some utility associated with reserving, within the planned activity pattern, the potential to participate in unplanned activities, i.e., the flexibility to meet unforseen needs. This potential is, in the most general sense, a function of the number of activity locations that an individual can

access within a time sufficient to participate in the activity, i.e.,

$$V_j^X = f(Y_j) \tag{3.16}$$

where

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Y_j = the number of activity locations that an individual

can travel to and participate in unplanned activity j

The number of activity locations, Y_j, is itself a function of the volume of the space-time prism, the spatial and temporal distributions of activity j locations, and the time required to complete the activity, i.e.,

$$V_j^X = f'(\nu, \rho_j, \lambda_j, \eta_j^*) \tag{3.17}$$

where

ν = volume of the space-time prism

ρ_j = spatial distribution of activity j

λ_j = temporal distribution of activity j

The space-time prism, θ, is defined as the set of all points (k,t) in space-time such that,

$$t \geq t_{\ell_i} + T_{\ell_{i,k}} \tag{3.18a}$$

$$t \leq t_{\ell_{i+1}} - T_{\ell_{k,i+1}} \tag{3.18b}$$

i.e., $\theta = \{(k,t) \mid t_{\ell_i} + T_{\ell_{i,k}} \leq t \leq t_{\ell_{i+1}} - T_{\ell_{k,i+1}} \}$ \hfill (3.19)

where

t_{ℓ_i} = time an individual is free to leave location i

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$t_{\ell_{i+1}}$ = time an individual must arrive at location $i+1$

$T_{\ell_{i,k}}$ = the travel time from location i to location k

$T_{\ell_{k,i+1}}$ = the travel time from location k to location $i+1$

Furthermore, the geographical region, R, encompassing all the locations that the individual can reach and still satisfy the coupling constraints he/she confronts is defined by all locations k such that,

$$T_{\ell_k} \leq (t_{\ell_{i+1}} - t_{\ell_i}) \tag{3.20}$$

i.e.,

$$R = \{k \, | T_{\ell_k} \leq (t_{\ell_{i+1}} - t_{\ell_i})\} \tag{3.21}$$

where

T_{ℓ_k} = the travel time from location i to location $i+1$ through location k (i.e., $T_{\ell_k} = T_{\ell_{i,k}} + T_{\ell_{k,i+1}}$) .

Let

Γ_k^* = the constrained maximum duration of time spent at location k .

Then:

$$\Gamma_k^* = (t_{\ell_{i+1}} - t_{\ell_i}) - T_{\ell_k} \, . \tag{3.22}$$

Also, let

τ_k^* = the set of all possible durations contained in the segment of time Γ_k^*

The potential opportunities associated with each location $k \in R$ can now be characterized by both the set of activities that can be performed at

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location k and the set of durations contained in the segment of time defined by the constrained maximum duration of time spent at location k, i.e.,

$$\Omega = \left\{ (\underset{\sim}{A}_k, \tau_k^*)_{k \in R} \right\} \tag{3.23}$$

where

Ω = the set of total potential opportunities

$\underset{\sim}{A}_k$ = the subset of activities that can be performed at location k

Although Γ_k^* represents the maximum duration that an individual could spend at location k given the coupling constraints $(t_{\ell_i}, t_{\ell_{i+1}})$, more important is the maximum amount of time an individual can spend <u>participating in activities at location k</u> given these same constraints.

Let: $t_{j,k}^S$ = the starting time of the temporal availability

of activity j at location k

$t_{j,k}^f$ = the ending time of the temporal availability

of activity j at location k

Then the <u>unconstrained</u> maximum participation duration for activity j at location k, $\Gamma_{j,h}$, is given by

$$\Gamma_{j,k} = t_{j,k}^f - t_{j,k}^S . \tag{3.24}$$

Denote by $\tau_{j,k}$ and $\tau^*_{j,k}$ the set of possible durations contained in the segment of time $\Gamma_{j,k}$ and $\Gamma^*_{j,k}$, respectively, where the latter time segment corresponds to the <u>constrained</u> maximum participation duration for activity j at location k (i.e., determined

from $\Gamma_k{}^*$). Then,

$$\tau^*_{j,k} = \tau^*_k \cap \tau_{j,k} \quad . \qquad (3.25)$$

Furthermore, the geographical region, R^*, encompassing all the locations that an individual can travel to and spend the <u>required</u> amount of time participating in a specific activity given the coupling constraints is defined by

$$R^* = \{ k \mid \Gamma^*_{j,k} \geq \eta^*_j \} \qquad . \qquad (3.26)$$

Now, each location $k \in R^*$ can be characterized by both the set of activities available at location k and the set of durations contained in the segment of time defined by the constrained maximum participation duration, i.e.,

$$\Omega^* = \left\{ \begin{matrix} (A_k, \tau^*_k) \\ \forall k \in R^* \end{matrix} \right\} \qquad (3.27)$$

which defines the set of <u>feasible</u> locations for participation in activities, should the need arise, subject to the constraints imposed by participation in planned activities.

The utility of reserving flexibility in the planned activity pattern for such unforeseen events is dependent upon the likelihood that they may arise. Specifically, it is postulated that the utility of the potential to participate in unplanned activity j at location k is equal to the expected utility of time spent participating in unplanned activity j at location k, i.e.,

$$U(V_{j,k}{}^x) = U(D_{j,k}{}^x) \cdot P_t\{D_{j,k}{}^x \mid x_j\} \cdot P_t(x_j) \qquad (3.28)$$

where

$U(V_{j,k}{}^X)$ =   the utility of the potential to participate in - unplanned activity j -at location k

$U(D_{j,k}{}^X)$ =   the utility of time spent participating in unplanned activity j at location k

$P_t(D_{j,k}{}^X | x_j)$ =   the probability that unplanned activity j will be participated in at location k given that unplanned activity j occurs during time t

$P_t(x_j)$ =   the probability that unplanned activity j will occur during time t.

The probability of occurrence of an activity is dependent both on the frequency of occurrence of the activity as well as on the time that has elapsed since the last occurrence of the activity, i.e.,

$$P_t (x_j) = f(\gamma_j, \xi_j) \qquad\qquad (3.29)$$

where: γ_j = the average time interval between occurrences of activity j

        ξ_j = the elapsed time since the last occurrence of activity j

The elapsed time since the last occurrence of a particular activity is, in general, not evident in standard travel diary information for all activities that occur less frequently than the time period under consideration. Consequently, the measurement time origin with respect to the activity arrival process must be considered as random.

Under such conditions it can be verified that

$$P_t (x_j) = \frac{1}{\gamma_j} \qquad\qquad (3.30)$$

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where γ_j is measured in unitless terms relative to the time interval $t_1 - t_0$.

The probability that participation in unplanned activity j will take place at location k <u>given that unplanned activity j occurs during time t</u> is manifest in the relative number of visits to location k for unplanned activity j, i.e.,

$$P_t\left(D_{j,k}^X \mid x_j\right) = \frac{N_{k,j}}{N_j} \qquad (3.31)$$

where

$$N_{k,j} = \text{the number of trips to location } k \text{ for activity } j$$

$$N_j = \text{the number of trips to all locations for activity } j$$

$$= \sum_k N_{k,j}$$

Then,

$$U(V_{j,k}^X) = \left[U(D_{j,k}^X)\right] \cdot \left[\frac{N_{k,j}}{N_j}\right] \cdot [1/\gamma_j] \qquad (3.32)$$

If it is assumed that the utility of time spent participating in unplanned activity j is constant regardless of location, i.e.,

thus,
$$U(D_{j,k}^X) = U\left(D_j^X\right); \quad \forall k \epsilon \Omega^* \qquad (3.33)$$

$$U(V_{j,k}^X) = U(D_j^X) \cdot \frac{N_{k,j}}{N_j} \cdot \frac{1}{\gamma_j} \qquad (3.34)$$

The utility of the total potential to participate in unplanned activities, $U(V^X)$, is (assuming utilities are linearly additive)

$$U(V^X) = \sum_{\forall j} \sum_{\forall k \epsilon \Omega^*} U(D_j^X) \cdot \frac{N_{k,j}}{N_j} \cdot \frac{1}{\gamma_j} \qquad (3.35)$$

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If, as in the case of planned activities, it is assumed that the utility of time spent participating in an activity is constant for a specific type of activity,

$$U(V^X) = \sum_{\forall j} \sum_{\forall k \epsilon \Omega^*} \omega_j \cdot \frac{N_{k,j}}{N_j} \cdot \frac{1}{\gamma_j} \qquad (3.36)$$

3.6.5 The Utility of Travel to Unplanned Activities

In addition to the utility that is associated with an individual's potential to perform unplanned activities, there will also be some utility (disutility), $U(T_j^X)$, associated with the additional travel time that may be incurred if the individual participates in an unplanned activity. As in the case of planned activities, it is assumed that the utility of the additional travel time spent traveling to participate in an unplanned activity is directly related to the importance of the activity and inversely related to the amount of time spent traveling, i.e.,

$$U(T_j^X) = f(-T_j^X, m_j) \qquad (3.37)$$

However,

$$T_j^X = f(x_j, \ell_j^*) \qquad (3.38)$$

and, since both x_j and ℓ_j^* are unknown before the need to perform x_j arises, then,

$$U(T_j^X) = f(-E\{T_j^X\}, m_j) \qquad (3.39)$$

where

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$$E\{(T^X)\} = \sum_{\forall j} \sum_{\forall k \varepsilon \omega^*} T_{j,k}{}^X \cdot \frac{N_{k,j}}{N_j} \cdot \frac{1}{\gamma_j} \qquad (3.40)$$

where: $T_{j,k}{}^X$ = the additional travel time associated with participation in unplanned activity j at location k.

$$= (T_{\ell_{i,k}} + T_{\ell_{k,i+1}}) - T_{\ell_{i,i+1}} \qquad (3.41)$$

in which

$T_{\ell_{i,k}}$ = the travel time from the location of the ith planned activity to location k

$T_{\ell_{k,i+1}}$ = the travel time from location k to the location of the $(i+1)$st planned activity

$T_{\ell_{i,i+1}}$ = the travel time from the location of the ith planned activity to the location of the $(i+1)$st planned activity

3.6.6 The Utility of Time Spent Waiting to Participate in Unplanned Activities

As in the case of planned activities, individuals are assumed to derive no direct utility from expected time spent waiting to participate in unplanned activities, i.e.,

$$U(W_j{}^X) = 0 \; ; \; \forall x_j \qquad (3.42)$$

3.6.7 The Utility of Participation in Discretionary Home Activities

As discussed in a previous section, the home location occupies a special position in activity pattern formulation. The concept of complex travel behavior (trip chaining) itself is defined relative to the number of sojourns that take place in a tour prior to the return home. As such, questions involving an individual's decision whether or not to return home following completion of any out-of-home activity are fundamental to this research.

As in the case with out-of-home activities, in-home activities may be planned in advance of the action period. Such cases do not differ fundamentally from out-of-home planned activities. A similar statement may be advanced regarding unplanned in-home activities. However, there is a third category of in-home activities that has no real counterpart in the away-from-home world--those that arise as a by-product of decisions that form the out-of-home activity schedule. For example, the decision not to chain two successive trips together explicitly creates an in-home activity that may simply be a default state for the individual.

In general, there may be many options within an activity program to include in-home activities. It is postulated that the utility of time spent participating in home activities is a function of the activities available to the individual during the stay at home, i.e.,

$$U(D_j^h) = f(\underset{\sim}{H}_j) \tag{3.43}$$

where: $U(D_j^h)$ = the utility of time spent participating in home activities during the jth stay at home

$\underset{\sim}{H}_j$ = the set of activities available to an individual during the jth stay at home

$$E\{(T^X)\} = \sum_{\forall j} \sum_{\forall k \epsilon \omega^*} T_{j,k}^{X} \cdot \frac{N_{k,j}}{N_j} \cdot \frac{1}{\gamma_j} \qquad (3.40)$$

where: $T_{j,k}^{X}$ = the additional travel time associated with participation in unplanned activity j at location k.

$$= (T_{\ell_{i,k}} + T_{\ell_{k,i+1}}) - T_{\ell_{i,i+1}} \qquad (3.41)$$

in which

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$\underset{\sim}{H}_j$ = the set of activities available to an individual during the jth stay at home

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Information concerning the specific _nature_ of activities available to individuals at home is, in general, unobtainable from conventional travel diaries and, as a result, $\underline{H}$ is unknown. However, it appears reasonable to assume that the utility of time spent at home is directly correlated to the _number_ of activities available to the individual and that this number, in turn, is highly related to both the amount of time spent at home and the number of household members at home during the stay, i.e.,

$$U(D_j^h) = f'(N_j^h) \qquad (3.44)$$

and

$$N_j^h = f''(D_j^h, I_j^h) \qquad (3.45)$$

where: I_j^h = the number of household members at home during the jth stay.

N_j^h = the number of activities available to an individual during the jth stay.

In general, I_j^h may not be constant over the temporal range of the jth stay at home. Additionally, since the number of household members at home at any time is dependent on their activity patterns (which are stochastic in nature), an individual does not know with certainty the value of I_j^h but, rather, is assumed to act relative to the expected value. Then,

$$U(D_j^h) = f''' \; E \; D_j^h | I_j^h = i \qquad i = 1, 2, \ldots, N \qquad (3.46)$$

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3.6.8 The Utility of Travel to Home Activities

The utility of travel time to home activities which are planned in advance of the action period does not differ, in any fundamental respect, from that associated with planned activities in general. For those home activities which arise as a by-product of activity/trip scheduling decisions, however, the trip purpose dependency is degenerative and the utility of the travel time associated with the trip to home is assumed to be inversely related to only the expected amount of time spent traveling, i.e.,

$$U(T_j^h) = f(-E\{T_j^h\}) \qquad (3.47)$$

3.6.9 The Utility of Time Spent Waiting to Participate in Home Activities

There is no waiting time inherent to home activites that arise as by-products of activity/trip scheduling decisions. Waiting time associated with planned home activities does, however, differ fundamentally from that associated with out-of-home activities and is equivalent to time spent on activities that arise as by-products. The corresponding utilities associated with such time are also equivalent.

3.7 The Activity Schedule

The sequencing, prior to the action period, of the activities in the activity program constitutes the individual's planned activity schedule, S, i.e.,

$$S = (c_1,s_1),(c_2,s_2), \ldots, (c_j,s_j), \ldots (c_N,s_N) \qquad (3.48)$$

where:

S = an individual's activity schedule

c_j = the jth planned activity

s_j = the start time of the trip to the jth activity

The implementation of this schedule, subject to the possibility of unforeseen occurrences such as unplanned activities or travel delays, constitutes the individual's activity pattern, AP. It is the fundamental tenet of this research that the observed activity pattern is the manifestation of the individual's attempt to select the activity schedule which maximizes the utility of the activity pattern that can be expected to be executed during the action period.

More specifically, let

AP_k = the expected activity pattern that will arise from activity schedule S_k

ψ = the set of feasible activity schedules available to an individual.

Then, it is assumed that the individual will select activity schedule S_k if

$$U(AP_k) > U(AP_p) \qquad S_p \in \psi \qquad (3.49)$$

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where

$$U(AP_k) = \text{the total utility of the expected activity pattern arising}$$
$$\text{from activity schedule } S_k.$$

This view is consistent with the notion that observed activity patterns which contain unplanned activities are derived from activity schedules which allowed for the possibility of their occurrence. (This position has rather significant implications regarding estimation which will be discussed in a subsequent section.)

The total utility of the expected activity pattern derived from activity schedule S_k then can be represented as being comprised of the individual components of utility associated with each element of the pattern, i.e.,

$$U(AP_k) = f\{[U(D_j{}^c), U(T_j{}^c), U(W_j{}^c); \forall C_j \epsilon L],$$
$$[U(D_j{}^h), U(T_j{}^h); \forall h_j \epsilon S],$$
$$[U(V^x), U(T^x), U(W^x); \forall \theta \epsilon S]\}$$

CHAPTER FOUR

The Operational Model

4.1 General Approach

A comprehensive methodology has been developed to examine the formation of household travel/activity patterns utilizing a simulation approach. The methodology is comprised of six stages:

(1) Specification of individual activity programs from an examination of household activity programs and constraints, and the interactions between the household members given the existing supply environment.

(2) Generation of the set of feasible, individual travel/activity patterns through a proposed constrained, combinatoric scheduling algorithm.

(3) Identification of distinct members of the set of feasible travel/activity patterns by means of pattern recognition techniques.

(4) Identification of a non-inferior (perceived) pattern set for individual choice utilizing a multi-objective programming approach.

(5) Specification of a representative activity pattern set (if necessary), forming the choice set for each household member, utilizing pattern recognition and classification theory.

(6) Formulation of a pattern choice model, which specifies individual travel/activity pattern choice probabilities.

The proposed methodology is discussed in detail in the following subsections.

4.2 Analysis of Household Interaction and the Specification of

Individual Activity Programs

In light of the theoretical development concerning the interactive household forces that affect the formulation of individual activity programs, it is necessary to simulate these interactions to adequately treat the issue of activity program generation.

Although opinions differ on the actual decision-making unit, whether the household or the individual, household interactions do constrain the range of alternatives available to the individual. It is assumed that the household itself has an activity program, that is, a list of activities that can be classified as subsistence (such as work or school), maintenance (such as shopping or personal business), or leisure (general social/entertainment/recreational). Certain activities are associated with specific individuals (particularly subsistence activities) and must be completed by that individual. Other activities provide the household utility, but not from the necessary participation of specific individuals (such as maintenance shopping), and are assigned by the household through some constraint process.

If activities are assigned to individuals according to their flexibility, beginning with subsistence activities which by definition are least flexible in space, time and participation, the ability of household members to perform more flexible activities is iteratively

reduced as each activity is assigned. The ability to perform remaining activities is greatly affected by the distribution of the activity locations, the necessary activity durations, destination time constraints and the availability of transport modes within the household, the latter a function itself of the assignment of inflexible activities.

A series of household, in-home constraints reduce the assignment potential, as household members interact jointly, in and out of the home, and share the household automobile(s). The assignment of the automobile itself may be a function of activity priority to the household, or a function of individual priority over the automobile.

The first simulation module (TROOPER) models these interactive forces internally, so that the resultant individual activity program (or programs) reflects these household contraints.

The specification of the individual pattern choice sets is produced in the remaining four modules. These patterns can be compared among household members to examine the results of the simulated interactions. If the discrepancy is significant, the household constraints, priorities, allocations, and automobile availability are altered for each affected member and the process repeated.

4.3 A Constrained, Combinatoric Scheduling Algorithm for the Generation of Feasible Activity Programs

Once the set of activity programs corresponding to each household member is specified, the set of feasible activity patterns is generated through a constrained, combinatoric scheduling algorithm (SNOOPER), the

home activity (either planned or discretionary (inserted)) may a change of mode occur. In other words, each tour is mode specific, the mode choice decision assumed to occur when the tour is initiated.

These assumptions disallow: (1) non-home-based tours which utilize a different mode such as leaving work for lunch by an alternate mode (a non-home based tour is considered as part of a larger, home-based tour), (2) multi-modal tours with direct access of one mode by another (such as park and ride), and (3) the consideration of walking trips from any sojourn of a tour to another. Locations accessed by walking as a second mode will considered as made by the primary mode.

Use of a coded travel network facilitates modal analysis for private modes, given the spatial and temporal flexibility of the automobile. Even the inclusion of walking trips is possible through a modification of the network, and possibly a distance restriction for pattern feasibility. The integration of public travel modes, however, is considerably more complex due to the their characteristic inflexibility--both spatial and temporal. The restrictions of fixed routes and fixed schedules produce more rigorous constraints on the feasibility of any given pattern. A test for spatial connectivity, by a specific public mode, must be performed followed by a calculation of travel time based on the appropriate schedules.

The issue of connectivity for transit involves not only the consideration of direct routes, but also connectivity through transfer to intersecting routes. This, of course, complicates the timing calculations as the scheduling problem must consider the transfer route,

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and its temporal availability. To complicate matters further, the feasibility of the entire simulated tour must be established rather than feasibility on a link by link basis as with automobile. Since it has been assumed that changes in mode may occur only at home, a restriction imposed by combinatorics, a tour is mode specific. If any one link of a tour cannot be successfully completed, due either to system connectivity or suitable scheduling, then that tour and simulated pattern become infeasible.

The number of mode choice decisions is equal to the number of tours, the latter being itself a function of the number of planned activities (NFILE). For a choice set of M modes, the number of potential modal combinations, c^M, for any activity sequence is

$$c^M = M^{NTOUR} \tag{4.3}$$

where NTOUR = number of executed tours.

Assuming a binary mode choice, potentially 32 modal sequences may arise for each activity pattern of five planned activities. An extension to 3 modes finds this maximum to increase to 243; these combinations being applied to each activity sequence generated in the second element. In the transit sub-module, a feasibility test for spatial connectivity is made and a maximum distance restriction placed on walk trips (if desired) to insure overall feasibility of the tour. Once feasible modal sequences are assigned, a test of scheduling feasibility is performed.

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Variable Description	Activity	
	1	2
TB Earliest Unconditional Starting Time	8:00	9:30
TD Activity Duration (hrs.)	3.0	1.0
TES Earliest Conditional Starting Time	8:00	12:00
TT Travel Time (hrs.)		1.0
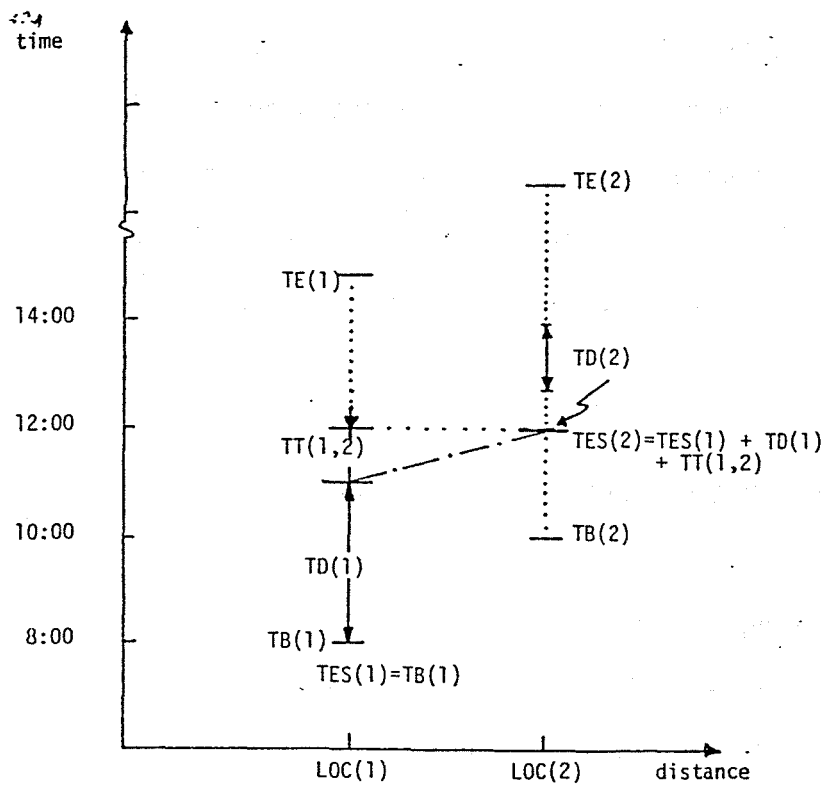
FIGURE 4.3 COMPUTATION OF EARLIEST CONDITIONAL STARTING TIME

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duration). The process proceeds iteratively forward through the activity sequence. The travel times utilized are, of course, mode specific.

The latest conditonal starting time, TLS(I), may be interpreted as the latest an activity may commence given the scheduling restrictions of activities which follow. Together with the TES vector, TLS serves to further restrict the actual clock scheduling of each activity. The TLS vector is computed in an iterative fashion similar to TES, but proceeding backward through the activity sequence as follows:

$$TLS(N) = TE(N)-TD(N) \qquad (4.5a)$$

$$TLS(I) = MIN[TY(I),TZ(I)], I=(N-1),(N-2),...,1 \qquad (4.5b)$$

where

$$TY(I) = TE(I)-TD(I) \qquad (4.5c)$$

$$TZ(I) = TLS(I+1)-TD(I)-TT(I,I+1) \qquad (4.5d)$$

$$TE(I) = \text{latest unconditonal ending time of activity I}$$

and all other variables are as defined before. Figure 4.4 illustrates the computation of TLS vector. In summary, the latest conditional starting time, TLS(I), of an activity is taken as the minimum of: (1) the latest ending time for the activity minus its duration, and (2) the latest conditional starting time of the following activity, adjusting for the former activity's duration and travel time between the two. The process is executed iteratively backward through the activity sequence.

The last task of this element is to determine scheduling feasibility of the proposed pattern through a comparison of the earliest conditional starting time, TES(I), and the latest conditional starting time, TLS(I). The pattern schedule is feasible if the following inequality holds:

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Variable	Description	Activity J	N (or J+1)
TE	Latest Unconditional Ending Time	8:00	9:00
TD	Activity Duration	1.0	2.0
TT	Travel Time		(1.0)
TLS	Latest Conditional Starting Time	7:00	4:00
TB	Earliest Unconditional Starting Time	7:00	3:30
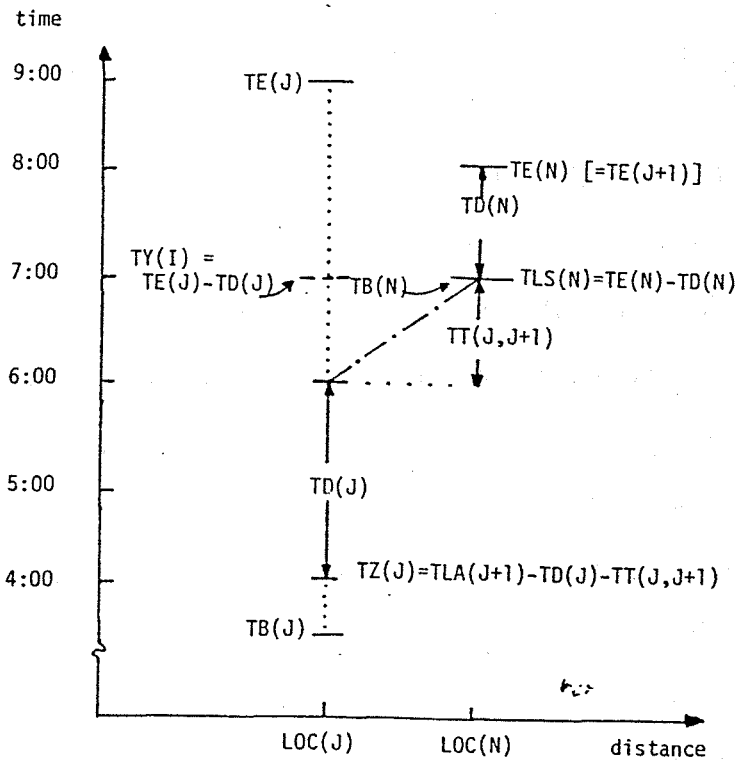
FIGURE 4.4 COMPUTATION OF LATEST CONDITIONAL STARTING TIME

$$TLS(I) \geq TES(I), \text{ for } I = 1,\ldots,N \tag{4.6}$$

The scheduling flexibility of various activities (taken here as a positive difference between the latest and earliest conditional starting times) may produce a range of similar, yet distinct patterns. The actual simulation of the full activity pattern schedule occurs in the fifth element.

4.3.5 Activity Scheduling

The number of potential starting times, $IRNG(1)$, for the initial activity of a sequence is computed based on the flexibility described above as

$$IRNG(1) = [TLS(1)-TES(1)]/DT + 1 \tag{4.7}$$

where DT is a model parameter which establishes the basic time unit for analysis. A value of DT from 0.1 to 0.25 (corresponding to 6 minutes to 15 minutes) is suggested to properly capture the scheduling of activities. This value may be considered the smallest time increment in which the individual decision-maker operates.

All succeeding planned activities on the simulated tour are assigned a range of one $[IRNG(I)=1, I=2,N]$, that is, they occur as soon as possible after the execution of the previous activity. The time associated with a scheduling delay due to conditional starting tmes is considered waiting time. It is important to realize that at no time in the constrained combinatoric scheduling algorithm is any attempt made to establish the superiority, or inferiority, or any given activity pattern. This second program module's sole function is to produce the entire set of feasible activity patterns available to each household member.

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$$TI(1) = 0 \tag{4.10b}$$

$$TF(1) = TS(1)+TD(1) \tag{4.10c}$$

For each succeeding activity, the arrival time, $TA(I)$, is set to the previous activity's finishing time $TF(I-1)$, plus the travel time between the two locations. The activity start time, $TS(I)$ is taken as the maximum of the arrival time, $TA(I)$ and the earliest unconditional start time, $TB(I)$. Wait time before activity commencement, $TI(I)$, is the difference between start and arrival times, and activity finishing time is simply start time, $TS(I)$, plus activity duration, $TD(I)$, or

$$TA(I) = TF(I-1) + TT(I-1,I) \tag{4.11a}$$

$$TS(I) = MAX[TA(I),TB(I)] \tag{4.11b}$$

for $I=2,\ldots,N$

$$TI(I) = TS(I)-TA(I) \tag{4.11c}$$

$$TF(I) = TS(I)+TD(I) \tag{4.11d}$$

A full pattern is specified for every combination accepted based on:

(1) insertion of home activities

(2) activity permutations

(3) modal permutations, and

(4) individual activity scheduling.

The simulation is completed for each individual in the household in question, for as many households as desired.

4.3.7 Summary of the Second Module

The constrained, combinatoric scheduling algorithm has been discussed in detail and several observations should be made. Primarily, the algorithm generates the full set of potential activity patterns available to an individual given a specified activity program. No decision rules or basic behavioral hypotheses have been invoked, and no claim is made on the nature of the results being representative of an actual individual choice set. The third and fourth modules of the simulation model produce a tractable choice set for the individual and his/her household. The importance of the present module is its simultaneous consideration of the range of choice attributes in the formation of an activity pattern. Not only is sequence and duration simulated, but a fully scheduled activity pattern results. Implicit to the formation of the patterns are the concepts of tours and mode selection and, most importantly, an extensive range of household and environmental constraints are imbedded in the resultant structure.

4.4 Reduction to a Distinct Pattern Set

The individual's feasible pattern set resulting from the second simulation module may be of considerable magnitude in even a significantly constrained situation. There is not, in general, any guarantee that the alternatives of the feasible set are perceived by individuals as distinct options. Certain sets of activity scheduling decisions, because of their similarity on several dimensions, may be perceved as indistinguishable and therefore should not be treated as

separate options for the individual. When such similarities arise, the set of feasible patterns must be modified in such a way that each of the resulting options is as distinct as possible. Recent empirical research (Recker et al., 1980; 1981; Pas, 1981) has demonstrated the potential of various classification techniques in formulating "representative activity patterns" (RAP's) defining homogeneous groups of distinct patterns. An added result of classification is reduction of the feasible set to a manageable option set, defined by the classification algorithm as independent (in the statistical sense), alternate activity patterns.

The third simulation module (GROOPER) has been developed and implemented to identify an independent pattern set through the specification of representative activity patterns. Although the present formulation has focused on a method explicitly devised for pattern analysis--a multiple scale, scoring function classification technique, the potential for analysis by other techniques is imbedded (such as pattern transformation by Walsh/Hadamard or Haar transformation algorithms[5]). The scoring function classification is presented in detail, with the algorithm separated into four elements for clarity.

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[5]These transforms are discussed explicitly in Recker et al. (1980, 1981). A rotational transform is used, the transformed data matrix reduced, classified and inverted, and the representative patterns are produced.

4.4.1 Data Transformation

The scoring function classification technique treats discrete and continuous variables separately in a cluster-based classification algorithm, a necessity due to the presence of both explicitly discrete data (e.g. activity type, mode, and the existence of a return trip home after a planned activity) and also continuous data (temporal and spatial characteristics). Figure 4.5 schematically illustrates the flow logic of the entire module.

Data must be categorized as not only discrete or continuous, but also as nominal or ordinal (e.g. mode is both discrete and nominally scaled, activity type is both discrete and ordinally scaled--assuming an ordered fixity in type specification[6]--and duration is continuous and, at least, ordinally scaled). Discrete value range must be specified. The following set of descriptive variables is proposed to classify an activity pattern:

(1) actual pattern position of activity (including any home insert activity)

(2) activity position in tour

(3) number of sojourns in the tour

(4) tour number

(5) sojourn location

(6) activity arrival time

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[6]Recker et al. (1980) develop a ordinal activity type scale based on observed fixity of activities by purpose. This scale will be adapted for this study.
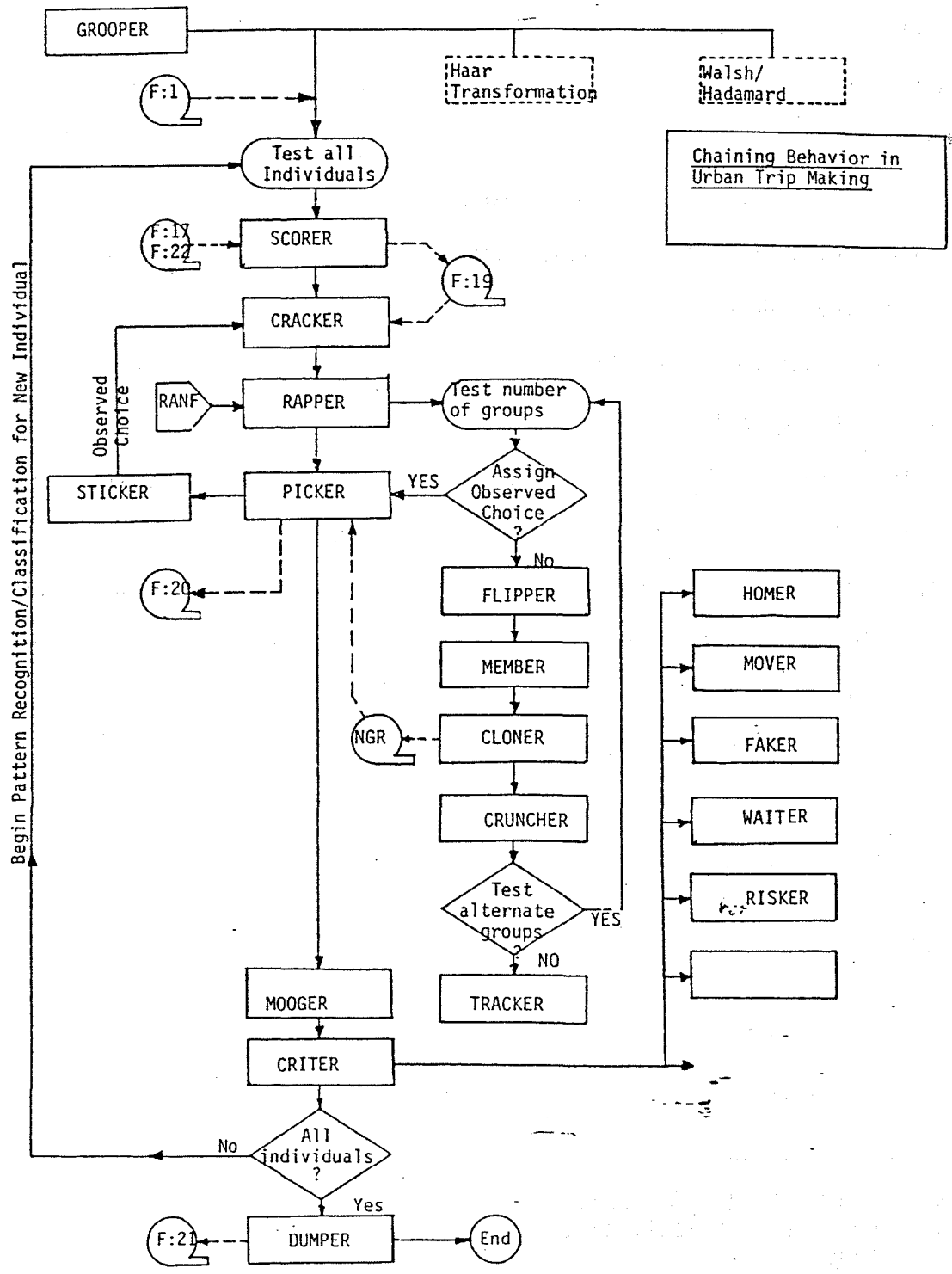
FIGURE 4.5 GROOPER MODULE

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(7)   activity start time

(8)   activity duration

(9)   mode used to activity

(10) whether activity is followed by a return home,

(11) travel time to home, and

(12) duration at home (if returned)

These variables are specified directly from the set of feasible patterns. Additional attributes may include accompanying individuals and activity waiting time (pre-and post-). The variables are listed in the original order of activities in the activity program to insure that characteristics of a specific planned activity will be compared with similar characteristics in alternate patterns for the same planned activity. Pattern sequence (variables 1 through 4 above) is implicit to the classification process. This procedure follows intuitively since activity information should be compared with similar information in alternate patterns to produce meaningful representative patterns.

4.4.2 Pattern Recognition

Several feasible patterns are randomly selected and assigned as representative patterns to initiate the scoring function for each individual. A range of desired groupings (i.e. number of RAPs) is specified, influenced perhaps by the size of the feasible pattern set, or by limitations associated with a realistic choice set. For example, an average individual may consider a range of seven to nine distinct alternatives as a maximum.

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The random assignment of patterns commences an iterative process where succeeding patterns are assigned to the RAP with which it is scored closest. After all patterns are assigned, new RAPs are estimated, and the assignment process repeats. The process converges when all feasible patterns are assigned to the "best" representative activity patterns, and the process is stabilized. The algorithm provides for alternate random initialization points and automatically adjusts the range of RAPS acceptable at each iteration.

4.4.3 Classification of Activity Patterns

The pseudo F-ratios associated with each homogeneous grouping (RAP) executed are compared, with the pattern set associated with the maximum F-ratio considered the "best" distinct pattern set. The full set of feasible activity patterns generated in the constrained, combinatoric scheduling algorithm are now depicted as "members" of a limited set of fully specified, representative activity patterns. The opportunity set of feasible patterns is now reduced to the option set of representative patterns.

4.4.4 Consideration of Observed Choice

The observed activity pattern for each household member, translated into classification variables, is now compared to each RAP in the selected option set. A pairwise comparison is made by re-entering the pattern recognition algorithm, utilizing the option set RAP's as the random patterns, and assigning the observed pattern to the "best" RAP.

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4.5 Alternate Specifications of the Choice Set Formation Model

Implicit in the approach outlined above is the assumption that the number of representative activity patterns (i.e., alternatives) resulting from the pattern recognition/classification algorithm is of sufficiently small size so that the individual decision maker can compare the utility of each alternative and select the one that maximizes his/her utility. However, those individuals who have very few constraints imposed on them by their environment will have, in general, a large number of opportunities available to them which, in turn, may result in a large number of distinct alternatives. Recent studies in the fields of psychology and marketing research have presented evidence that there exists a strong relationship between the complexity associated with a choice situation and the decision rule used by an individual. Results obtained from controlled experiments conducted by Payne (1976) and Park (1976) revealed that individuals often use non-compensatory decision rules (often some type of conjunctive rule) in complex choice situations and compensatory decision rules in choice situations involving small numbers of alternatives. Forester (1977) states in his conclusions that transportation researchers and planners should "...consider the possibility of non-additive decision rules and test a broad range of choice models before adopting any one model as an explanation of individual choice behavior." As a preliminary attempt at investigating whether individuals do, in fact, employ different decision mechanisms based on the size of the decision problem, two alternate choice set formation models have been formulated.

As was discussed previously, each individual is assumed to possess a set of objectives that he/she seeks to accomplish while performing the activities contained in his/her activity program. The choice of a specific activity pattern is therefore viewed as a multi-objective decision problem:

$$\text{MAX } \underset{\sim}{Z}(AP_1, AP_2, \ldots, AP_i, \ldots, AP_N) =$$

$$\text{MAX}[Z_1(AP_1, AP_2, \ldots, AP_i, \ldots, AP_N), Z_2(AP_1, AP_2, \ldots, AP_i, \ldots, AP_N), \ldots,$$

$$Z_p(AP_1, AP_2, \ldots, AP_i, \ldots, AP_N), \ldots, Z_R(AP_1, AP_2, \ldots, AP_i, \ldots, AP_N)] \quad (4.12)$$

where: $\underset{\sim}{Z}(AP_1, AP_2, \ldots, AP_i, \ldots, AP_N) = $ the multiobjective objective function

$Z_p(AP_1, AP_2, \ldots, AP_i, \ldots, AP_N) = $ the pth objective function

AP_i = the ith alternative

If a single alternative is found which simultaneously satisfies these optimality criteria (i.e., optimizes the R functions in Eq. (4.11)) then a unique optimal solution is obtained. There will, in general, be conflicts between objectives and consequently, it will not be possible to obtain an optimal solution (i.e., a solution that is optimal with respect to one of the R objectives will usually be non-optimal for the other R-1 objectives).

One concept that is inherently tied to decision making in the presence of multiple, conflicting objectives is the concept of non-inferiority. A feasible solution to a multiple-objective decision-making problem is non-inferior if there exists no other feasible solution that will yield an improvement in one objective without causing a degradation in at least one other objective. As an illustration of

this definition, consider the choice situation depicted in Table 4.2. In this example, the individual is assumed to have three opportunities (I, II, and III) available to him/her and each of these opportunities has associated with it two decision objectives (A and B). The values of the objectives for each of the opportunities are shown in the cells of the matrix.

Table 4.2. Choice Situation

DECISION OBJECTIVE

OPPORTUNITY	A	B	
I	V_{1A}	V_{1B}	$V_{1A} > V_{1B}$
II	V_{2A}	V_{2B}	$V_{2A} < V_{2B}$
III	V_{3A}	V_{3B}	$V_{3A} > V_{3B}$

$$V_{1A} > V_{3A} > V_{2A} \quad V_{2B} > V_{1B} > V_{3B}$$

If the individual sought to maximize objective A and minimize objective B, then opportunities I and III would be considered non-inferior since neither opportunity allows the individual to optimize both of the objectives simultaneously. (Opportunity I yields the maximum amount of objective A while opportunity III yields the minimum amount of objective B). On the other hand, opportunity II is inferior to both I and III since it offers less of A and more of B than either of the other two opportunities. Alternatively, if the individual chose to maximize both A and B, then opportunities I and II would be considered non-inferior and

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opportunity III would be inferior (with respect to opportunity I). This last point helps illustrate the dependence of the non-inferior solutions on the specific nature of the decision objectives.

As an initial step in the formulation of alternative choice models, it is assumed that each individual possesses an acceptability threshold (α_i) that defines the minimum level of acceptability for an opportunity and only those opportunities that equal or exceed this acceptability threshold are included for subsequent evaluation. This opportunity "screening" process can be expressed as,

$$P(AP_j \, \epsilon \, C_i) = \begin{array}{l} 1, \text{ if } AP_j \geq \alpha_i \\ 0, \text{ if } AP_j < \alpha_i \end{array} \qquad (4.13)$$

where: $P(AP_j \, \epsilon \, C_i)$ = the probability that the jth activity pattern is included in individual i's choice set, C_i

In general, it is hypothesized that α will be a function of the individual's specific decision objectives, i.e.,

$$\alpha_i = \zeta(Z_i) \qquad (4.14)$$

where: α_i = the acceptability threshold of individual i

Z_i = the set of decision objectives associated with individual i

ζ = a function

Having previously defined the concept of non-inferiority (and inferiority) with respect to multiple, conflicting objectives, it is assumed that individuals maximize the utility they can achieve from the set of non-inferior opportunities (as opposed to the set of total opportunities) and, as a result of this assumption, α can be defined as the threshold of non-inferiority. The set of non-inferior opportunities (Q_i) can be expressed as,

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$$Q_i = \Phi(\alpha_i) \text{ o } F_i \qquad\qquad (4.15)$$

where: Q_i = the set of non-inferior opportunities

$\Phi(\alpha)$ = a transformation process that operates on the opportunity set

but, since $\alpha_i = \zeta(Z_i)$ then,

$$Q_i = \Phi^*(Z_i) \text{ o } F_i \qquad\qquad (4.16)$$

Under this assumption, the choice set formation model can be expressed as,

$$C_i = \psi \text{ o } Q_i \qquad\qquad (4.17)$$

where: C_i, Q_i and ψ are as previously defined

Equation (4.17) states that the feasible opportunities actually evaluated using a utility maximization decision rule are those opportunities judged by the individual to be non-inferior based on his/her decision objectives. Implicit in the model formulated above is the assumption that the individual will consider all the distinct non-inferior solutions. However, as the number of distinct non-inferior solutions increases, the probability that the individual will be able to consider all of them decreases. As a result, a second model has been developed that assumes individuals select a subset of the total non-inferior solutions to be evaluated via utility maximization. This model can be thought of as representing a type of "satisficing" behavior, since in this model individuals do not evaluate all the non-inferior solutions.

To estimate these two models, a multi-objective programming algorithm has been developed that identifies those solutions that are non-inferior based on a set of decision objectives. The algorithm (SMOOPER)

initializes the first feasible activity pattern as non-inferior and iteratively adds subsequent non-inferior patterns to the set whenever a feasible pattern has a higher value on at least one objective than each pattern already contained in the set. Any pattern within the set which subsequently is found inferior as new patterns are added is deleted from the non-inferior set. Once these non-inferior solutions are identified they are input to the classification algorithm (to determine the choice set) and choice probabilities can then be estimated. In the former model, all the non-inferior alternatives are input to the classification algorithm, while in the case of the latter, a random sampling procedure is envoked to select a subset of the total noninferior solutions.

To test the hypothesis that the complexity of the decision problem determines the set of decision rules employed by the individual, each of the models are estimated for each individual in the sample. Comparisons between the predictive accuracy of the various models can be tested using Cochran's generalization of McNemar's two sample correlated proportions test (Cochran, 1950). This test involves the scoring of correct predictions as 1's and incorrect predictions as 0's and the computation of a statistic (Q) which has an asymptotic chi-square distribution. Cochran's Q statistic can be used to test the equality of the true proportion of correct predictions for all of the models and can also be used to test specific contrasts between models or groups of models. Thus it is analogous to the standard analysis of variance.

Cochran shows that an overall test of equality may be performed by computing the statistic

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$$Q = \frac{\Sigma[T_j - T]^2}{[J\Sigma T_i - \Sigma T_i^2][1/J(J-1)]}$$ (4.18)

where: $T_j = \sum\limits_i S_{ij}$

$T_i = \sum\limits_j S_{ij}$

$T = \sum\limits_j T_j / J$

J = the number of models

$S_{ij} = \begin{array}{l} 1, \text{ if model } j \text{ correctly predicts individual } i\text{'s choice} \\ 0, \text{ otherwise} \end{array}$

A schematic of the flow logic of the SMOOPER module is shown in Figure 4.6.

4.6   Specification of the Pattern Choice Set

The reduction of the distinct feasible activity pattern set to the subsidiary non-inferior set was executed primarily to eliminate inferior pattern alternatives from individual consideration. The effect of this operation also produces a more tractable alternative set. Figure 4.1 depicts the translation of the opportunity set, made up of feasible patterns, into the option set composed of non-inferior patterns. If desired, the size of this option set may be reduced further by application of the fifth module, REGROOPER, to produce a distinct choice set of any size mandated either by computational limitations or theoretical implications. (The tradeoff in the reduction is, of course, the clarity of the definition of the patterns in the choice set.)

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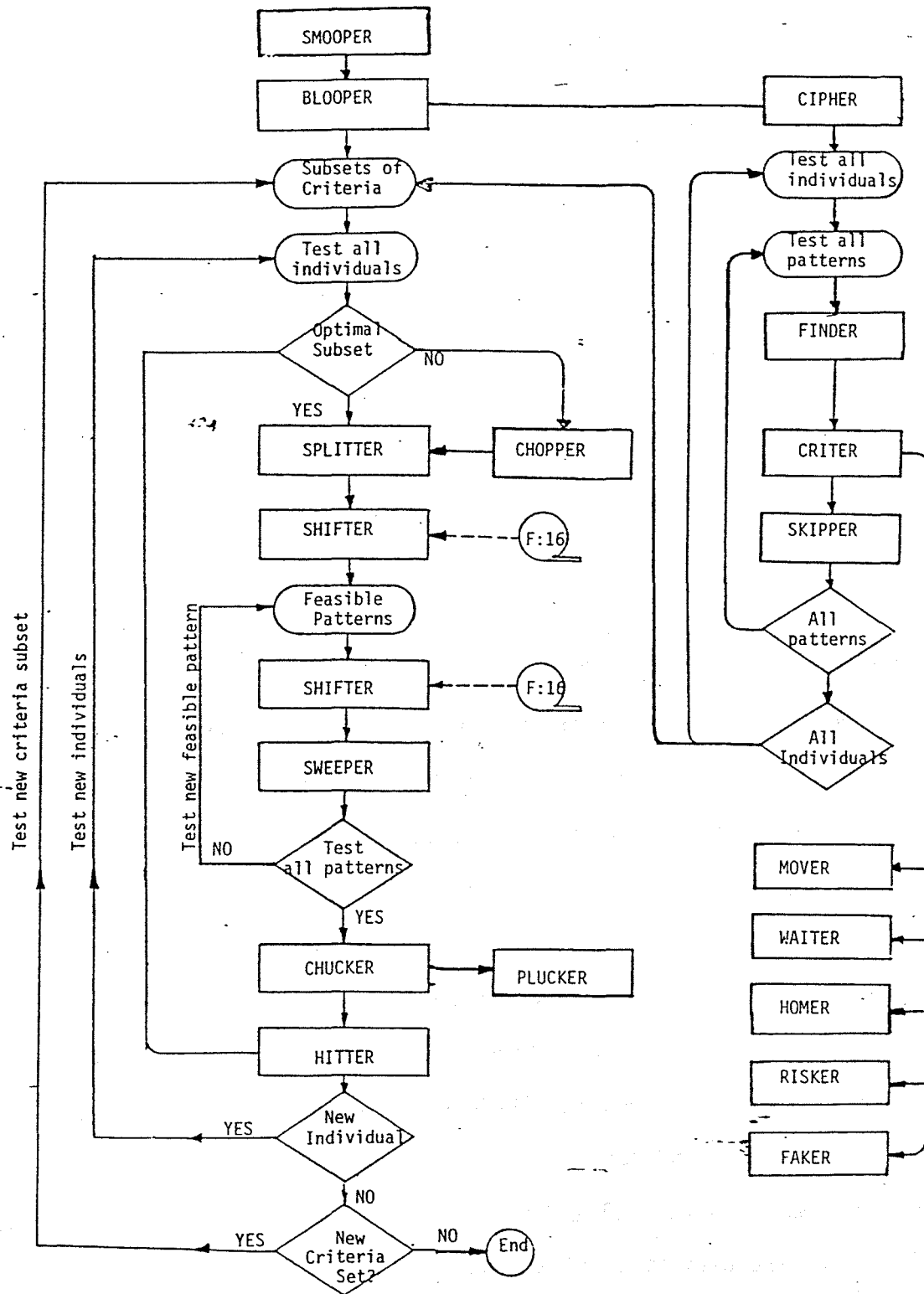
FIGURE 4.6   SMOOPER MODULE

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The same objectives defined and utilized in the fourth simulation module to identify non-inferior patterns are reapplied to estimate their corresponding value for each RAP, one of which is identified above as the observed pattern choice. This last element thus produces a well-specified choice set defined along the same dimensions for analysis through a desired choice model, the sixth and final module of the simulation model.

These representative patterns implicitly contain activity program constraints and a fully specified activity pattern, and each RAP is defined along the same dimensions (due to the third module) resulting in the formulation of an abstract choice problem.

4.7 Activity Pattern Choice Model

Any existing choice model (e.g., random utility (LOGIT) or non-compensatory (SEQUEL)) may be utilized to establish pattern choice based on the specified choice set from the fifth module.

4.8 Summary of the Proposed Simulation Model

A six-module simulation procedure for the analysis of household activity patterns has been formulated. Shortcomings in travel/activity analysis as identified in the literature review lead to the development of the various aspects of the simulation, and the integrated approach appears to be the first proposed in the field which considers virtually all aspects of the activity pattern, and produces a choice model of patterns per se.

The model takes on a simulation format due to the inherent complexity of activity pattern analysis. Each module is formulated around a set of research objectives and is summarized below.

Module 1 - Analysis of Household Interaction and Activity Program Specification

The role of household interaction and the resulting constraint analysis enables the formulation of activity programs to be determined as individual-based, household-based, or individual-based but household constrained (as hypothesized). The role of the household supply environment, particularly the issue of automobile availability and allocation, is examined.

Module 2 - The Constrained, Combinatoric Scheduling Algorithm

This module represents an attempt to integrate a full range of pattern attributes in modeling the activity pattern choice process. Each attribute of the activity program is simulated in the formulation of feasible activity patterns.

Module 3 - Pattern Recognition and Classification

Novel methods of pattern recognition and classification are utilized to establish representative activity patterns which form a fully specified choice set. Various classification techniques are implemented. Furthermore, the individual activity patterns may be compared to the RAPs of that individual's household to establish a household choice set.

Module 4 - Multi-objective Programming Algorithm

The complexity of individual decision processes requires several assumptions be made within this module. The module identifies non-inferior courses of action and may be used to reduce the size of the choice set and to address issues raised by independence from irrelevant alternatives.

Module 5 - Generation of the Pattern Choice Set

Model limitations associated with choice set size are incorporated within the model system in this module, which permits user-specified limits to be placed on the definition of the choice set while maximizing the independence of the alternatives.

Module 6 - Activity Pattern Choice Model

Existing choice models (either random utility or non-compensatory structures) are utilized to estimate pattern choice probabilities. In addition, chosen patterns for household members may be compared to establish household activity patterns, and to examine the interaction between patterns. Furthermore, patterns may be compared across either individuals or households to test, respectively, role and life cycle group theories.

A complete source code listing of the model system is provided in Appendix A.

CHAPTER FIVE

Operationalization of the Utility Components

5.1 Introduction

The basic assumption embodied in the theory developed in Chapter 3 is that individuals choose their daily activity schedule in such a way that they maximize their utility. The utility associated with an activity schedule is assumed to be comprised of six components:

(1) the time spent traveling to planned activities

(2) the time spent participating in planned activities

(3) the time spent participating in discretionary home activities

(4) the time spent traveling to discretionary home activities

(5) the potential time spent participating in unplanned activities

(6) the potential time spent traveling to unplanned activities

The operationalization of this theory requires development of quantifiable measures of the six utility components.

5.2 Participation in Planned Activities

The expected utility associated with time spent participating in planned activity j is given in Chapter 3 as

$$E\{U_t(D_j^c)\} = \mu_j \cdot P_j \quad \text{for } t_0 \le t \le t_1 \tag{3.12}$$

The utilities defined by Eq. (3.12) are operationalized in the model by first assuming that the μ_j are dependent only on the <u>importance</u> of the activity rather than on the actual type of activity. To effect this assumption, activities were categorized into four importance levels:

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(1) Very important

(2) Important

(3) Relatively unimportant

(4) Unimportant

consistent with information contained in the data set used for estimation of the prototype model.

To calculate the probability (P_j) that sufficient time will be available to complete the planned activity associated with the jth position in the tour, a probability density function (pdf) for the random component of travel time (ε) must be assumed. For example, considering the first activity in a tour, if it is assumed that:

$$f_1(t) = \begin{cases} 1/t_{0,1}^{max} - t_{0,1}^{min} & ; \ 0 \le t \le t_{0,1}^{max} - t_{0,1}^{min} \\ 0 & ; \ elsewhere \end{cases} \tag{5.1}$$

where: $t_{0,1}^{max} = $ the maximum travel time from location 0 (home) to the location of the 1st planned activity.

$t_{0,1}^{min} = $ the minimum travel time from location 0 (home) to the location of the 1st planned activity.

then the cumulative distribution function, $F_1(t)$ is:

$$F_1(t) = \begin{cases} 0 & ; \ t < 0 \\ t/t_{0,1}^{max} - t_{0,1}^{min} & ; \ 0 \le t \le t_{0,1}^{max} - t_{0,1}^{min} \\ 1 & ; \ t > t_{0,1}^{max} - t_{0,1}^{min} \end{cases} \tag{5.2}$$

If δ_1 is defined as $t_{0,1}^{max} - t_{0,1}^{min}$, then the probability that an

individual will be able to participate in the first activity in the tour
is:

$$P_1 = F_1(t_1^f - t_0^d - E\{T_{0,1}\} - D_1) \tag{5.3}$$

$$= \begin{cases} 0 & ; t_1^f - t_0^d - E\{T_{0,1}\} - D_1 < \delta_1 \\ (t_1^f - t_0^d - E\{T_{0,1}\} - D_1)/\delta_1; & 0 \le t_1^f - t_0^d - E\{T_{0,1}\} - D_1 < \delta_1 \\ 0 & ; t_1^f - t_0^d - E\{T_{0,1}\} - D_1 > \delta_1 \end{cases}$$

where: t_1^f = the ending time of availability of participation in the 1st activity

t_0^d = the departure time from home

$E\{T_{0,1}\}$ = the expected travel time from home to the location of the 1st activity in the tour

D_1 = the duration of participation in the 1st activity of the tour.

The expression:

$$t_1^f - t_0^d - E\{T_{0,1}\} - D_1$$

can be thought of as the "slack time" associated with the 1st activity in the tour since it is the difference between the expected completion time of participation in the first activity and the latest time that participation can take place. If the slack time associated with an activity is large, then an individual could arrive at the activity location later than he/she planned and still participate in the activity.

The probability that an individual will be able to participate in the second activity in the tour can be expressed as:

$$P_2 = \int_{-\infty}^{\infty} f_1(t_1) F_2(t_2^f - t_1^d - E\{T_{1,2}\} - D_2 - t_1) dt_1 \qquad (5.4)$$

or:

$$P_2 = \int_0^{\delta_1} \frac{1}{\delta_1} F_2(\mu - t_1) dt_1 \qquad (5.5)$$

where:

$$F_2(\mu - t_1) = \begin{cases} 0 & ; \mu - t_1 < 0 \\ (\mu - t_1)/\delta_2 & ; 0 \le \mu - t_1 \le \delta_2 \\ 0 & ; \mu - t_1 > \delta_2 \end{cases} \qquad (5.6)$$

and:

$$\delta_2 = t_{1,2}^{max} - t_{1,2}^{min} \qquad (5.7)$$

$$\mu = (t_2^f - t_1^d - E\{T_{1,2}\} - D_2) \qquad (5.8)$$

Although the exact results of the integration vary depending on the values of μ, δ_1 and δ_2, in each case,

$$P_2 = O(\frac{\mu^2}{\delta_1 \delta_2}) \qquad (5.9)$$

and in general,

$$P_j = O(\frac{\mu^j}{\delta_j!}) \qquad (5.10)$$

Equation (5.10) states that as the variation in the travel time from the (j-1)st activity to the jth activity increases (i.e., as $t_{j-1,j}^{max} - t_{j-1,j}^{min}$ increases) relative to the amount of slack time available, the probability that an individiual will be able to participate in the jth activity decreases. Although other assumed density functions will in general,

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produce other forms for P_j, the simple uniform density assumed in this example is used in the estimation of the prototype model.

To use equation (5.10) to calculate the probability of fulfilling a planned activity participation, the minimum and maximum travel times for each origin-destination pair are obtained together with the latest times that participation in the various activities could take place (i.e., the t_j^e's). For each activity (j) in a given tour, the slack time (μ) is calculated as

$$t_j^f - t_{j-1}^d - E\{T_{j-1,j}\} - D_j$$

and, correspondingly,

$$P = \begin{cases} 0\left(\dfrac{\mu}{\delta_j!}\right) & ; \text{ if } \mu^j < \delta_j! \\ 0(1) & ; \text{ if } \mu^j > \delta_j! \end{cases} \qquad (5.11)$$

where:

$$\delta_j! = (t_{j-1,j}^{max} - t_{j-1,j}^{min}) \cdot (t_{j-2,j-1}^{max} - t_{j-2,j-1}^{min}) \cdot \ldots \cdot (t_{1,2}^{max} - t_{1,2}^{min}) \cdot (t_{0,1}^{max} - t_{0,1}^{min})$$

5.3 Travel to Planned Activities

Individuals are assumed to travel only as a result of their need to participate in activities that are spatially separated, and consequently, are assumed to derive no utility from travel other than within the context of the activity being accessed. Since the act of traveling consumes time (which could otherwise be spent performing activities) it is hypothesized that individuals desire to minimixe the amount of time spent traveling. It is also hypothesized, however, that individuals

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place different weights on the utility they receive from traveling to activities based on the specific nature of the activities. For example, a trip to a doctor's office may not result in as much disutility to an individual as would a trip of the same length to a post office. However, if the individual needed to mail a payment for a bll that day or else pay a substantial fine for late payment the disutility of the time spent traveling to the post office may be the same as that associated with the trip to the doctor's office. This example suggests that it is not the actual type of activity that influences the disutility of the associated travel but rather the importance to the individual of participation in the activity. Correspondingly, the total amount of time spent traveling to activities in each of the four importance categories was calculated and distinct utility weights were proposed to exist for each of these four variables.

5.4 Participation in Unplanned Activities

It is hypothesized that individuals consider their potential to participate in unplanned activities (i.e., activities that were not explicitly planned at the beginning of the day) when selecting an activity schedule. The utility of the total potential to participate in unplanned activities was formulated in Chapter 3 as:

$$U(V^X) = \sum_j \sum_{k \in \Omega^*} w_j \cdot \frac{N_{k,j}}{N_j} \cdot \frac{1}{\gamma_j} \qquad (5.12)$$

Since w_j, N_j, and γ_j are constant for each particular value of j and $N_{k,j}$ is constant for any specific k,j pair, then

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the utility of the potential to participate in unplanned activities will increase as the set of feasible activity locations increases. Before actually determining the set of feasible activity locations the total set of locations at which activity type j can be performed must be identified as well as the space-time constraints (the locations of the planned activities and the times than an individual must arrive and is free to leave these locations). The following notation will be used in the description of the procedure employed to determine the feasible locations:

t_k^a = expected time of arrival at location k

t_{i+1}^a = expected time of arrival at the location of the (i+1)st planned activity

t_i^d = time of departure from the location of the ith planned activity

t_k^d = time of departure from location k

$t_{k,j}^s$ = start of participation in unplanned activity j at location k

$t_{k,j}^b$ = beginning of availability of unplanned activity j participation at location k

$t_{k,j}^f$ = ending of availability of unplanned activity j participation at location k

$T_{i,k}$ = travel time from location i to location k

$T_{k,i+1}$ = travel time from location k to location i+1

η_j^* = required duration of the jth unplanned activity

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The steps of the procedure are:

Step (1.) - Calculation of time of arrival at location k

$$t_k^a = t_i^d + T_{i,k} \tag{5.13}$$

Step (2.) - Calculation of start time of participation in unplanned

activity j at location k

$$t_{k,j}^s = MAX \{ t_{k,j}^b ; t_k^a \} \tag{5.14}$$

Step (3.) - Calculation of time of departure from location k

$$t_k^d = t_{k,j}^s + n_j^* \tag{5.15}$$

Step (4.) - Calculation of time of arrival at the location of the $(i+1)$st

planned activity

$$t_{i+1}^a = t_k^d + T_{k,i+1} \tag{5.16}$$

The actual equation used for calculating the time of arrival at the
location of the $(i+1)$st planned activity is:

$$t_{i+1}^a = \left\{ \left\{ MAX[t_{k,j}^b ; t_i^d + T_{i,k}^d] \right\} + n_j^* \right\} + T_{k,i+1} \tag{5.17}$$

Location k is included in the set of feasible locations if and only if
the following two conditions are satisfied:

(a.)   the individual's expected time of completion of participation in
        unplanned activity j at location k is less than or equal to
        the ending of the availability of participation in unplanned
        activity j at location k, i.e.,

$$t_{k,j}^s + n_j^* \leq t_{k,j}^f \tag{5.18}$$

(b.)   the individual's expected time of arrival at the location of the
        $(i+1)$st planned activity is less than or equal to the time that

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the individual is required to commence participation in the (i+1)st planned activity, i.e.,

$$t^a_{i+1} \leq t_{i+1} \tag{5.19}$$

These two conditions state that a location is included in the set of feasible locations if there is sufficient time for an individual to travel to the specific location, spend the desired amount of time participating in the activity and then reach the next planned activity prior to the time when he/she must participate in it.

The procedure outlined above determines whether or not a specific location (k) should be included in the set of feasible locations for a particular type of activity (j). This procedure is then repeated for each of the other locations at which activity j could be performed, as well as for all other types of activities and for each pair of space-time constraints contained in the activity schedule.

To achieve some computational efficiency, the individual activity locations must be aggregated into zones and a travel time matrix containing the travel times from the zonal centroids constructed. The set of feasible activity locations (i.e., the number of zones in which an individual could perform an unplanned activity) are then determined as previously outlined using the zone travel time matrix instead of the individual location-specific travel time matrix. In addition, the set of activity types that are evaluated as potential unplanned activities, are aggregated into the following five categories:

(1) grocery shopping

(2) clothes/small appliance shopping

(3) shopping other than (1) and (2)

(4) restaurant

(5) other (banking, post office, visiting a friend, etc.)

It is assumed that the probability of an unplanned need to perform one of these five activity types arising was significantly larger than the probabilities associated with the other activities (e.g., work, school, public meetings, etc.). The probability of participating in unplanned activity j in a particular zone, k, was calculated by summing the number of trips made to all locations in zone k for activity j and dividing this number by the total number of trips made for activity j. The mean duration of each of the five activity types listed above was calculated and used as the required duration of the unplanned activities. Only the durations of activities that were planned less than twenty-four hours in advance were included in the calculation of the mean durations. Finally, the probability of an individual participating in unplanned activity j was set equal to the inverse of its frequency since it was shown in Chapter 3 that this probability was equal to the mean time interval between occurrences of activity j.

5.5 Travel to Unplanned Activities

In addition to the utility that would result from an individual's participation in an unplanned activity there would also be some disutility associated with the travel time to and from the location of the unplanned activity. This disutility would not, however, be

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associated with the _total_ amount of time spent traveling to and from the location of the planned activity but rather with the additional amount of time spent traveling over and above that which would be spent traveling directly from one planned activity to another (i.e., the additional travel time resulting from participating in an unplanned activity at location k). This additional travel time must then be multiplied by the probability of participating in the unplanned activity at location k to yield the expected utility (disutility) of travel to unplanned activity location k. This process is repeated for all other feasible locations (zones), activity types and space time constraints and the values summed to obtain the total expected disutility of travel to unplanned activities.

5.6 Participation in Discretionary Home Activities

The utility that an individual receives as a result of participating in activities at home has been hypothesized to be a function of both the amount of time the individual spends at home and the number of household members present at the same time. The number of household members at home during the individual's jth stay at home (I_j^h) is, however, in general not constant over the entire period of time. Therefore, the total amount of time an individual spends at home during the jth stay must be separated into different categories based on the number of household members present.

As such, time spent at home was categorized as:

(1) time spent at home when _no other_ household members are present $(I_j^h = 1)$

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(2) time spent at home when <u>all other</u> household members are present $(I^h_j = N)$

(3) time spent at home when at least one other household member is present but at least one other household member is not present $(1 < I^h_j < N)$

5.7 Travel to Discretionary Home Activities

Since these activities are discretionary (i.e., the individual is not obligated to return home at the observed time to perform a particular activity) the importance of these activities is generally not available. As a result, the utility (disutility) associated with traveling to home was hypothesized to be simply a function of the amount of time spent traveling. By calculating the total amount of time spent traveling to home for all discretionary activities and treating this as a separate travel time variable the differential weighting of the disutility of travel from home (for planned activities) and travel to home could be investigated.

CHAPTER SIX

Data

6.1 Procedure for Selection

Prototype testing of the simulation model presented some rather stringent data requirements. The model is specified in terms of data not commonly associated with traditional travel surveys. Since the study was constrained to draw from existing data sources, a careful review of those available was conducted and a procedure established to select an existing source which most closely satisfied the requirements of the model. The procedure consisted of five basic steps:

(1) An inventory of data sets describing individuals' travel/activity behavior was compiled,

(2) Information that was essential to the testing of the behavioral hypotheses contained in the model was identified,

(3) Each data set included in step (1) was examined to determine whether or not it contained all the information identified in step (2), and if not, was removed from subsequent consideration,

(4) Additional information that was considered desireable (although not essential) for the testing of the model was identified, and

(5) Each of the data sets remaining, after step (3) were analyzed to determine how much of the information identified in step (4) they contained and the data set possessing the most information was selected.

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A major component of the complex travel behavior simulation model involves household interaction. It is hypothesized that individuals' travel/activity decisions are to some extent constrained by the travel/activity decisions of the other members of their household and travel/activity information; the test of this hypothesis requires detailed travel data for each member of the household. Another set of constraints that is hypothesized to influence individual travel/activity behavior arise from the specific nature of the transportation and activity system environments. These constraints arise because:

- individuals can only occupy one location at a given time,

- not all activities can be performed at all times or at all locations,

- individuals cannot travel between activity locations instantaneously, and

- individuals cannot travel to every location at all times and by all modes.

As a result of these constraints and the highly disaggregate nature of the simultation model, a second requirement is that the origins and destinations of all activities (and hence, trips) be locationally coded in spatial units of analysis that permit examination of the sensitivity of activity patterns to changes in activity location and or scheduling.

Information on the mode used for travel was also considered to be essential for the model estimation and in the case of automobile travel, this information consisted of the specific automobile used during each trip, as well as the number and relationships of the people accompanying the driver.

6.2 Analysis of Data Sources

Twenty-one data sets were analyzed according to the procedure outlined (Table 6.1). Six of these (Detroit, 1965; San Francisco, 1975; Bedford, U.K., 1974; Watford, U.K., 1969, Amsterdam, 1977 and the Netherlands, 1975) contained travel/activity information only on select members of different households and were eliminated from further consideration. Seven other data sets (Washington, D.C., 1968; Buffalo, 1973; Fresno-Clovis, 1971; Minneapolis/St. Paul, 1970; Tel-Aviv, Israel, 1972; NPTS (U.S.) 1977 and NTS (U.K.), 1975) utilized zonal levels of geocoding that were judged too coarse and were also removed from subsequent analysis. The Baltimore, 1977 data was also geocoded on a zonal basis. However, the average size of the zones are small enough (less than one square mile) to be utilized in the simulation model. Finally, the Vancouver, B.C., 1972 and Toronto, Ontario, 1979 data sets were classified as unacceptable as a result of insufficient information on automobile usage.

Although each of the remaining six data sets contains all the information essential to the model estimation, there is considerable variation in the amount and types of additional information they possess. To determine the most appropriate data set, a second list of information was constructed which included data that would aid the estimation procedure. This list included information on:

(1) the temporal flexibility of non-home activities

(2) the spatial flexibility of non-home activities

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DATA SOURCE	YEAR
Amsterdam, Netherlands	1977
Baltimore, Maryland	1977
Banbury, U.K.	1976
Bedford College, U.K.	1974
Buffalo, New York	1973
Detroit, Michigan	1965
Fresno/Clovis, California	1971
Minneapolis/St. Paul, Minn.	1970
Netherlands	1975
NPTS (U.S.)	1977
NTS (U.K.)	1975
Orange County, California	1976
San Francisco, California	1975
Tel-Aviv, Israel	1972
Toronto, Ontario	1979
Uppsala, Sweden	1977
Vancouver, B.C.	1972
Watford, U.K.	1969
Washington, D.C.	1968
West Los Angeles, Calif.	1979
Windham, Connecticut	1980

Table 6.1

(3) the individual's maximum acceptable waiting time at activity locations

(4) the activities participated in at home

(5) the temporal flexibility of home activities

(6) the importance of specific activities to the household

(7) the frequency of activity participation

(8) the level of advanced planning associated with non-home activities

(9) the length of time spent at current residence

(10) the length of time spent at current job location

(11) the alternative modes, destinations, times, activity sequences and travel patterns chosen by individuals on prior occasions

(12) reasons for choosing (or not choosing) specific alternatives.

The data sets were then analyzed to determine whether or not they contained information on each of the twelve categories shown above. The results of this analysis are shown in Table 6.2. Examination of this table reveals that the Windham data set contains the most information on the desired categories and was judged best suited for use in the testing of the simulation model.

This data base, although not perfect, incorporates the necessary constraint information required in the simulation of pattern formation. The results of the 1980 home interview survey of over 600 households in the Windam, Connecticut Planning Region includes a comprehensive, single day, travel activity diary for each household in addition to a basic

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Information	Data Sets					
	Banbury, U.K.	Baltimore	Orange Co. Ca.	Uppsala, Sweden	Windham, Conn.	W. Los Angeles Ca.
Temporal flexibility of non-home activities	X	X		X	X	X
Spatial flexibility of non-home activities	X	X		X	X	X
Maximum acceptable waiting time					X	
Types of home activities	X					X
Temporal flexibility of home activities	X				X	X
Importance of non-home activities					X	
Frequency of activity participation		X		X	X	
Level of advanced planning				X	X	
Length of time at current residence	X		X			
Alternatives chosen in the past	X					
Reasons for choosing (or not choosing) alternatives	X				X	X

TABLE 6.2

socio-economic profile and transportation supply inventory. A simple, random sample of households was drawn from the predominantly rural, Windham region. Davis et al. (1981) provides detailed descriptions of both the Windham area and of the sampling methodology.

The major purpose of the questionnaire was to elicit individual and household information concerning the potential for ridesharing within the planning region. At such, a battery of questions focused on the temporal (and spatial) flexibility of activity sojourns and tours which provided, in addition to conventional purpose, location and mode variables, information concerning earliest departure times, allowable waiting times, fixed constraint times, and latest return times. These variables are discussed in detail in the development of the simulation model.

Further information was provided regarding the importance, temporal and spatial flexibility, and degree of advanced planning associated with each activity. This information will potentially eliminate many of the restrictions associated with single day diaries (Hanson and Burnett, 1981) as it is possible to establish the nature of the travel day reported as being typical of the actual travel patterns of the households.

Travel diaries were collected for all memebers of th household. Features of the Windham data source allow the simulation model to be extended to the analysis of household interaction rather than simply an analysis ofindividual pattern formation in absence of explicit household constraints. In addition to the temporal constraint information discussed above, the usage of alternate modes in conjunction with household members and out-of-household individuals allows pegs to be

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placed in each individual's desired activity program to establish an analysis of household interaction.

The discussion of the simulation model treats the above concepts in detail. A coding manual depicting the available information in the data set is presented in Appendix B.

6.3 Synthesis of Travel Time Data

The second module (SNOOPER) of the complex travel behavior simulation model requires a matrix input of some measure of travel impedance between the locations specified in the activity program. The present version of the simulation model utilizes travel time, although actual distances may be introduced with minor reprogramming.

Consistent travel times are necessary in the scheduling phase of the algorithm to insure that the generated patterns reflect travel which corresponds in degree with those times reported in the travel diaries used to specify the activity programs. If reported times do not closely approximate those of the generated matrix, then certain patterns which are actually feasible, perhaps the observed pattern itself, may not be produced in the simulation. Conversely, generated "feasible" patterns may indeed be infeasible if inconsistent travel times are utilized.

Base travel times utilized in this study are conventional network times provided by the Connecticut Department of Transportation which correspond to the locational coding used in the original Windham regional study (Davis et al, 1981). The process of developing matrices from this

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base that are consistent with those reported in the survey consisted of three phases:

I. Construction of Travel Time Matrix from Skim Trees

The 10-town Windham Planning Region (WPR) (see Figure 6.1) road network has been coded by the Connecticut Department of Transportation. A total of 276 nodes have been identified and free flow automobile travel times specified for adjacent zone pairs.[1] The full travel time matrix was constructed using a modified Moore shortest path algorithm (Hutchinson, 1974).

Locations in the Windham data are coded with a 6-digit scheme--the first three representing a unique town number, the other three indicating a node within the town. An analysis of origins and destinations by town number indicated a significant proportion of trips involving locations outside the 10 towns that comprise the Windham Planning Region. A political map of Connecticut was utilized to identify the locations of all such external trips and (after eliminating trips outside of the State or those to regions isolated from other destinations) an additional 56 towns were added, with the subsequent region of analysis being roughly the eastern half of the State (see Figure 6.2). As no detailed networks were available for these latter towns, zonal centroids were established and a second travel time matrix was computed in a manner similar to that

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[1] Coded network maps appended.

138
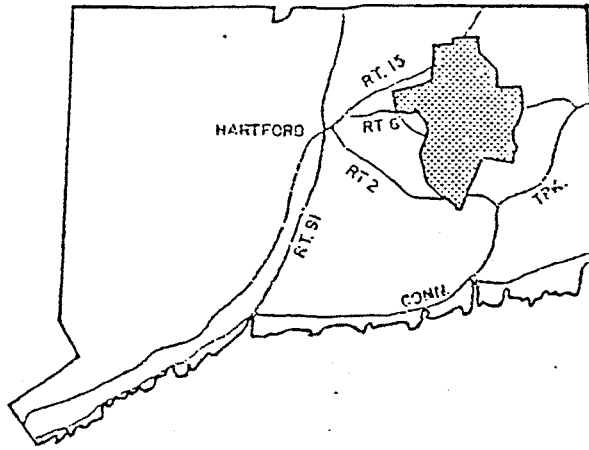
LOCATION MAP
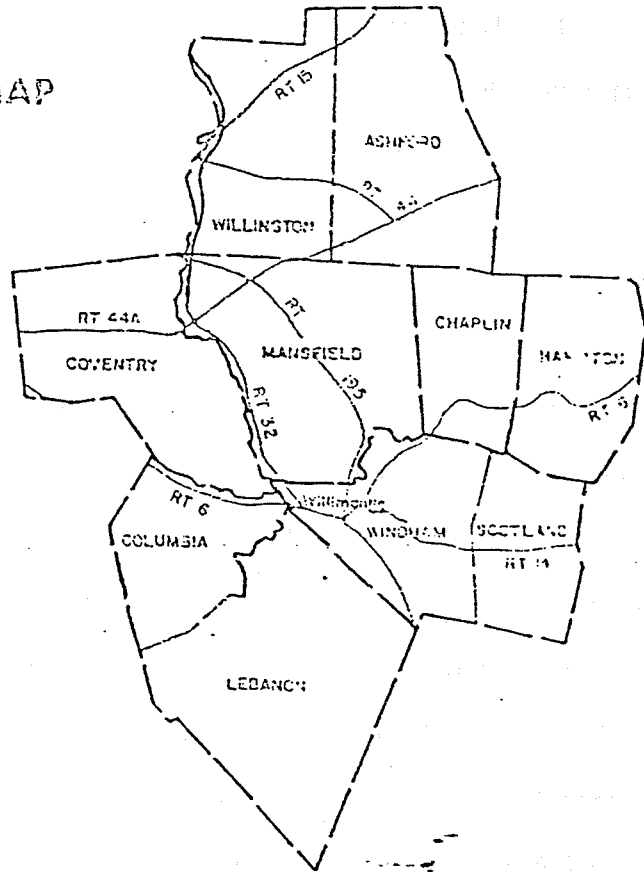
WINDHAM

PLANNING

REGION

FIGURE 6.1 - WINDHAM STUDY AREA

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FIGURE 6.2 - DELINEATION OF EXTENDED STUDY AREA

used in the WPR. The resulting matrix also incorporated centroids of the 10 WPR towns, yielding a 66 by 66 matrix.

II. Comparison of Alternate Measures of Travel Time

Some discrepancy between network-coded travel time and those reported in travel surveys is expected. Research by Talvitie and Dehghani (1979) and by Talvitie and Anderson (1979) are examples of comprehensive analyses of travel time data and their application in modeling. Virtually all such studies indicate major errors between observed (actual) travel time and the corresponding coded value, due in part to expected congestion effects and variable driver habits. Also revealed is a discrepancy involving reported travel times, which significantly differ from observed and network times. A major problem in travel time research involves the relationship between reported travel times and those actually perceived by the trip maker, the perceived times being those generally agreed to be the proper decision variable in travel decisions (Guttman, 1975). Stopher and Meyburg (1975) summarize several hypotheses explaining this discrepancy but the issue is rather academic as the reported times only are available. In a traditional demand model framework, Stopher and Meyburg suggest the appropriateness of reported travel times in explanatory models, but due to the inability to forecast perceived or reported values, they also suggest using measured (network) values in predictive models. Linear transformations for random disturbances around the various measures have been assumed. Limited

research into the appropriate mathematical relationships, however, has been inconclusive (Stopher and Meyburg, 1975).

The simulation model proposed in this study represents an approach to modeling travel behavior which requires a consistency between the reported and network times as previously discussed. An analysis of the relationship between the reported times of the Windham survey and Connecticut Department of Transportation coded network times was performed to achieve consistency between the two. The perceived (reported) travel times for each trip in the Windham survey were compared to the corresponding network-coded times. For a trip within the Windham region, the full node-to-node time matrix was used. For trips into or out of the region, or occurring entirely outside, the town level matrix was utilized. Initially, simple, linear regressions were made between the reported and network times. Although town level trips indicated fairly good correspondence ($R^2 = 0.67$), the nodal level produced no linear relationship with acceptable confidence.

A frequency distribution of reported times strongly indicated that individuals tend to perceive and/or report travel times rounded to five-minute (or, in cases of relatively long times, ten-minute) intervals. Consequently, network times were rounded up to five or 10 minute intervals, following the frequency distribution. A "perception ratio" was then computed by dividing the reported time by the network time for each trip across all households. Table 6.3 gives the intervals and the corresponding mean perception ratios (across all trips in the interval), as well as standard deviations and sample size.

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Table 6.3 - Mean Perception Ratio

Network Travel Time (Min)	Mean Perception Ratio*	Standard Deviation	Number of Trips
0.0 - 5.0	2.31	0.75	1,061
5.1 - 10.0	1.52	0.35	525
10.1 - 15.0	1.37	0.30	293
15.1 - 20.0	1.21	0.35	183
20.1 - 25.0	1.22	0.60	74
25.0 - 30.0	1.00	0.17	77
30.1 - 40.0	1.04	0.23	89
40.1 - 50.0	1.06	0.16	126
50.1 - 60.0	0.96	0.14	66
>60.0	0.95	0.16	16
TOTAL			2,510*

*The remaining 433 trips reported in the Windham survey were either non-automotive or outside of the study area.

The resulting relationship, plotted in Figure 6.3, indicates a distinctly non-linear decreasing function of trip length characterized by an approximate, asymptotic approach to unity as network travel times increase. This result contrasts with Stopher and Meyburg's suggestion that a roughly linear transformation should be evident. Also plotted is the standard deviation for each category illustrating the parallel decreasing nature of that statistic as well as the mean. The 20.1 to 25 minute category proves anomalous in both mean and standard deviation. Several explanations are possible. In general, the graph indicates that reported time, a proxy for perceived travel time, better approximates
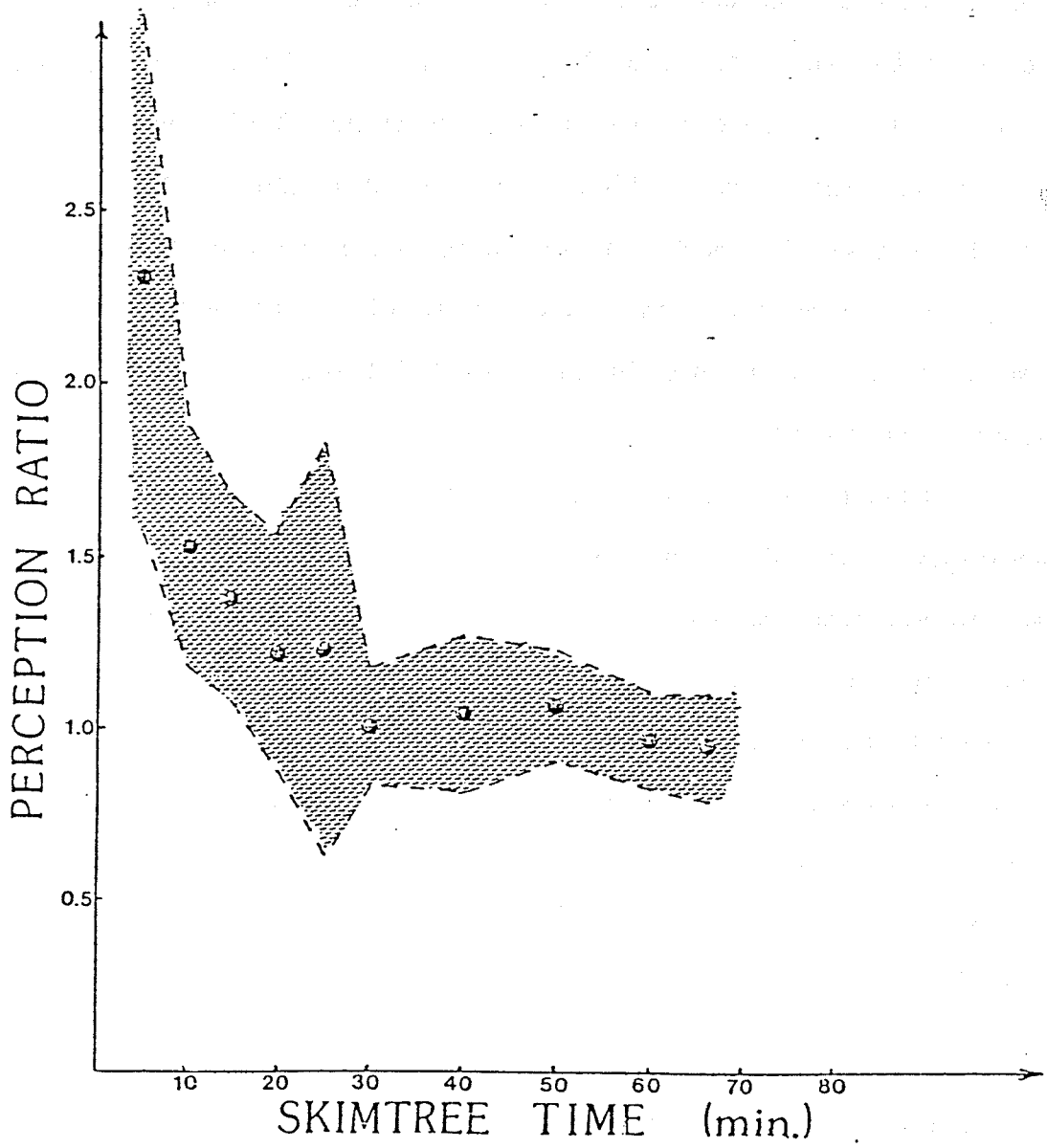
FIGURE 6.3 PERCEPTION RATIOS

Perception Ratio $= \dfrac{\text{Reported Travel Time}}{\text{Network Travel Time}}$

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adjusted network times as the latter increases. For all reported times over 25 minutes, the correspondance was extremely accurate. Individuals appear to be much less accurate for trips less than 25 minutes. Since network values correspond to in-vehicle travel time, individuals could overestimate total travel time (which is reported in the continuously recorded diary) for shorter trips where out-of-vehicle time comprised a larger portion of the total. As travel times increase, out-of-vehicle time plays a smaller role in the reported time, and the estimated time becomes more accurate.

The anomaly of the 20.1 to 25 minute category could represent a perception scale shift on the part of the respondent. The categories were formed after an analysis of the frequency distribution of reported times. Values were centered at 5 minute intervals up to 30 minutes, then appeared to follow a 10 minute estimation range. If individuals do shift scales at this point, it could explain the increased error in the mean perception. The significant increase in the standard deviation may be attributed to the same phenomena or, more likely, to the relatively small sample size at that portion of the curve.

III. Construction of Individual Activity Travel Time Array

The results of the previous analysis indicate that network travel times should be adjusted by the appropriate perception ratio to produce values compatible with reported travel times. All adjusted values were then rounded up to the nearest category limit, since the network times were similarly rounded in the construction of the perception ratio.

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Since perception ratios were considered uniform over each category, a lower category travel time could exceed a higher category value which has a lower ratio. This situation was adjusted by computing the transition points on the perception scale, and constraining the resultant travel times to be uniformly increasing. Table 6.4 reflects the adjustments made.

Table 6.4. Network Travel Time Conversions

Coded Value Range	Adjusted Value
0.0 - 2.1	5
2.2 - 6.5	10
6.6 - 10.9	15
11.0 - 16.5	20
16.6 - 20.4	25
20.5 - 25.0	30
>25.0	Round up to nearest 5 minutes

The independent travel time matrices for the WPR 10-town nodal system and for the 66 town centroid system were used in conjunction with the Windham travel survey diaries to produce separate travel time matrices for each traveller in the sample. The matrix reflects the appropriate value based on the nodal matrix for intra-regional travel and the centroid matrix for inter-regional travel. Each distinct destination location as well as the home location is present in the matrix. The resultant file, keyed by household and person identities, serves as partial input to the SNOOPER module of the simulation (McNally and Recker, 1982).

146

LEBANON

607

147

COLUMBIA

703
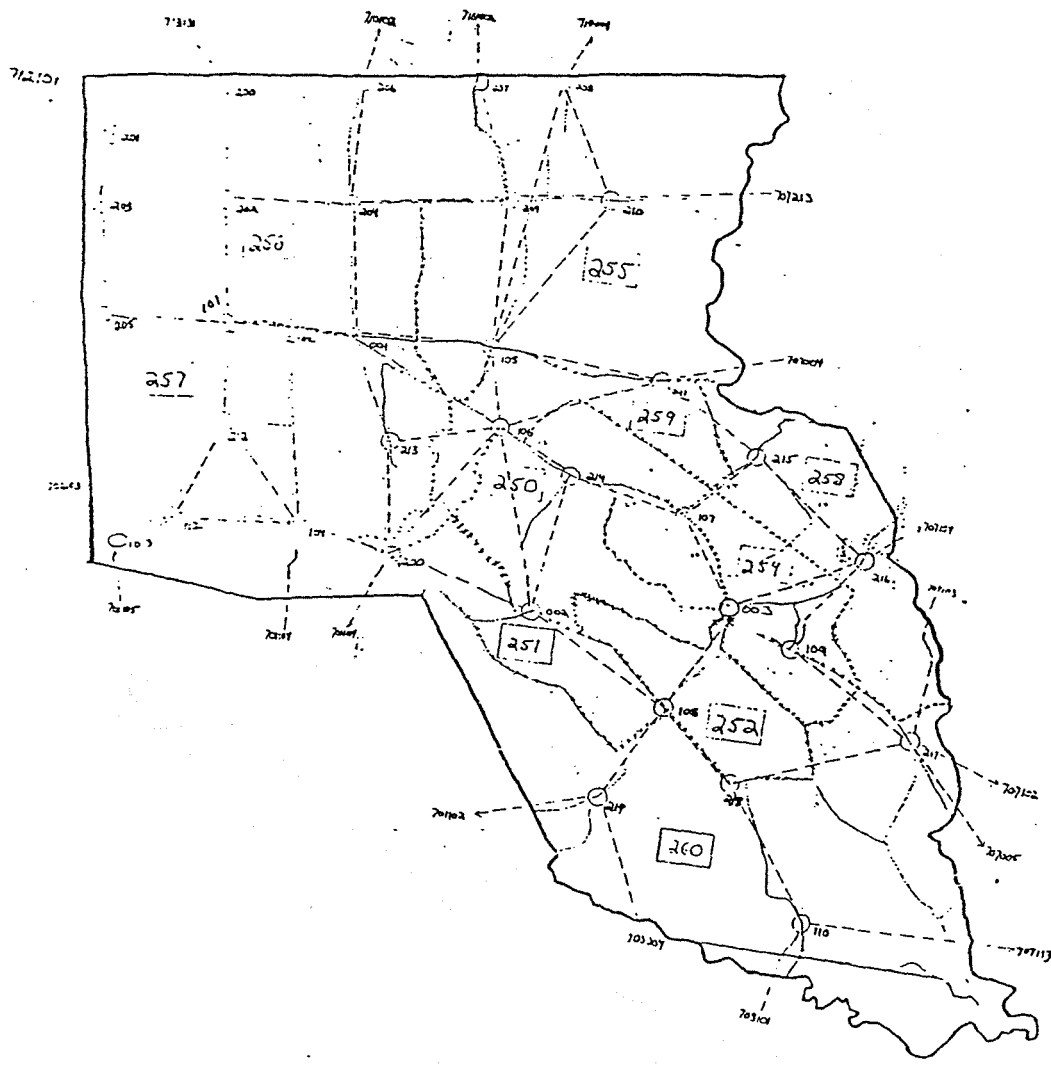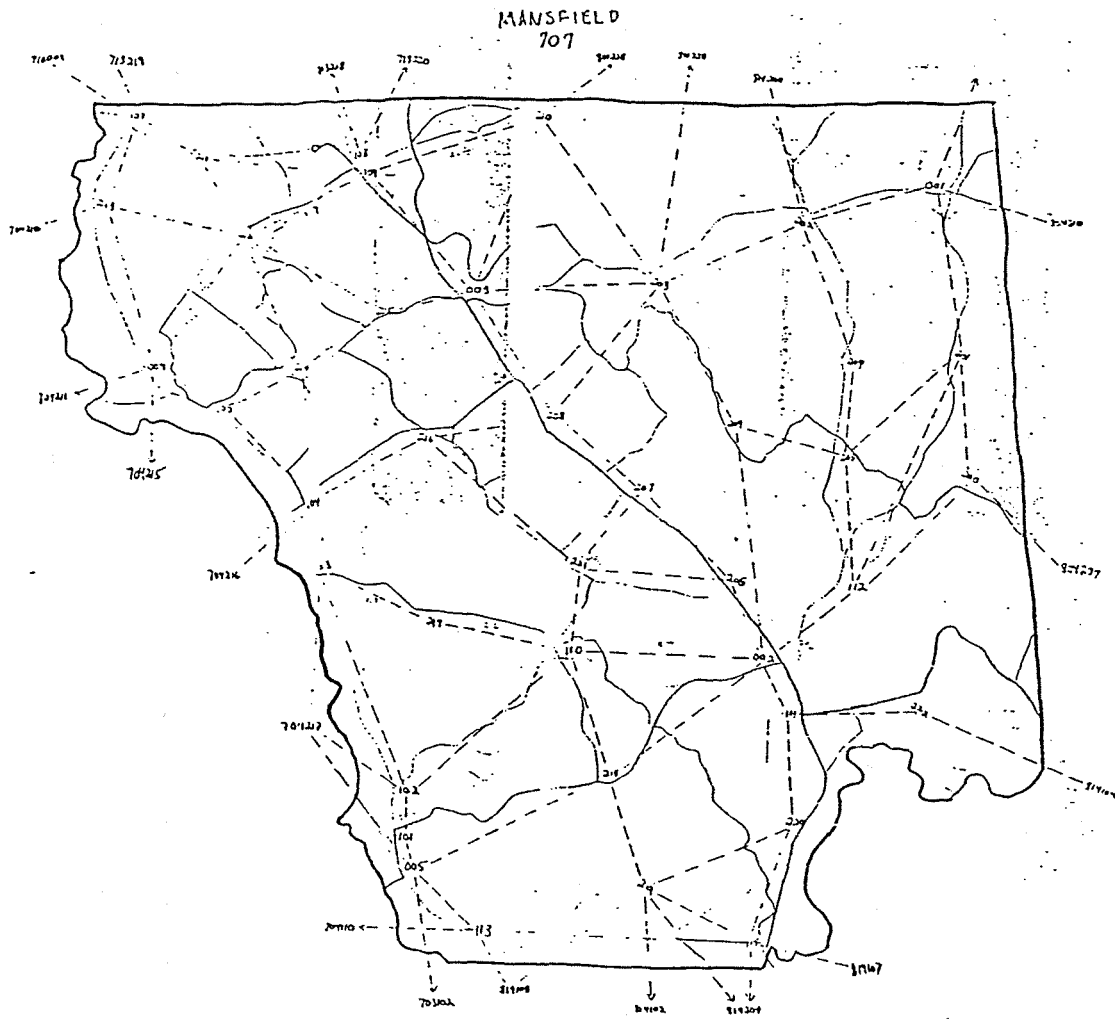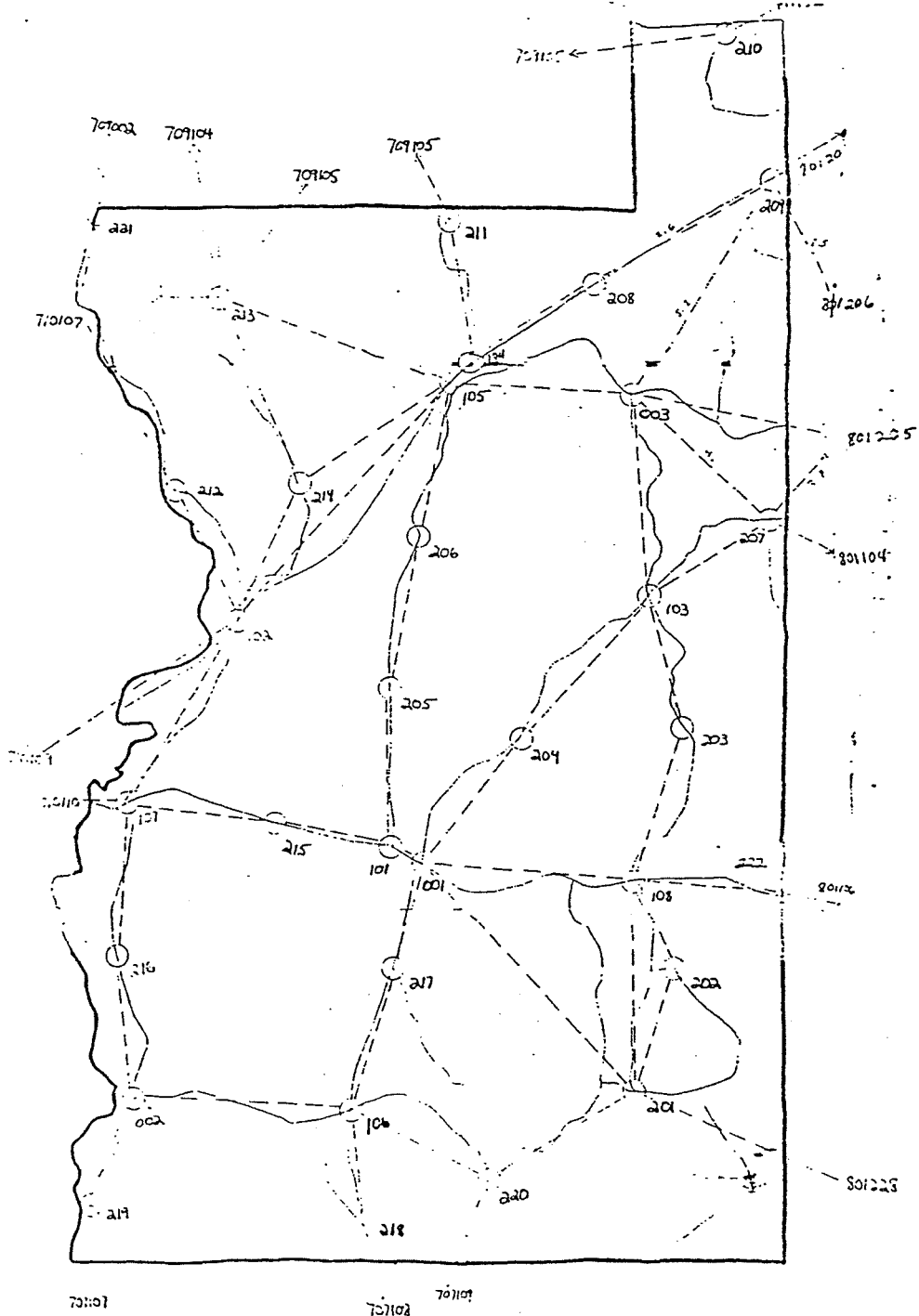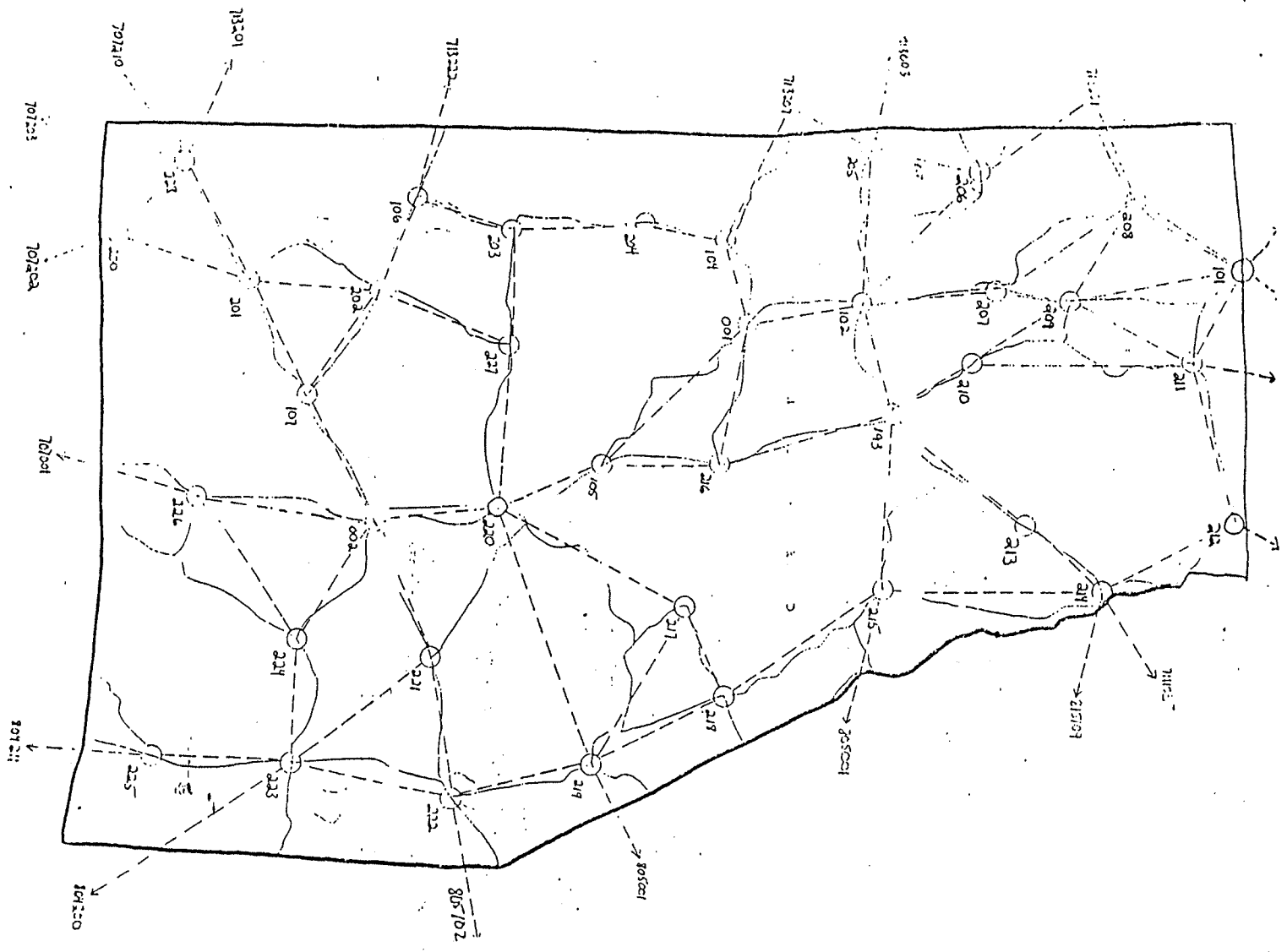
COVENTRY

704

MANSFIELD
707

WILLINGTON

713

CHAPLIN

804

153

805103

809105

804200

809103

105

2C4201

104

205

001

203

204

103

101

106

804203

107

802003

108

102

202

804204

002

802106

109

201

811211

803001

811102

HAMPTON

806
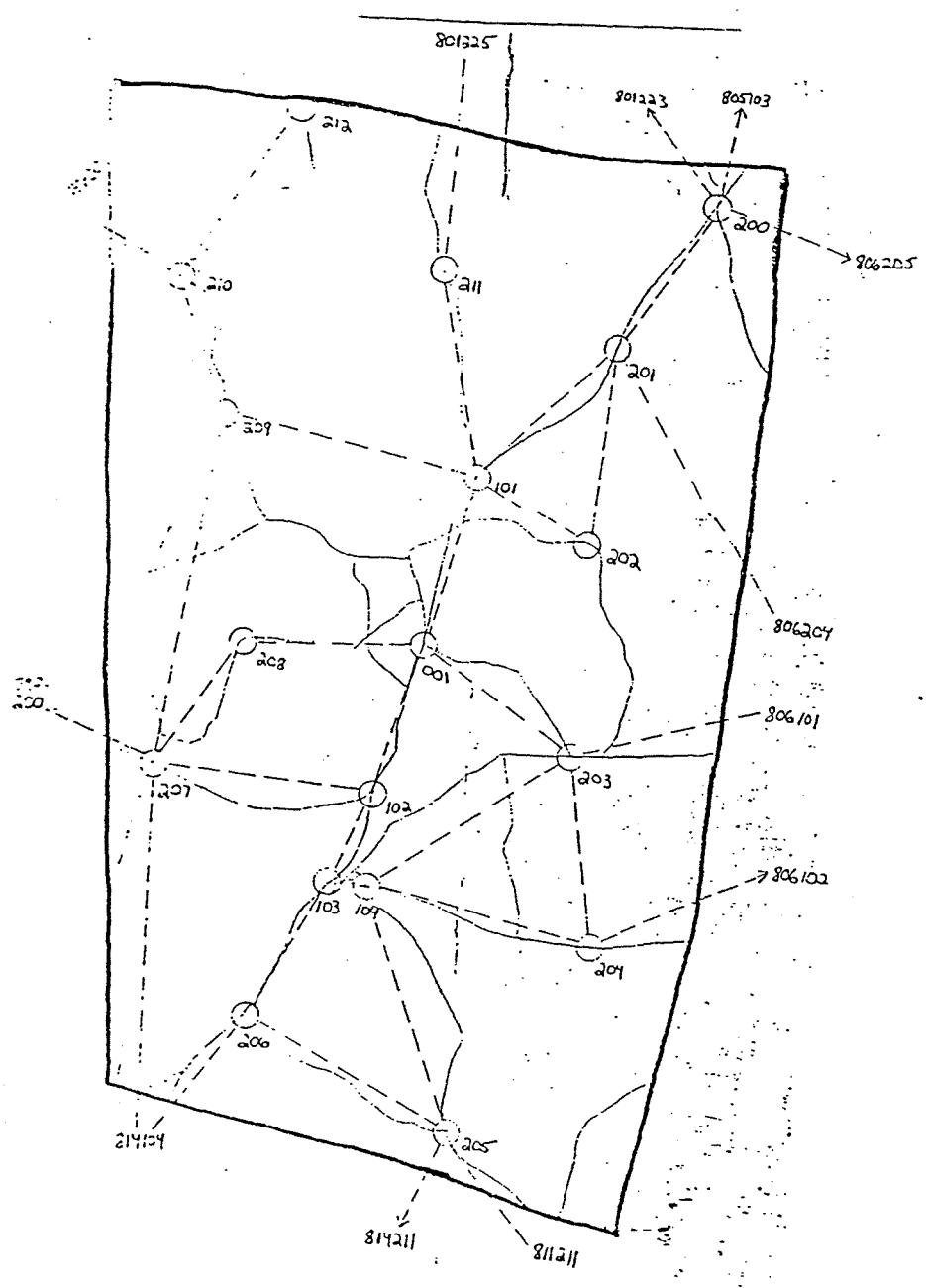
7	Clothes, appliance shopping
8	Other shopping
9	Church
10	School
11	After-school activity
12	Voluntary association
13	Public meeting
14	Restaurant
15	Medical, dental, legal appointment
16	Return home
17	Other

The discussion that follows focuses on general characteristics of the aggregate behavior of the sample vis-a-vis their participation in these activity types. Because of their importance to this study a more detailed analysis of two of these characteristics, activity duration and destination choice, is also presented.

7.2 General Characteristics

7.2.1 Activity Frequency

Activity frequency was divided into four categories: daily, weekly, monthly and occurring less often than once a month. The vast majority (approximately 85%) of the activities reported in the Windham Survey occur on a daily basis, while another 12% fall in the weekly category. The majority of the activities that occur daily are work activities (54%), which accounted for 45% of all activities reported in the survey.

School was the only other activity type which had a significant daily frequency of occurrence (accounting for approximately 20% of activities in this category). Activities in the weekly frequency category are dominated by activity type 6 (grocery, small item shopping, etc.) which accounted for 33% of activities placed in this grouping.

7.2.2 Mode Choice

Mode choice was heavily dominated by automobile use. The automobile was used for 87% of all trips (77% - personal auto, 7% - other private auto, 3% - other auto). Only school activities made significant use of any other mode. Approximately 50% of those surveyed used public school transportation for these activities.

7.2.3 Persons Accompanying Traveler

As discussed previously, interaction of the traveller both with other members of the household as well as with other individuals in general places constraints on the travel options available. This is explicitly characteristic of trips which involve passengers. Approximately 75% of vehicle trips were without passenger. Most of these were associated with the work trip.

7.2.4 Waiting Time Tolerated

Time spent waiting is an important consideration both in linking activities as well as in utilization of travel modes with fixed schedules. A significant portion of the sample (greater than 10%)

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indicated a willingness to wait at least 30 minutes both before and after all activities in which they engaged. Many others (25%) were selectively willing to wait as long as 50 minutes for certain activity types, such as: church, medical and dental appointments, while 10% were willing to wait that long for: work, movies and theatres, other recreation, shopping, and after-school activities.

7.2.5 Stated Importance of Activity Participation

Over two thirds of the respondents characterized the activity types work, church, school and medical, dental, legal appointments as "very important" to the well-being of the household. Approximately two thirds of those surveyed categorized theatres and movies, spectator sports, grocery and small item shopping . . ., and after-school activities as either "very important" or "important." Trips associated with these two groups of activity types comprise 75% of the total trips in the sample. All other activity types were either considered unimportant or lacked a general consensus on the importance of the activity in question.

7.2.6 Schedule Flexibility

Participants in the survey were also questioned relative to the possibility that the activity could have been scheduled on a different day. In eleven of the fifteen explicit activity categories, the response was very consistent: all shopping and restaurant activities could be rescheduled; work, spectator and participatory sports, school and after-school activities, public meetings and medical, dental, legal

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appointments could not. For all other activity types the response was mixed.

7.2.7 Location

The survey also questioned participants concerning the possibility of the activity occurring nearer to home. A large majority of the responses indicated that people stayed as close to home as possible (85%). Of the remaining 15%, most people cited personal desires, lower costs of products or services, or that the activity was part of a series and not too far out of the way. In particular, people engaged in work, participatory sports, other recreation, clothes, appliance shopping, school, and restaurant activities tended to cite personal desires as the reason for travelling further. People engaged in grocery shopping activities travelled farther for lower prices, while respondents who stated that the activity was part of a series and not too far out of the way typically were engaged in other recreation, grocery shopping, banking etc., clothes, appliance shopping, voluntary associations, and restaurant activities.

7.2.8 Unplanned Activities

The last characteristic to be examined was the advance notice respondents had of the activity. With the exception of shopping and restaurant type activities (6,7,8,14), respondents tended to have at least one day advanced warning in over 75% of the cases, and even in the categories of activity types listed above, over 50% of those surveyed had at least one day advance notice. At the other extreme, work, school and

public meeting activities all involved advance notice of at least one week in over 85% of the cases examined.

7.3 Respondent Destination Patterns

Because of its importance both to the destination choice research component of this study as well as to the estimation of the utility of the space time prisms associated with the generated activity patterns, a detailed analysis of respondent destination patterns was conducted.

The locations of each activity reported in the sample were tabulated by trip purpose; the result is given in Tables 7.1 and 7.2. Table 7.1 details only trips within the 10-town region, using the 276-node coding scheme adopted for this study; Table 7.2 contains all trips within the larger study area, tabulated by town only.

Of the 19 trip purposes identified in the Windham region survey, 6 activity types were selected for more detailed anlaysis. These six purposes were: work, school, and return home (major activity types whose destinations are assumed to be fixed); major grocery shopping and restaurant (major activity types whose destinations are assumed to be non-fixed or discretionary); and small-item shopping/bank/post-office (henceforth referred to as "minor shopping/etc."). Since the separation of major grocery shopping trips from minor shopping/etc. trips was somewhat arbitrary,[1] the latter activity type was studied to determine

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[1] These two activity types are coded together on the questionnaire. In order to distinguish between them, the distribution of durations was examined, and trips lasting longer than 15 minutes were assigned to the major grocery shopping category.

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if those destinations differ significantly from major grocery shopping destinations.

Locations of these six selected activities (within the 10-town region) were mapped separately, and appear as Figures 7.1-7.6. Each activity type of interest is discussed below.

Work (Figure 7.1)

There were a total of 284 work trips taking place at 51 locations within the 10-town region. The town of Scotland had no work trips, and fewer than 15 took place in all the other towns except Windham (122 trips) and Mansfield (123 trips). Most Windham work trips had destinations in Willimantic, at nodes 252 (41 trips), 256 (28 trips) and 257 (35 trips). Mansfield work trips were concentrated at node 90 (68 trips), the University of Connecticut area.

School (Figure 7.2)

After return home and work, school activities (233 trips to 26 locations) formed the third largest category of trips with fixed destinations. A large number of school trips ended in Windham (Willimantic) at node 257 (55 trips) and also in Coventry at node 62 (45 trips). In Mansfield, node 90 (University of Connecticut area) drew 25 trips, and node 114 contained 17 trips. Elsewhere, school activities were scattered throughout the region, with no other node attracting more than 10 trips. Hampton had no school trips recorded at all.

Return Home (Figure 7.3)

Return home was, logically, by far the most common activity, occurring 1238 times, at 160 locations, for the 10-town region. Again, the largest number of return home trips took place in Windham (387), with the majority of those concentrated in Willimantic (271 trips at the six nodes 252, 256, 257, 258, 263, and 273). The towns with the next largest number of return home trips were Coventry (262) and Mansfield (254), respectively. Aside from Windham and node 90 (Storrs) in Mansfield (with 47 trips), no node in any other town contained more than 25 return home trips. Scotland (18) and Hampton (13) had the fewest number of trips; the other towns contained between 30 and 100 return home activities.

Restaurant (Figure 7.4)

There were 48 restaurant activities (at 22 locations) in the sample; over half of these (26) occurred in the city of Willimantic in Windham (nodes 252, 256, 257, 263, 273). No other nodes had more than three restaurant trips, and no other town had more than eight trips altogether (Mansfield and Willington had 8 and 6 trips, respectively, scattered at several different nodes in each town). There were no restaurant activities recorded for Ashford and Hampton.

Major Grocery (Figure 7.5)

There were a total of 191 trips in the 10-town region classified as major grocery shopping activities, taking place at 25 different destinations. These activities were concentrated at three nodes: node

105 (Eastbrook Mall) in Mansfield (50 trips) and nodes 252 (21 trips) and 256 (65 trips) in Windham (Willimantic). Node 100 in Mansfield attracted 13 trips. The other 42 major grocery trips were scattered at 21 locations throughout the region, with no other node containing more than 8 trips and most nodes containing only one or two trips. No major grocery trips took place in Ashford or Hampton, while Columbia, Lebanon and Scotland each contained only one or two trips at only one location.

Minor Shopping/Etc. (Figure 7.6)

Eighty-six trips were classified as small item shopping/bank/post-office activities, less than half the number of major grocery shopping trips. The distribution of these activities was quite different from that of major grocery trips. The largest single concentration of minor shopping/etc. trips was in Coventry at node 55 (12 trips). The three nodes 252, 256 and 257 in Windham contained a total of 25 trips. On the other hand, node 105 in Mansfield, which was an important attractor of major grocery activities, contained no minor shopping/etc. activities. The remaining 49 minor shopping/etc. trips were located throughout the region at 17 different destinations, with no destination attracting more than 6 trips.

7.4 Activity Duration

As developed in Section 3.6.4, the utility of the potential to participate in unplanned activities is dependent on the expected

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Table 7.1a
Tabulation of Destinations by Purpose
(10-town area)

Table 7.1b
Tabulation of Destinations by Purpose
(10-town area)

Table 7.1 c

Tabulation of Destinations by Purpose

(10-town area)

1. Work
2. Theater, movie, etc.
3. Spectator sports
4. Participatory sports
5. Other recreation
6. Major grocery
7. Clothes, appliance shopping
8. Other shopping
9. Church
10. School
11. After-school activity
12. Voluntary association
13. Public meeting
14. Restaurant
15. Medical, dental, legal appointment
16. Return home
17. Other
18. Small-item shopping, bank, post-office
19. Pick-up/drop-off

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Table 7.2
Tabulation of Destinations by Purpose

(by town)

1. Work
2. Theater, movie, etc.
3. Spectator sports
4. Participatory sports
5. Other recreation
6. Major grocery
7. Clothes, appliance shopping
8. Other shopping
9. Church
10. School
11. After-school activity
12. Voluntary association
13. Public meeting
14. Restaurant
15. Medical, dental, legal appointment
16. Return home
17. Other
18. Small-item shopping, bank, post-office
19. Pick-up/drop-off

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Figure 7.1a

Work Trips

(284)
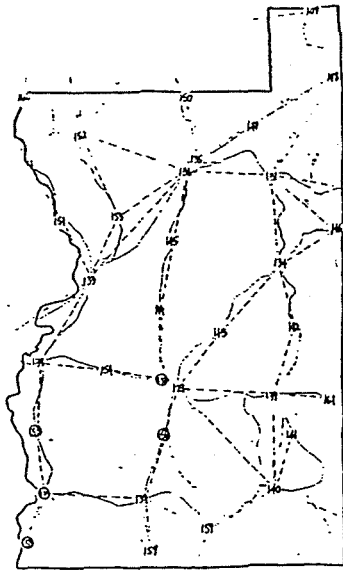
Willington
(6)

Ashford
(3)

Key

1-3	○
4-10	○
11-30	○
31-70	□
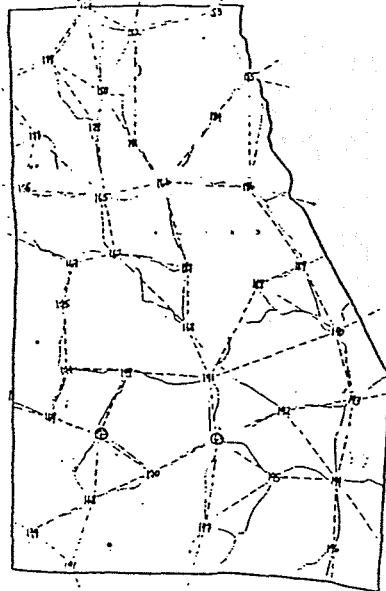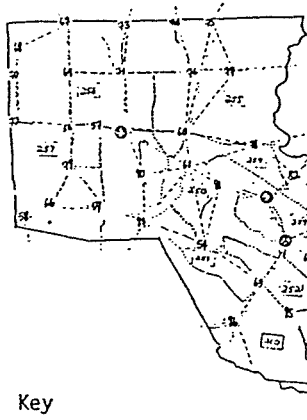
Coventry
(5)
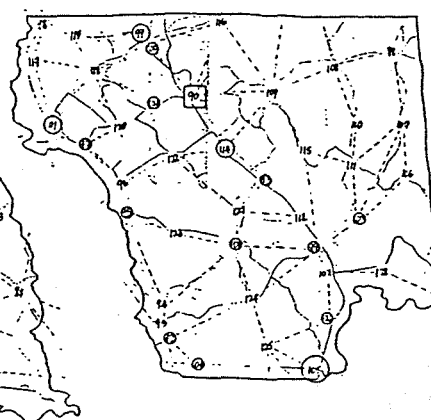
Mansfield
(123)

Chaplin
(6)

* not all maps are on the same scale

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Figure 7.1b

Work Trips
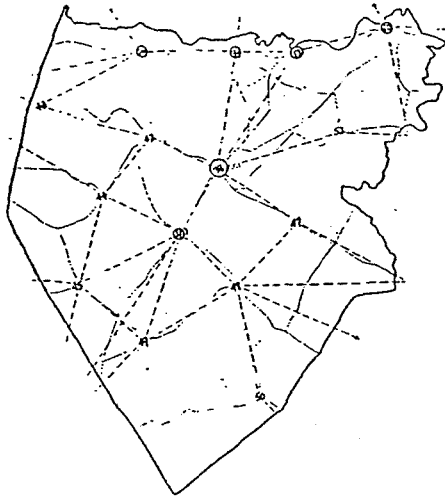
Columbia
(12)
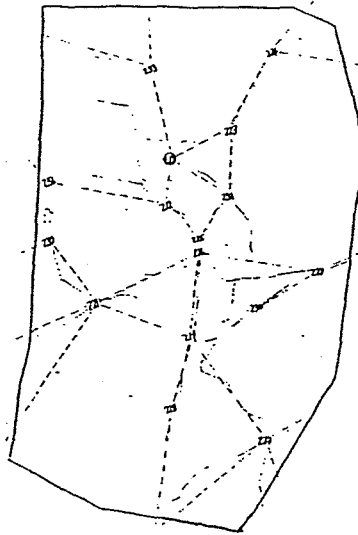
Hampton
(1)
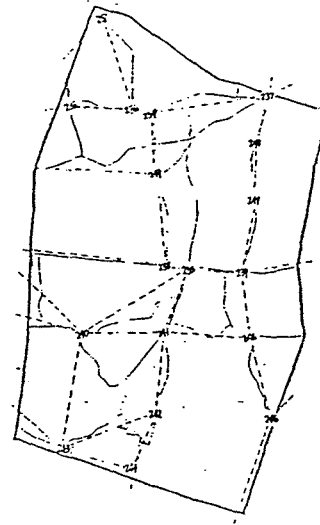
Scotland
(0)

Lebanon
(6)

Key
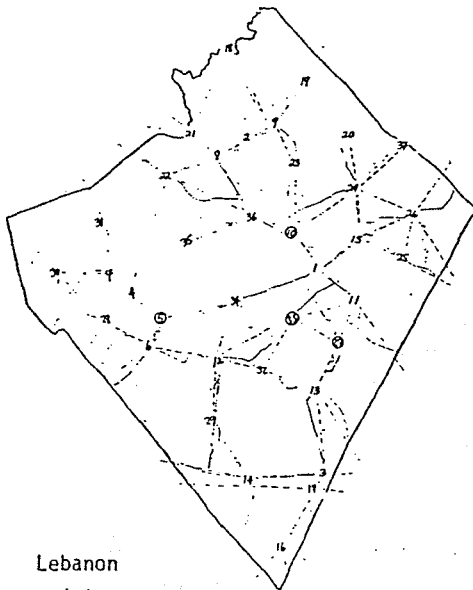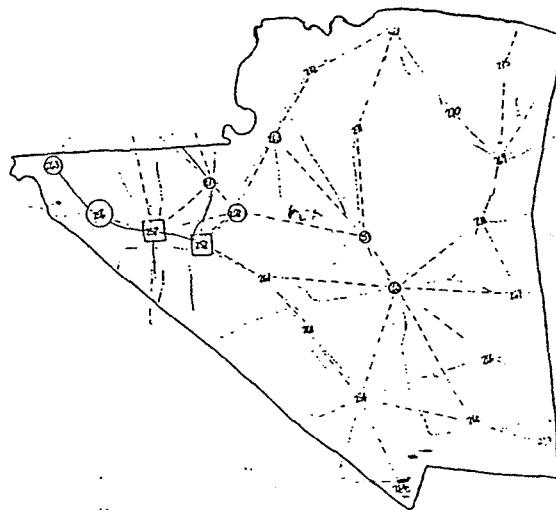
1-3 ○
4-10 ◔
11-30 ◯
31-70 ▢

*not all maps are on the same scale

Windham
(122)

171

Figure 7.2a
School Trips
(223)
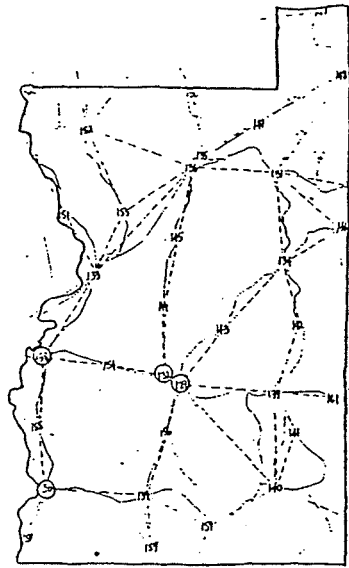
Willington
(9)
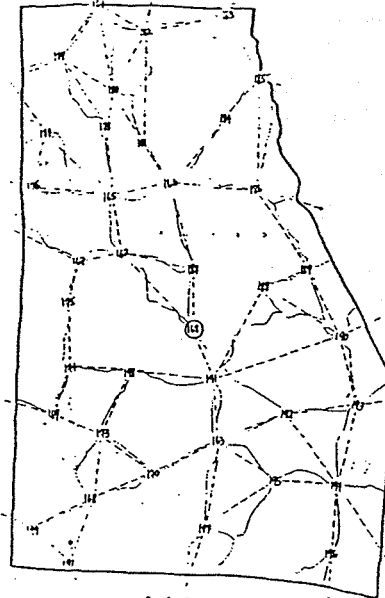
Ashford
(4)
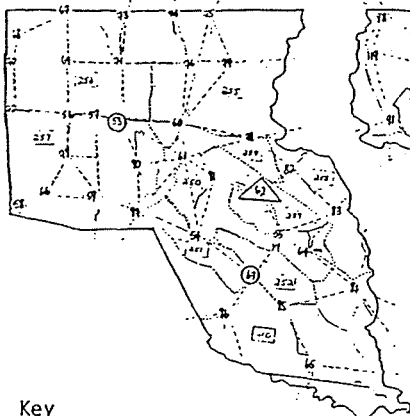
Coventry
(62)
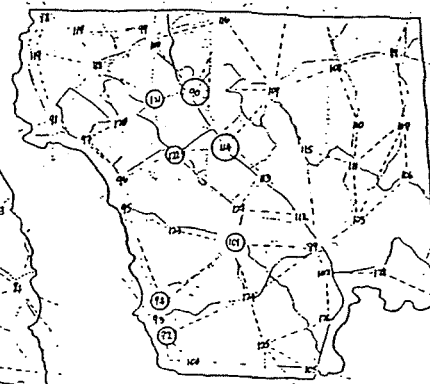
Mansfield
(52)
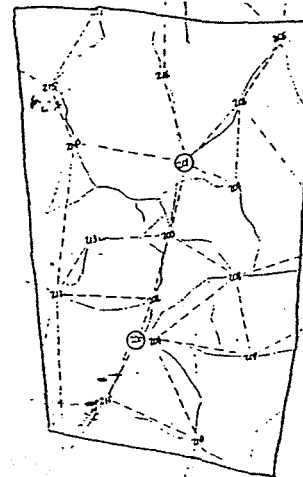
Chaplin
(5)

Key

1-10 ○
11-25 ○
26-55 △

*not all maps are on same scale

Figure 7.2b
School Trips

Columbia
(7)

Hampton
(0)

Scotland
(4)

Lebanon
(2)

Windham
(78)

Key

1-10 ○
11-25 ○
26-55 △

*not all maps are on the same scale

173
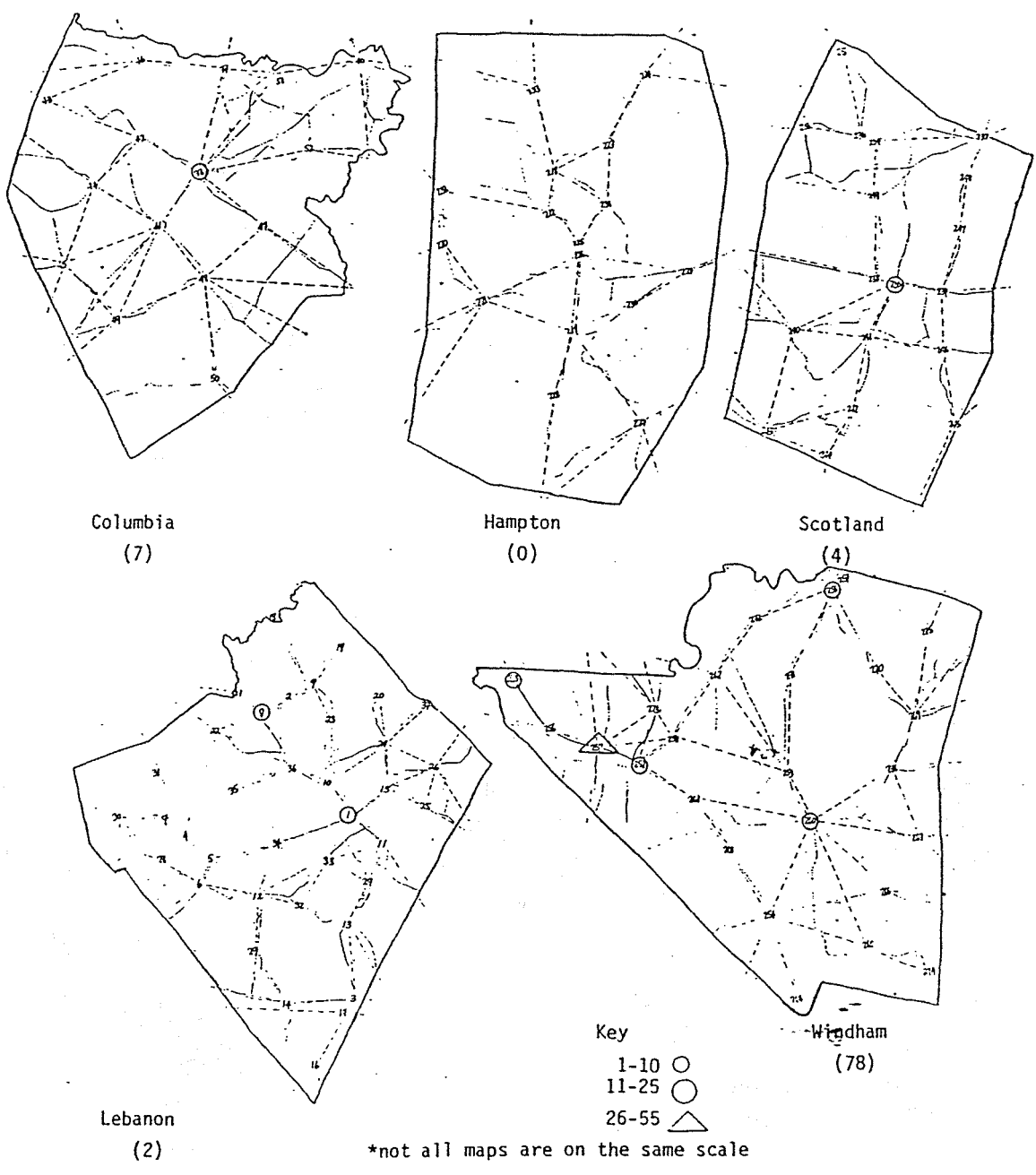
Figure 7.3a
Return Home Trips
(1238)
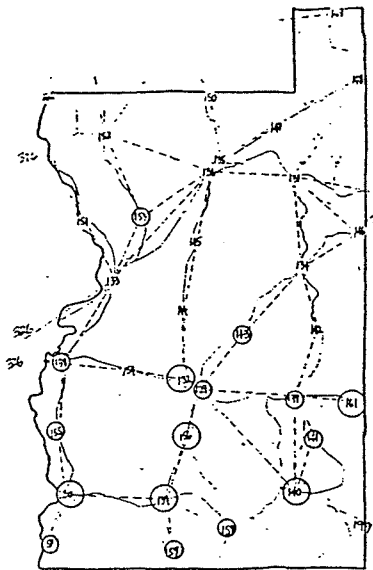
Willington
(96)
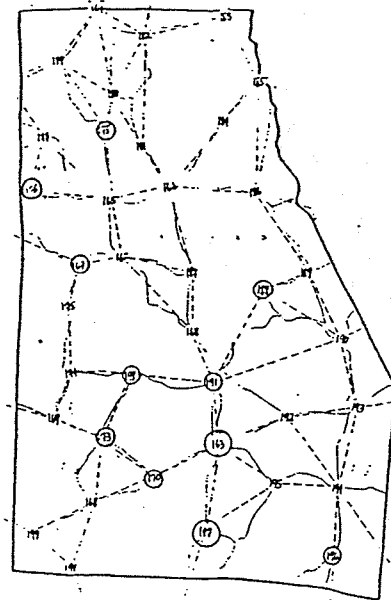
Ashford
(38)
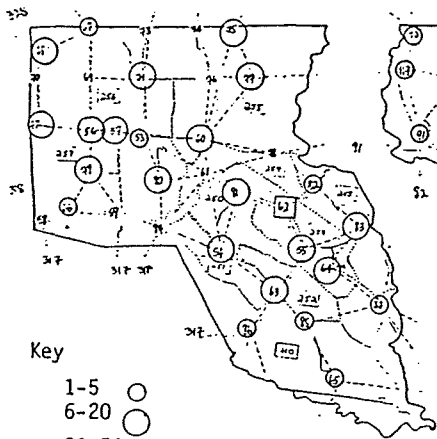
Key

1-5 ○
6-20 ◯
21-50 □
51-75 △

Coventry
(262)
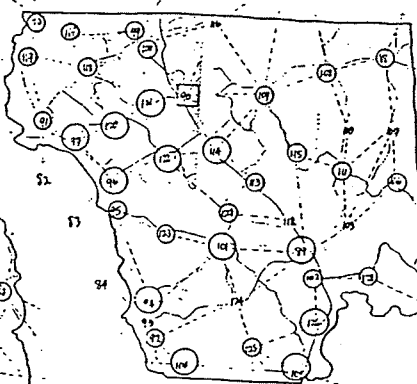
Mansfield
(254)
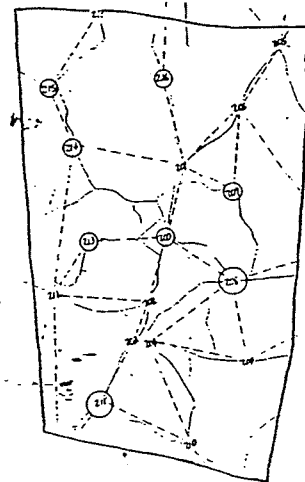
Chaplin
(32)

*not all maps are on the same scale

Figure 7.3b
Return Home Trips
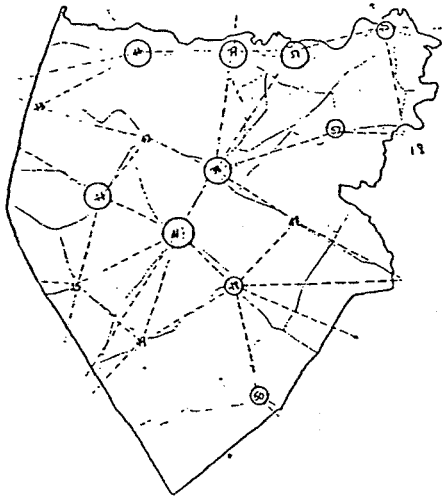
Columbia
(71)
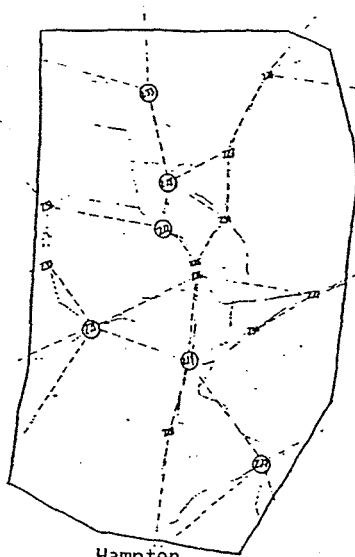
Hampton
(13)
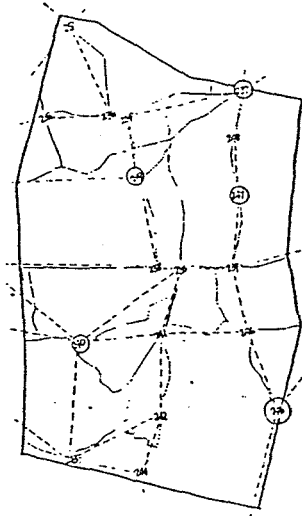
Scotland
(18)
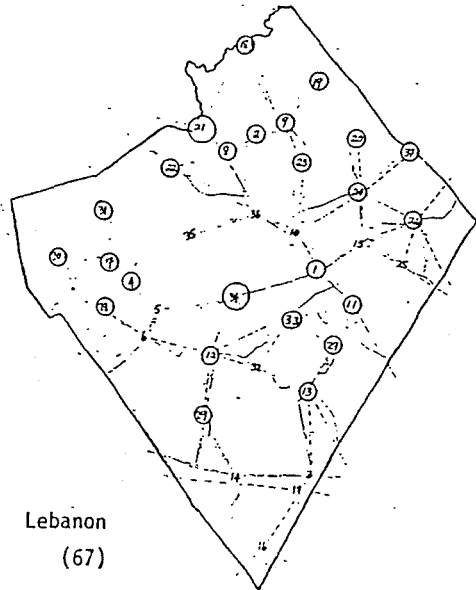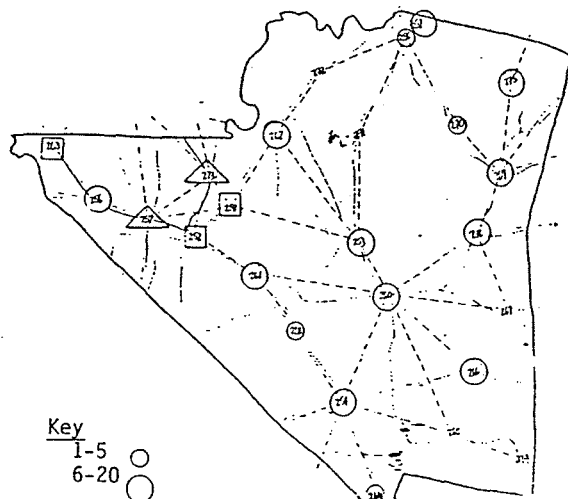
Lebanon
(67)

Key
1-5
6-20
21-50
51-75

Windham
(387)

*not all maps are on the same scale

Figure 7.4a
Restaurant Trips
(48)
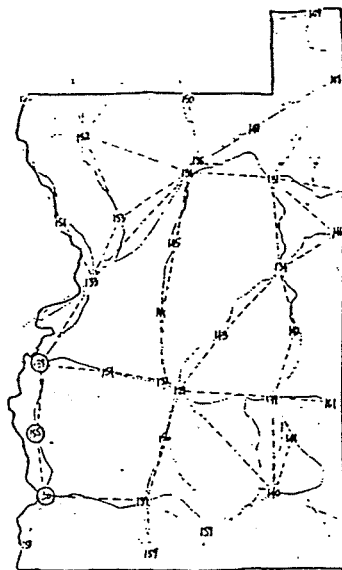
Willington
(6)
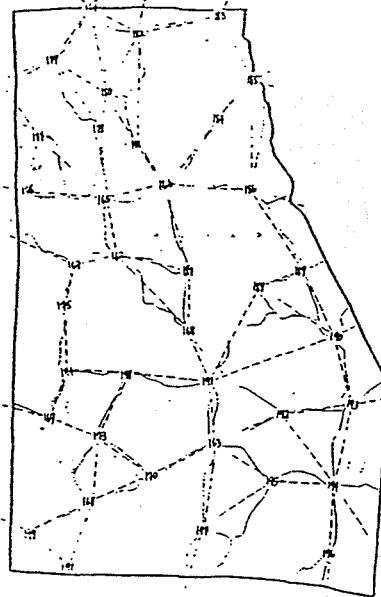
Ashford
(0)

Key
1-5 ○
6-10 ◯
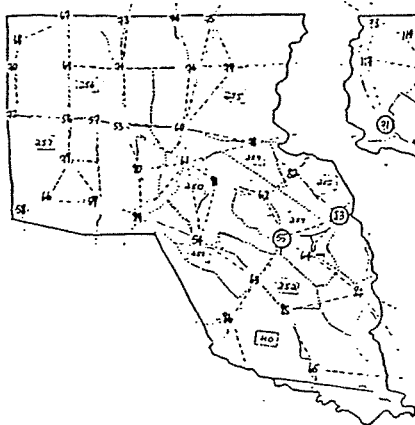
Coventry
(2)
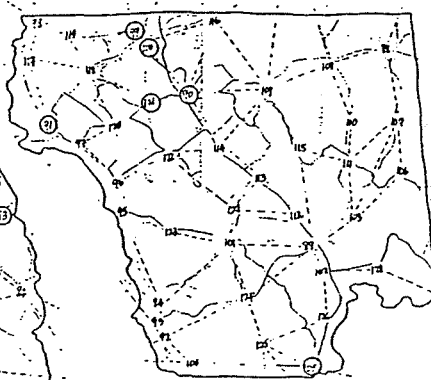
Mansfield
(8)
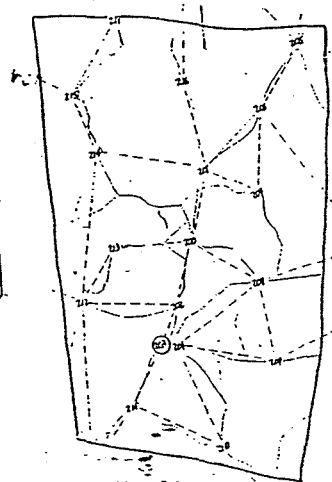
Chaplin
(1)

*not all maps to same scale

176

Figure 7.4b
Restaurant Trips
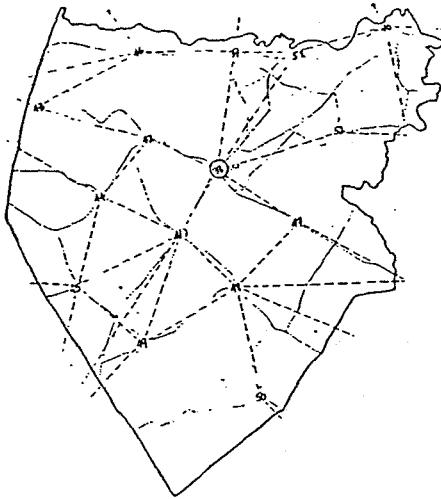
Columbia
(1)
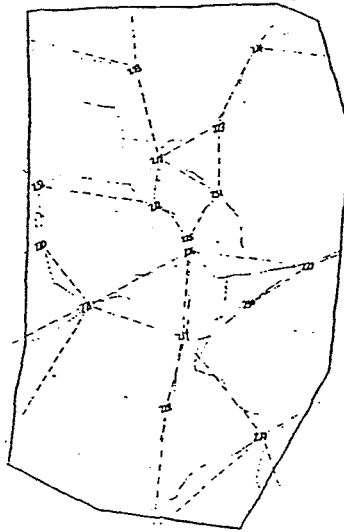
Hampton
(0)
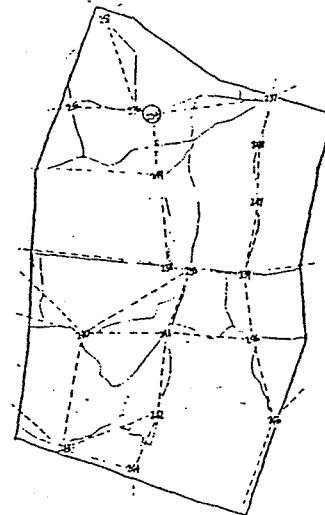
Scotland
(1)

Lebanon
(2)

Key

1-5　○
6-10　○

Windham
(27)

*not all maps are on the same scale

177
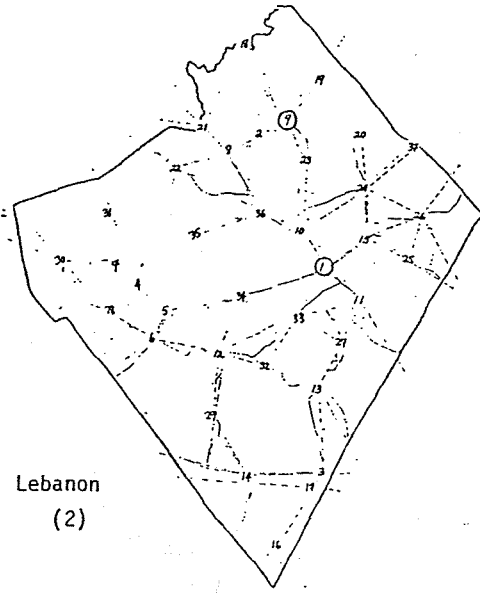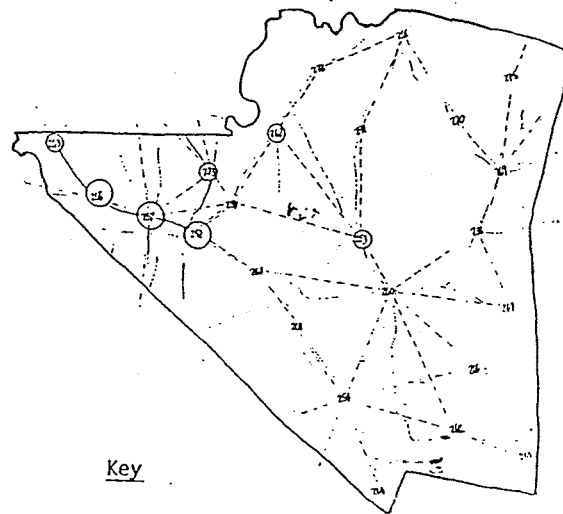
Figure 7.5a
Major Grocery Trips
(191)
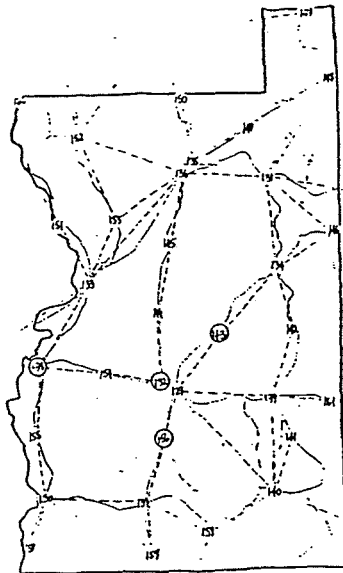
Willington
(5)
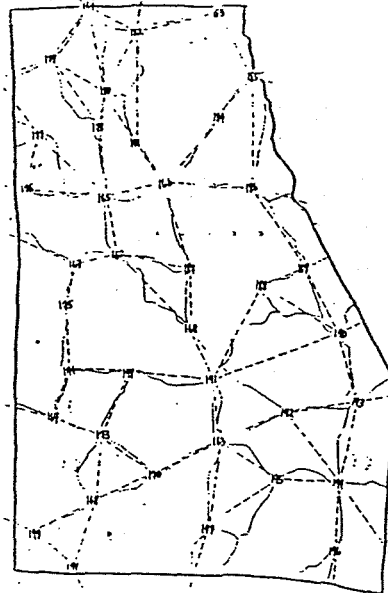
Ashford
(0)
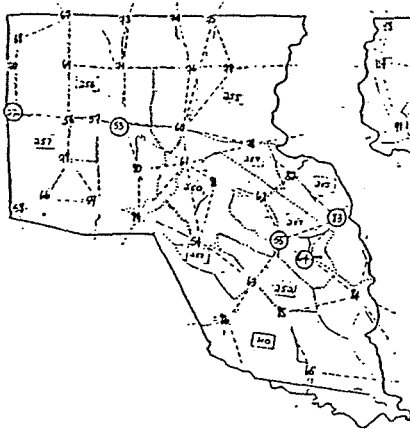
Coventry
(17)
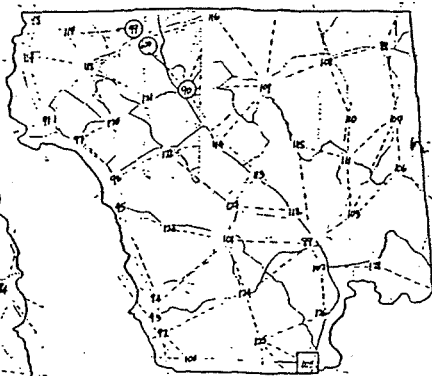
Mansfield
(68)
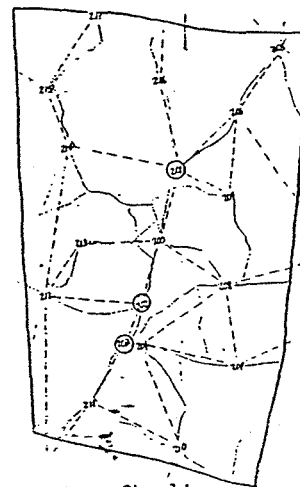
Chaplin
(5)

Key

1-15 ○
16-30 ◯
31-65 ▢

*not all maps are on the same scale

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Figure 7.5b
Major Grocery Trips

Columbia
(2)

Hampton
(0)

Scotland
(2)

Lebanon
(1)

Windham
(92)

Key

1-15	○
16-30	◯
31-65	▢

*not all maps are on the same scale

179
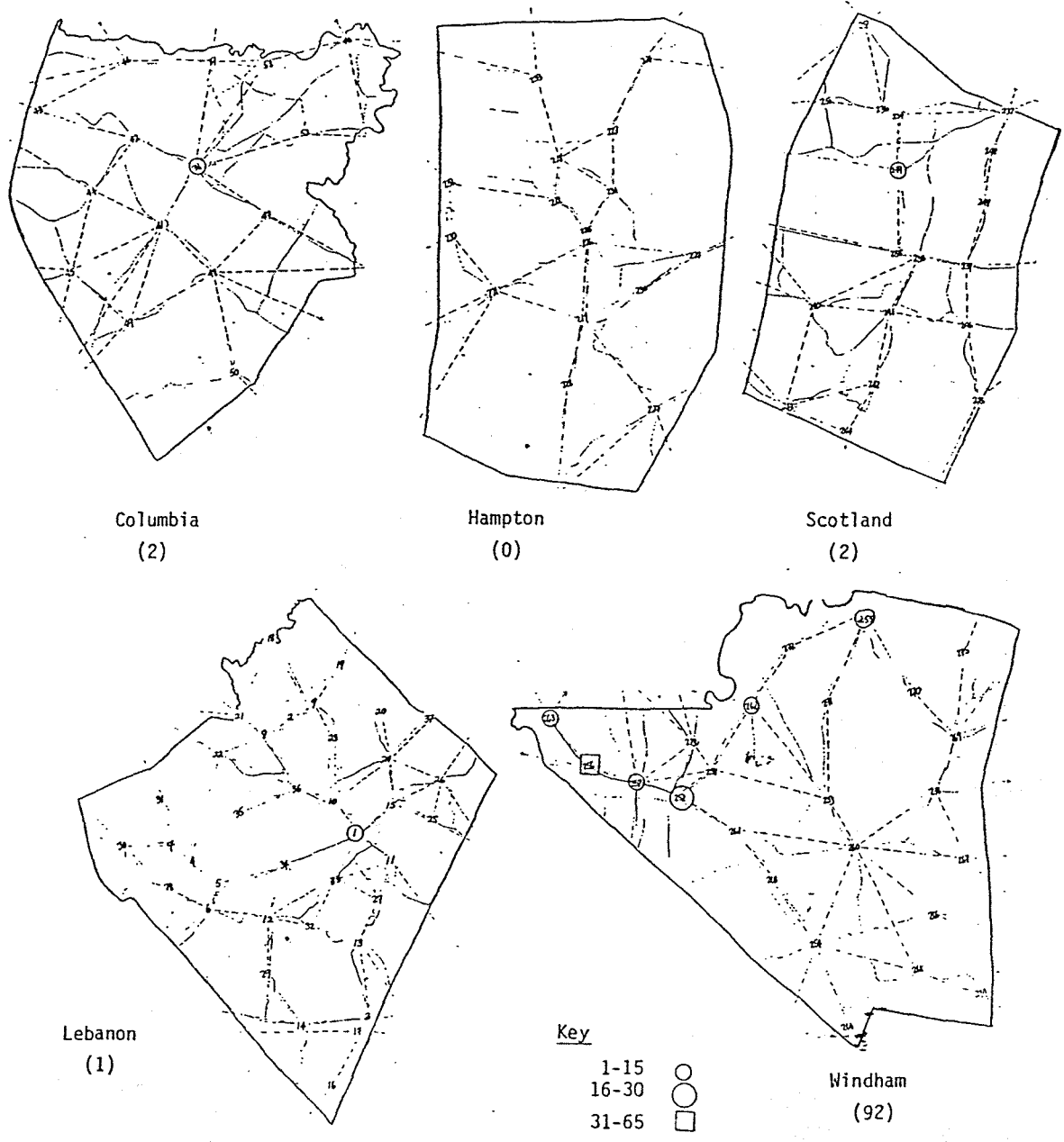
Figure 7.6a
Small Item Shopping/Bank/Post Office Trips
(86)
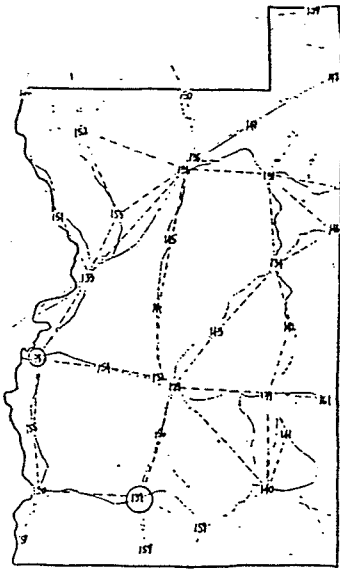
Willington

(8)

Ashford

(5)

Key

1-5 ○
6-12 ○
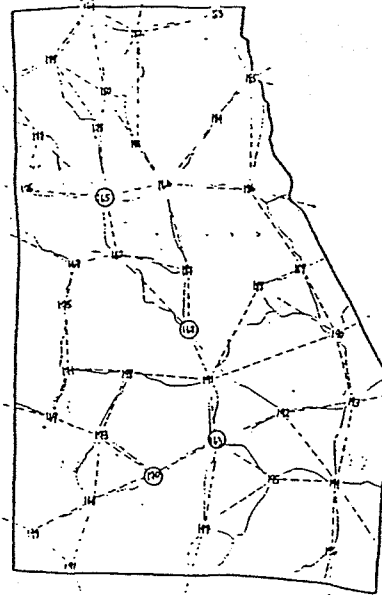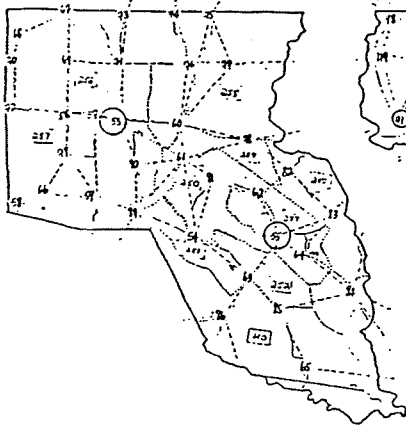
Coventry

(18)
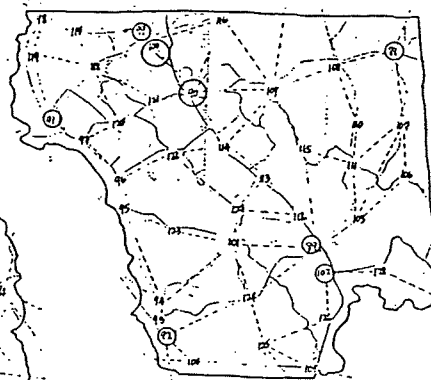
Mansfield

(22)

Chaplin

(0)
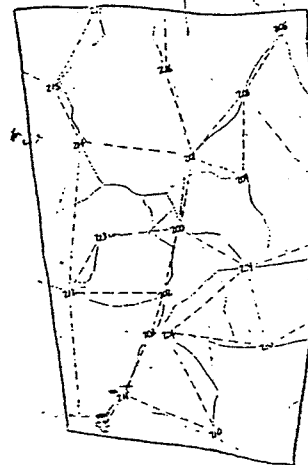
*not all maps are on the same scale

Figure 7.6b
Small Item Shopping/Bank/Post Office

Columbia
(6)

Hampton
(1)

Scotland
(0)

Lebanon
(1)

Key
1-5 ○
6-12 ◯

Windham
(25)

*not all maps are on the same scale
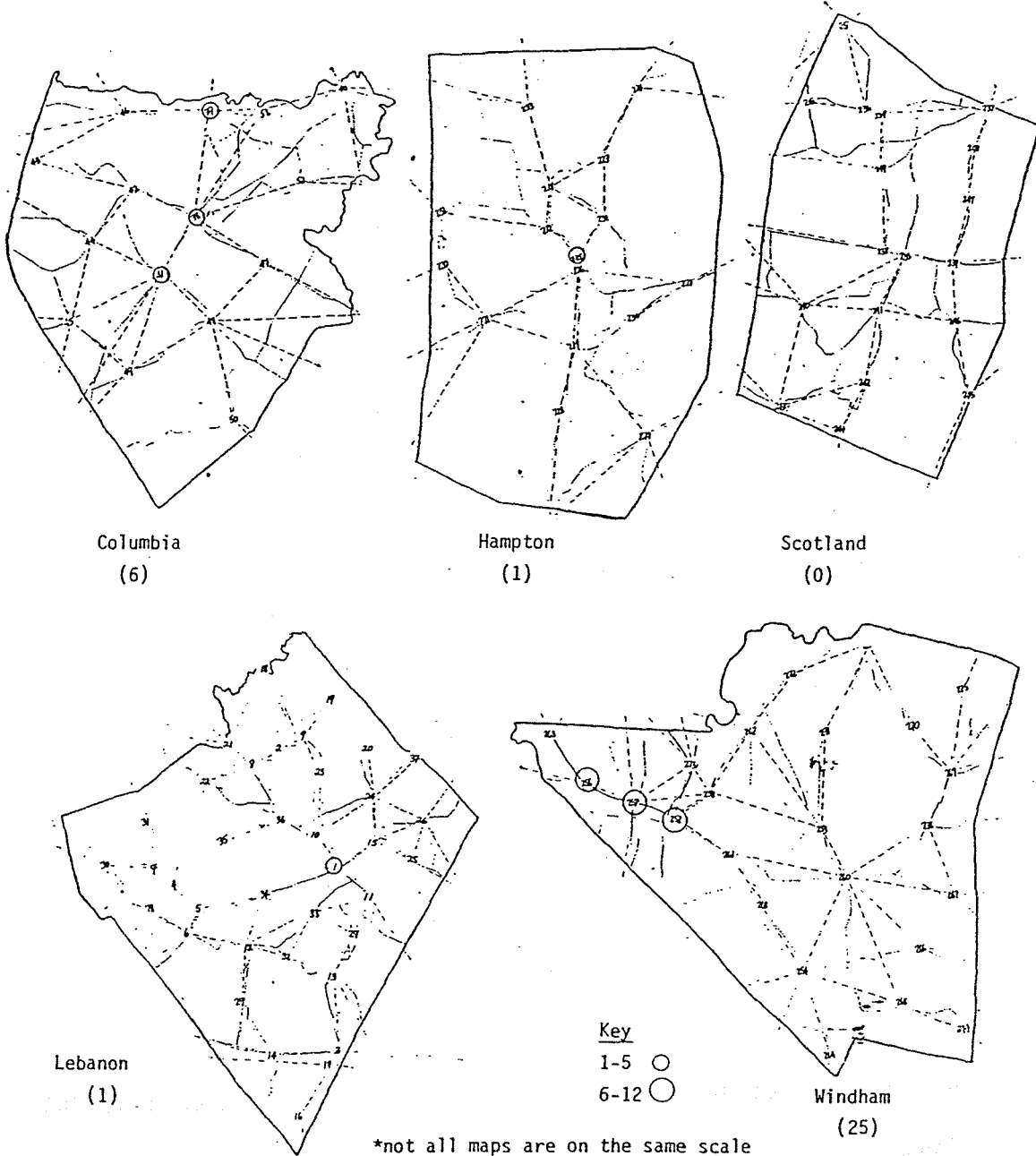
durations of those activities. Information on these values is obtained through an analysis of the actual durations experienced by the sample.

To help clarify the data, the households surveyed in the Windham data set were first separated into the following groups on the basis of characteristics and relationships within the household:

1. Households with only one individual (all individuals less than 65 years of age and non-students)

2. Households with at least one child 6 years of age or less and only one worker

3. Households with at least one child 6 years of age or less and two or more workers

4. Households with one or more children 7-17 years of age and only one worker (no children 6 years of age or less)

5. Households with one or more children 7-17 years of age and two or more workers (no children 6 years of age or less)

6. Households with no children (youngest person at least 18 years of age) and only one worker

7. Households with no children (youngest person at least 18 years of age and two or more workers)

8. Elderly households (either all people 65 years of age or older; or at least one person over 65 and no workers)

9. Student households (each person in household a student)

10. Unrelated individuals (each person in household unrelated to the others)

99 Households which did not fall into any of the 10 preceding
    groups. These households were not analyzed except as part of
    the entire sample.

0   Entire sample of 600 households.

The proportion of households in each group is presented in Fig. 7.7a.
The proportion of people in each group is presented in Fig. 7.7b. The
average number of people per household is displayed in Table 7.3.

For the purpose of the activity duration analysis, individuals were
classified as: (a) travelers who made a work trip, (b) travelers who
made no work trips, and (c) individuals who did not travel. This
information is displayed in Fig. 7.8.

The mean and standard deviations of activity durations by type for
the sample are shown in Table 7.4. A more aggregate assessment of
duration, in which activity types were grouped according to the
classifications of Fried et al (1979) as shown in Table 7.5, was also
made.

The average durations for all activity categories are shown in
Fig. 7.9, together with the total daily travel time, DT, for travelers in
each group. (It is noted that the daily travel is consistantly slightly
greater than one hour.) Because much of the college student group (9)
live on campus, their school related activities are not reported in the
travel survey. Thus, their computed activity durations are probably
underestimated. By far, the WC category predominates the average
travelers day.

Because of the nature of the fixed work activity for travelers who
made a work trip, a similar analysis as in Fig. 7.9 is shown in Fig. 7.10
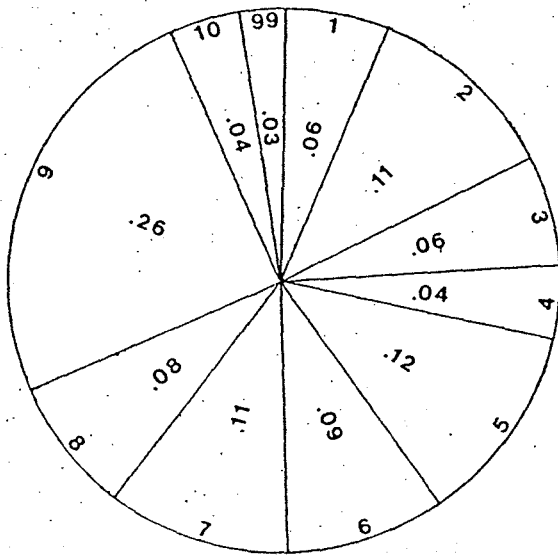
HOUSEHOLDS

TOTAL = 600

a.
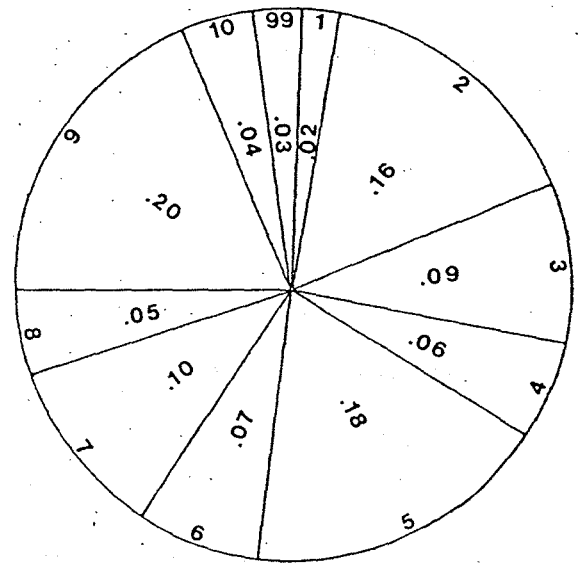
INDIVIDUALS

TOTAL = 1653

b

FIGURE 7.7 DISTRIBUTION OF HOUSEHOLD GROUPS

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TABLE 7.3

Group	# Households	# People	Avg People/HH
1	36	36	1.00
2	67	264	3.94
3	38	156	4.11
4	26	94	3.62
5	70	291	4.16
6	56	115	2.05
7	65	171	2.63
8	48	83	1.73
9	153	329	2.15
10	25	67	2.68
0	600	1653	2.76
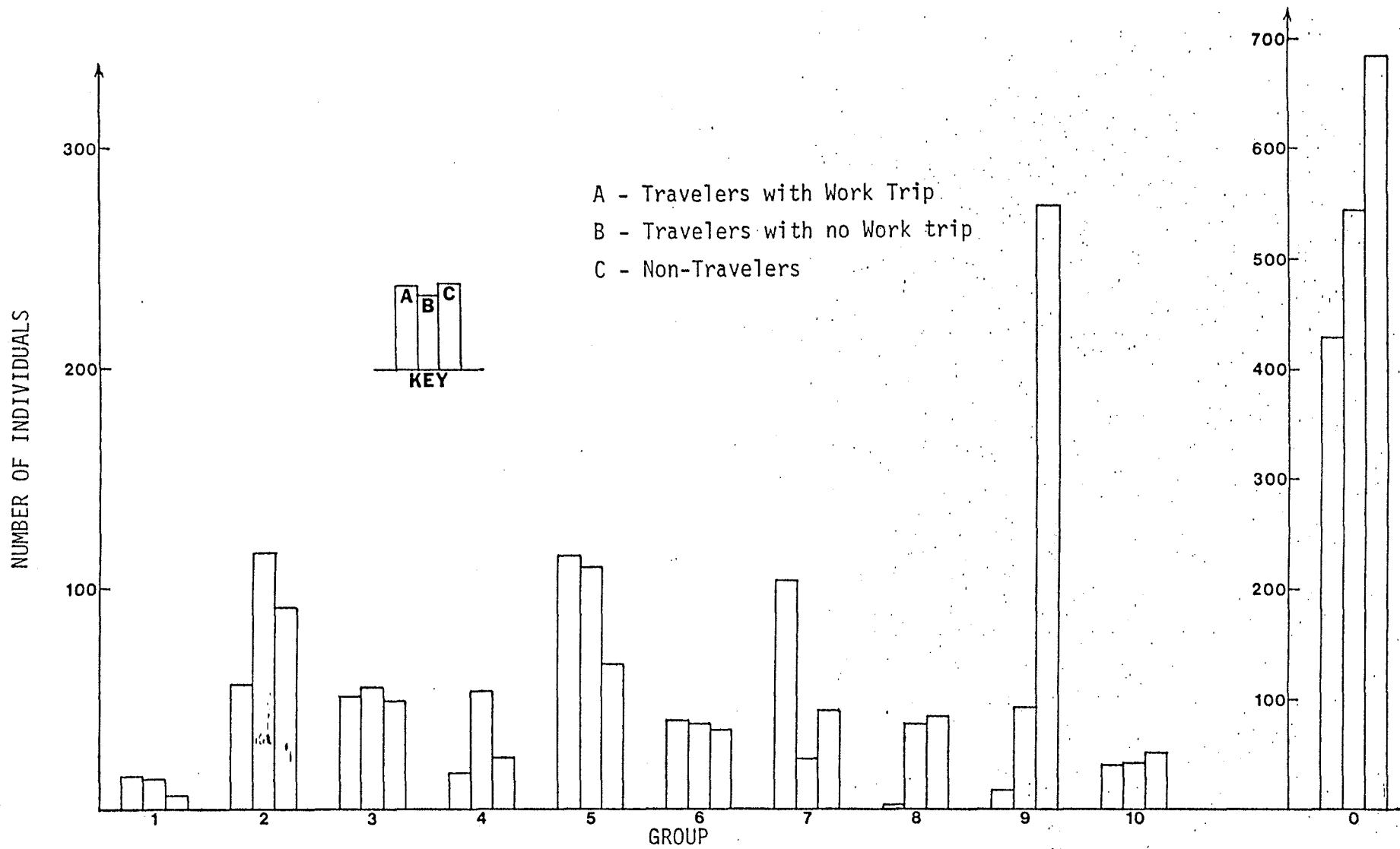
FIGURE 7.8   WORK TRIP CHARACTERISTICS

TABLE 7.4

Activity Durations

Activity #	Activity Type	N	Mean (hrs)	Std. Dev. (hrs)
1	work	466	7.50	2.63
2	movie	10	2.16	1.41
3	spectator sports	4	1.59	0.99
4	participatory sports	28	2.05	1.10
5	other recreation	64	2.11	2.60
6	grocery (small item) bank, post office	325	0.62	0.62
7	clothes, appliance shopping	26	0.90	0.87
8	other shopping	23	0.76	0.83
9	church	9	1.23	0.51
10	school	237	5.95	1.98
11	after school	22	1.65	2.01
12	voluntary association	46	0.99	1.70
13	public meeting	17	1.72	1.23
14	restaurant	63	1.88	2.45
15	medical, dental, legal	48	1.33	1.33
16	return home	274	2.76	3.49
17	other	307	1.54	2.84

TABLE 7.5

Activity Groups

Category Symbol	Category	Activities
HF	household/family	6 - grocery, banking, post office 7 - clothes, appliance shopping 8 - other shopping 16 - return home
WC	work/career	1 - work 10 - school
IS	interpersonal/social	9 - church 11 - after school 12 - voluntary association 13 - public meeting 15 - medical, dental, legal 17 - other
LR	leisure/recreation	2 - movie 3 - spectator sports 4 - participatory sports 5 - other recreation 14 - restaurant
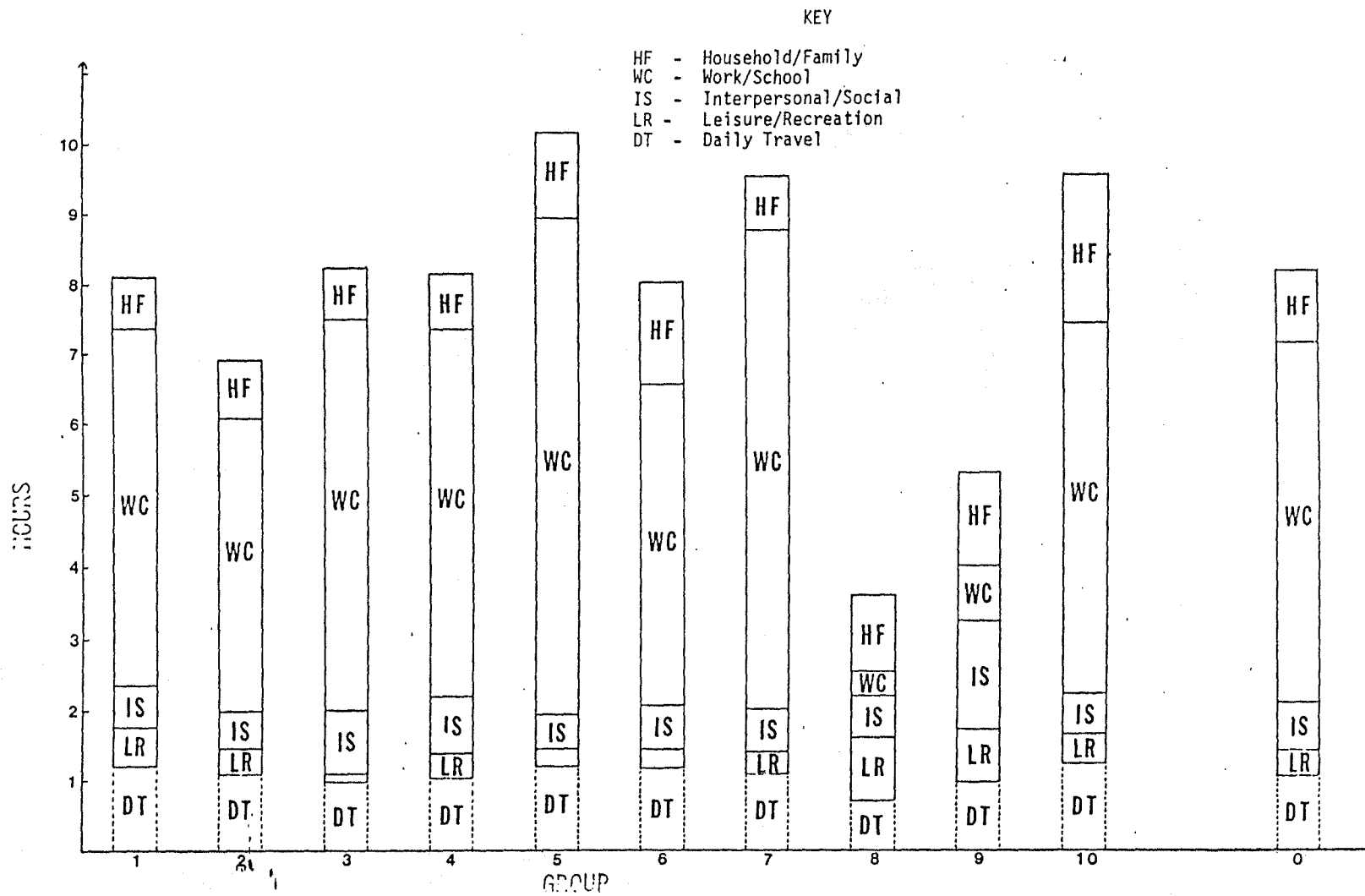
FIGURE 7.9 AVERAGE ACTIVITY DURATION
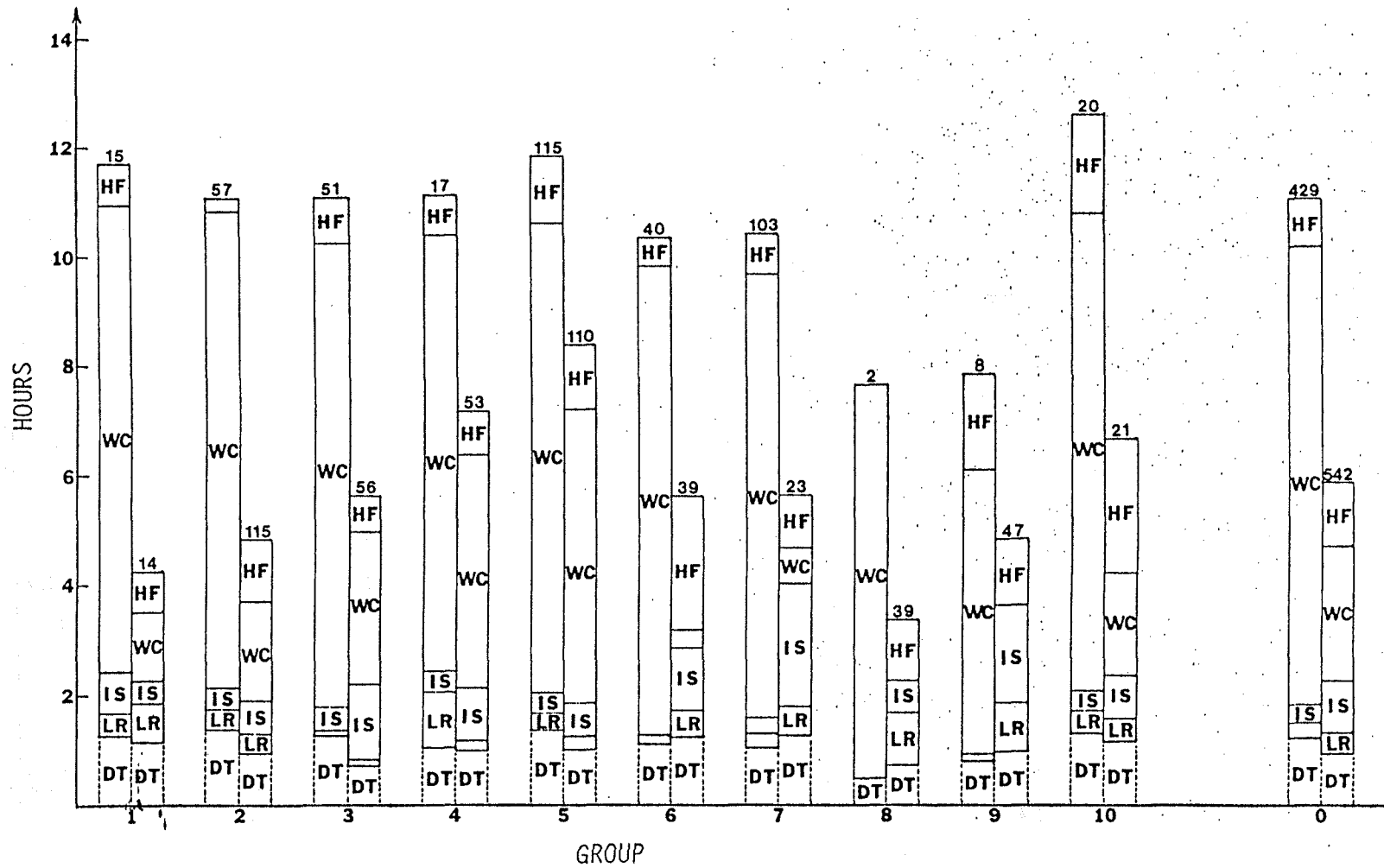
FIGURE 7.10   VARIATION OF AVERAGE ACTIVITY
DURATION WITH WORK TRIP STATUS

with travelers who made a work trip on the left bar versus travelers who made no work trips on the right bar for each life cycle group. Because the WC category includes only work and school activities, the WC duration on a left bar may include both work and school activities while the WC duration on the right bar is the average school activity time period. The numbers appearing at the top of each bar indicate how many people belong to that segment of analysis.

Each household proportions household time to activities and travel. The number of people residing in the household multiplied by 24 hours is 100% of the household time. The average number of travelers per household multiplied by the traveler durations shown in Fig. 7.9, divided by the number of person hours corresponding to 100% yields the average percentage of household time spent away from home (Fig. 7.11).

7.5 Summary Statistics

Finally, a series of summary statistics on a broad range of characteristics of the travel/activity behavior of the sample were computed. These are displayed in Table 7.6.
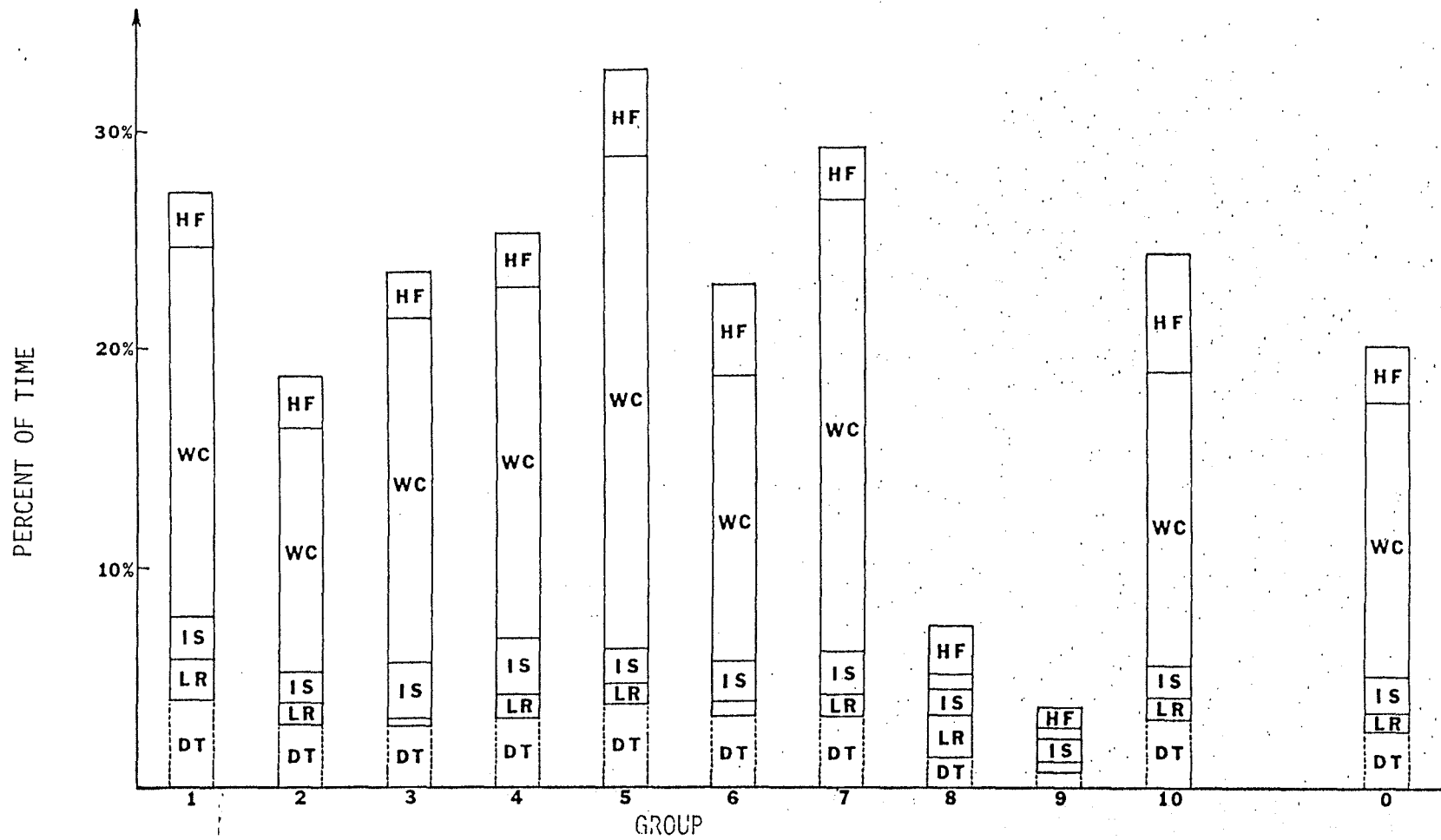
PERCENT OF TIME

FIGURE 7.11.   PERCENT OF HOUSEHOLD TIME
               DEVOTED TO ACTIVITY CATEGORY

TABLE 7.6

Summary Statistics

						Group						
	1	2	3	4	5	6	7	8	9	10		0
number of HHs	36	67	38	26	70	56	65	48	153	25		600
number of people	36	264	156	94	291	115	171	83	329	65		1653
number of travelers	29	172	107	70	225	79	126	41	55	41		971
% travelers	80.6	65.2	68.6	74.5	77.3	68.7	73.7	49.4	16.7	61.2		58.7
total number of tours	34	217	129	91	309	98	152	45	63	55		1223
tours/trav	1.17	1.26	1.21	1.30	1.37	1.24	1.21	1.10	1.15	1.34		1.26
total number of trips	98	547	319	226	704	228	367	104	146	138		2939
trips/tour	2.88	2.52	2.47	2.48	2.28	2.33	2.41	2.31	2.32	2.51		2.40
trips/trav	3.38	3.18	2.98	3.23	3.13	2.89	2.91	2.54	2.65	3.37		3.03
avg tour duration (hrs)	6.07	4.93	6.30	5.51	6.62	5.44	7.38	2.33	2.86	5.94		5.75
avg. trip time (min)	21.29	20.24	19.54	18.90	22.87	24.18	22.14	16.44	21.72	21.73		20.84
avg daily travel (min)	72.0	64.4	58.2	61.0	71.6	69.9	64.4	41.8	57.6	73.2		63.1
number of complex tours	16	58	34	17	53	17	35	9	13	17		270
% tours which are complex	47.1	26.7	26.4	18.7	17.2	17.3	23.0	20.0	20.6	30.9		22.1

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CHAPTER EIGHT

Activity Pattern-Based Approach to Destination

Choice Modeling

8.1. Introduction

The simulation model developed in this study and described in previous chapters assumes the following aspects of the individual's activity schedule to be fixed: the set of (non-home) activites to be performed, the duration of each activity, and the location of each activity. These assumptions, necessary at the outset to lend some tractability to an otherwise extremely complex problem, are nevertheless somewhat restrictive. The set of activities to be performed may change throughout the day as unexpected needs arise, as unexpected time is opened in the schedule, or as delays prevent some activities from being carried out. The duration of each activity is random; this is more important a consideration in "open-ended" activities such as shopping than for temporally fixed activities (however, there is significant flexibility even in such seemingly fixed activities as work). Finally, the location of many activities is not fixed but may be chosen based on aspects of the rest of the activity schedule, as well as the intrinisc attractiveness of the location itself.

The definition of objectives for activity patterns deals somewhat with the first two assumptions, in its notions of "risk" and "unplanned activities" (see Technical Memorandum CB-3). The purpose of this part of the study is to relax the third assumption and explicitly model the

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choice of activity location. While this component of the research currently stands alone, it is ultimately intended to be integrated with the existing simulation model. The following section discusses the conceptual framework of the approach taken in this part of the study, including potential interfaces with the rest of the research. Section 3 describes the methodology used in this study, and Section 4 presents the empirical results. Section 5 is a summary.

8.2. Conceptual Framework

There are two major aspects to the destination choice component of this research. The first is choice-set modeling, or finding the set of feasible destinations in a given context. The second is choice modeling, or analyzing the process of choosing one destination from the choice set. Each of these is discussed below.

8.2.1 Choice-Set Modeling

The simulation model of trip-making behavior takes a fixed set of activities with fixed durations and locations, and rearranges them within the constraints imposed on the individual to produce all "feasible activity patterns" (FAPs). Part of assessing feasibility of a particular ordering is determining whether the given locations can be reached within the time available. If the assumption of fixed location is removed, however, certain previously infeasible patterns will become feasible when a closer destination is available for the same trip purpose. In this

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situation, a "pattern" will be characterized by <u>locations</u> as well as <u>order</u> (and timing) of the same fixed set of activites, and determining feasibility will involve testing, for a given ordering, <u>which locations</u>, if any, can be reached in the time available.

Thus, in keeping with the existing context of FAP generation, this part of the research assumes that the set of activities, their durations, <u>and their order</u>, are fixed. It is then desired to find, for a given activity, the set of locations which can be reached within the time available.

Choice-set modeling clearly should not be done for every activity, since many activities take place at fixed locations. For the purposes of this research, activity types were divided into those with fixed locations and those with non-fixed locations, as shown in Figure 8.1. Some of these divisions are somewhat arbitrary (e.g., a "drop-off" or an "other" trip may not have a fixed location, a "restaurant" or a "bank" trip may have a fixed location), but in the absence of further information it was felt to be a reasonable categorization.

The most obvious aspect of Figure 8.1 is that 82.5% of the activities in the Windham sample take place at fixed locations. Thus, for the preponderance of trips, there is no choice of destination. These spatial constraints affect not only the fixed activities themselves, but also (in combination with temporal constraints) restrict the number of feasible locations for activities with non-fixed destinations.

An activity pattern for which every activity has a fixed location involves no destination choice, and will not be considered in this part

Figure 8.1. Activity Types by Type of Location

Fixed Location		Non-fixed Location	
Activity Type	Proportion of Trips	Activity Type	Proportion of Trips
work	.159	theater	.003
spectator sports	.001	other recreation	.022
participatory sports	.010	major grocery	.077
church	.003	clothes, appliance	
school	.081	shopping	.009
after-school	.007	other shopping	.008
voluntary association	.016	restaurant	.021
public meeting	.006	small-item shopping,	
medical, dental,		bank, P.O.	.034
legal appointment	.016		
return home	.422		.175
other	.059		
pick up/drop off	.047		
	.825		

of the research. Thus, every pattern studied here will imply that at some point the individual is at a fixed location (e.g., home, work), that one or more activities without fixed locations are to be performed, and that the individual returns to a fixed location, not necessarily the same as the first (cf. the concept of "deviations," introduced by Damm (1979) and followed by Landau, et al. (1982)). In the most general terms, the choice set is the set of jointly feasible locations for the set of non-fixed activities, and the choice involved is the joint choice of destinations.

8.2.2 Choice Modeling

Suppose for the moment that the location of only a single activity is to be modeled; i.e., the activities in the pattern follow the sequence fixed/non-fixed/fixed. Suppose also that the set of feasible destinations for the non-fixed activity has been generated, based on the spatial-temporal constraints of the rest of the pattern. The situation is then viewed as a typical discrete choice problem calling for a random utility approach such as probit or logit. The object is to evaluate, for each feasible location, the probability of choosing that location, where the probability is a function of the utility of that location to the individual. Utility, in turn, is typically modeled as a function of measures of the attractiveness (or benefit) of the location and measures of the accessibility or travel impedance (i.e., cost) of the location (cf. Recker and Kostyniuk, 1978; Koppelman and Hauser, 1978).

Calibration of the model on observed data will yield statistical estimates of the parameters of the utility function.

In concept, extension to the case of two or more non-fixed activities is not difficult. Richardson and Young (1982) describe the application of nested logit to the sequential destination choice problem. In this approach, the last choice is modeled first, conditional on all previous choices having been made. Then higher (preceding) choice levels are modeled, where each level contains a term (the "inclusive price" or "logsum" term) in the utility function representing the expected maximum utility of <u>succeeding</u> choices. That is, earlier choices are made based (in part) on some expected value contributed by succeeding choices to the overall utility.

In practice, actual estimation of the sequential destination choice problem in its most general form is not entirely straightforward. First, not everyone will have the same number of sequential non-fixed activities in a pattern: some will have none, some only one, some two, and so on. Thus, there will be differing numbers of "nests" or levels in the nested logit model. Second, the set of jointly feasible destinations will be different for each individual: different activity types will take place at different sets of locations; even within the same activity type, individuals will have different choice sets for a given trip due to the differing constraints on them; and even if at a single level in the sequence two individuals have the same choice set, the set of <u>jointly</u> feasible locations for a multi-trip sequence could be different due to differing constraints.

None of these difficulties seems to be insurmountable, and future efforts in activity pattern-based destination choice modeling should be directed at making the nested logit approach operationalizable. As a first step, however, the current research treats only the case of a single non-fixed activity. Since, in the sample, 80.8% of activities assumed to have a non-fixed destination are followed by activities with fixed destinations, not much is lost at the present time by concentrating on the isolated non-fixed activity. However, it is important to have the capability of modeling more complex situations to better evaluate policies which lead to more complex (trip-chaining) behavior.

Once an activity pattern-based destination choice model is calibrated, it can be used in a variety of ways. The model provides both a framework for analyzing how choices are made, and an estimate of the relative importance of various factors (e.g., attractiveness, accessibility) in those choices. Thus, policies which are aimed at changing either the choice set available to people (by expansion or contraction) or the factors involved in choosing from the feasible set may be evaluated.

As part of the activity simulation model developed in this study, the destination choice model contributes to the evaluation of the utility of the overall pattern. Clearly the same set of activities can have different utilities depending on the attractiveness and accessibility of the locations at which they are performed. Thus, a destination choice submodel allows the comparison, for example, between a pattern which includes an attractive destination but requires substantial travel time,

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and a pattern which involves a closer, less attractive destination but leads to a lower risk, more time at home, more flexibility, and so on.

In the following section the destination choice modeling methodology developed is described in the context of this study. While some aspects are specific to the data available and the requirements or assumptions of the general simulation model, the methodology in broad terms can stand alone as an activity pattern-based procedure for developing destination choice sets and modeling the destination choice itself.

8.3. Methodology

There are several steps in the activity pattern-based destination choice modeling methodology: defining the scenario, defining the choice set, and defining the choice variables. Each step is discussed in turn.

8.3.1 Defining the Scenario

As described in the conceptual framework section above, the general destination choice modeling problem is quite complex, allowing for different numbers of sequential non-fixed activities and different activity types. At the outset, it is necessary to simplify the problem somewhat to make it tractable. Once the groundwork has been laid, future efforts may be directed toward refining the methodology to handle more complex choice situations.

For the purposes of this research, then, several simplifications are made. First, only single destination decisions are treated. That is,

the only case studied is that in which an activity with a non-fixed location falls between two activities with fixed locations (or the non-fixed activity is the first trip in a home-based tour, and is followed by a fixed activity). As mentioned earlier, this case accounts for 80.8% of all non-fixed activities in the data set.

Second, only a single trip purpose is considered. Since each different purpose draws from a different set of locations, simultaneous treatment of all purposes would be difficult. More importantly, however, it is likely that the relative influence of each explanatory variable (e.g., attractiveness, impedance) on choice will vary for different trip purposes. Dealing separately with each purpose allows the parameters in the choice model to differ across trip purposes.

The activity type chosen for initial development of the methodology was the major grocery shopping trip. Major grocery trips form the largest category of trips with non-fixed destinations (7.7% of all trips and 44.0% of all non-fixed trips, as indicated by figure 8.1). As such, they are of substantive interest to transportation planners, as well as providing enough trips to give statistically reliable parameter estimates. Further, major grocery shopping is a relatively homogeneous purpose, unlike some of the other large categories such as "other recreation" and "small item shopping, bank, and post office."

Two other simplifications made were deleting individuals whose grocery trips took place outside the 10-town region, and deleting individuals who used a mode other than automobile. This resulted in a

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final sample of 122 people making a major grocery shopping trip between two fixed activities.

8.3.2 Defining the Individual Choice Set

The universe of major grocery shopping destinations was taken to be the set of all grocery shopping locations (within the 10-town region) visited by anyone in the Windham data set (cf. Adler and Ben-Akiva, 1976). There were 25 such locations, as shown in Table 8.1. Most trips went either to node 256, in Willimantic (34.0%), or to node 105, Eastbrook Mall in Mansfield (26.2%).

Conventional discrete choice models typically assume that everyone in the sample has identical choice sets. However, it is a major tenet of the activity-based approach to destination choice modeling that not all opportunities are open to all people, due to the spatial-temporal constraints on their schedule (see, e.g., Burnett and Hanson, 1979). Accordingly, an important aspect of this research is the elimination of alternatives from individual choice sets that cannot be reached in the time available to the individual. This process of elimination is described below.

As discussed in section 8.2, the activities, their durations, and their sequence are assumed to be fixed. If the starting and ending times of each activity (except of course the grocery trip being modeled) are also assumed to be fixed, then the set of available destinations is limited to the chosen destination and all closer locations (there are no explicit data available on actual wait time for each activity, so in

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general no slack time is observed between activities). However, there is often more flexibility in the schedule than is suggested by what is actually observed. That is, an individual often could have visited a more distant location, but chose not to, and simply started the following activity immediately upon completion of the former.

In the Windham survey, data were obtained on the earliest time the person could leave home to begin a tour, the latest time he/she could return home from a tour, and starting and ending times for activities that had fixed times. This information can be used to deduce the earliest starting, latest starting, earliest ending, and latest ending times possible for each activity, while still preserving sequence, duration, and temporally fixed points in the schedule. Then, the difference between the latest possible starting time of the activity succeeding grocery shopping and the earliest ending time of the preceding activity is the "window" available for the grocery shopping trip. Destinations for which the travel time at each end plus the duration of the activity exceeded the window[1] were excluded from the individual's choice set.

Table 8.2 displays the distribution of the number of alternatives available. A great majority (82.8%) of the sample has all 25

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[1]Actually, a tolerance was allowed so that the alternative was excluded only if the time involved exceeded the time available by more than 0.084 hours (5 minutes). This is because the travel times used in the calculations were computed externally (see Chapter 6) and therefore did not always agree exactly with the reported travel times. In some cases the destination actually visited would have been excluded from the choice set if a strict cutoff had been applied.

alternatives available, with the rest of the sample being more or less uniformly distributed over the range. This is in keeping with results obtained by Landau, et al. (1982) and this suggests that, in a static environment, assuming identical choice sets may not be too restrictive (at least in the instances cited). However, as Landau, et al. point out, the results of a model based on such an assumption will be biased for a (potentially managerially significant) segment of the population. Also, the effects of policies designed to expand or contract the choice set (e.g., increasing store hours, gasoline rationing) cannot possibly be adequately evaluated using such an assumption. Thus, it is important to be able to determine the choice set actually available to an individual and incorporate that set into the choice model.

8.3.3 Definition of Choice Variables

Having determined the choice set for each individual, the next step is to identify an expression for the utility of a location. It was mentioned earlier that destination choice models typically contain two kinds of explanatory variables: those relating to the attractiveness of the location itself, and those relating to the ease of reaching the location. Accordingly, utility will be defined in terms of these two types of variables.

Since the Windham data set was not collected with destination choice modeling in mind, there was no explicit information on the attractiveness of specific locations. Thus, it was necessary to use a proxy measure of

attractiveness. The measure chosen was simply the proportion of people in the overall data set who visited a given location. While this variable is admittedly crude (under this definition, a given destination will have the same attractiveness for every individual), it is essentially the only one available, and is probably a reasonable approximation to a "true" measure of attractiveness.

In developing a measure of impedance, it was reasoned that what is important to choice is not necessarily the conventional measure of travel time from the preceding location to the alternative being considered. What is important is whether the alternative is (roughly) on the way to or from the spatially fixed points in the pattern. Thus, an alternative which is distant from the preceding location but quite close to the (fixed) location of the succeeding activity should, ceteris paribus, have a higher probability of being chosen than an alternative which is somewhat close to the preceding location but in the opposite direction from the succeeding location.

Hence, in the activity pattern-based approach, a logical measure of impedance is the deviation travel time. That is, if

TT_{ps} = the travel time from the preceding location to the succeeding location,

TT_{pa} = the travel time from the preceding location to the alternative being evaluated, and

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TT_{as} = the travel time from the alternative to the succeeding

   location, then

$$DTT_a = TT_{pa} + TT_{as} - TT_{ps} \qquad (p \neq s) \qquad\qquad (8.1)$$

is the travel time variable used in this research (see Figure 8.2). Thus, DTT_a is the amount added to the base travel time TT_{ps} by visiting destination a in between p and s. If a is directly on the way to s from p, DTT_a will be zero. In the case of a single-trip tour, where p=s (e.g., home-shop-home), DTT_a is defined to have the conventional value TT_{pa} rather than the true deviation value $TT_{pa} + TT_{as}$ ($-2TT_{pa}$ if travel time is symmetric).

The utility function is assumed to be a linear combination of these two variables. Thus, the observed portion of the utility of individual i for alternative a is

$$\beta_1 ATTR_a + \beta_2 DTT_{ia} \, ,$$

where $ATTR_a$ = the proportion of people visiting destination a,

   DTT_{ia} = the deviation travel time of individual i for
      destination a, and

   β_1, β_2 are parameters to be estimated.

Figure 8.2

Deviation and Conventional Travel Time Measures
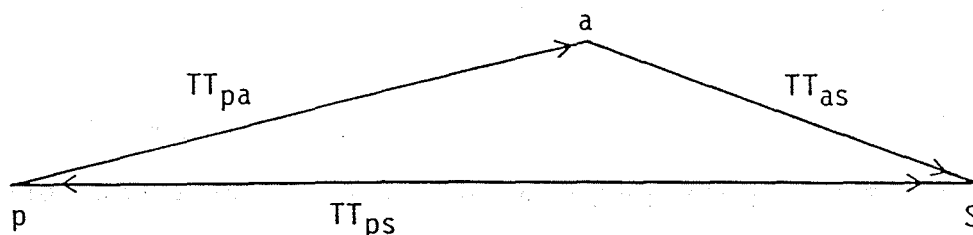
conventional measure: TT_{pa}

deviation measure: $DTT_a = TT_{pa} + TT_{as} - TT_{ps}$

8.4. Empirical Estimation

8.4.1. Hypotheses to be Tested

It is of interest to compare the activity pattern-based approach to destination choice modeling against the conventional approach. The method developed in this research differs from the conventional in two important respects: (a) the choice set is constrained based on spatial and temporal restrictions imposed by the activity pattern, and (b) the travel time variable adopted measures the deviation from the line joining the spatially fixed endpoints of the activity sequence. Landau, et al., (1982) compare predicted choice probabilities using constrained choice sets to those using the full sets, but in both cases they applied an existing destination choice model which had been calibrated previously

assuming the full choice set to be available to everyone. It is argued here that such a model is already biased at calibration (see the hypotheses below), and therefore does not provide a fully valid comparison. A more useful test requires the separate <u>estimation</u> of models for each case.

In this study, four sets of estimations were performed: two models based on the restricted choice sets, one using the conventional travel time measure (TT_{pa}) and one using the deviation measure (DTT_a); and two parallel models based on the full choice sets. Two hypotheses with respect to these comparisons are discussed below.

<u>Full vs. constrained choice sets:</u>

Since alternatives are eliminated from the full choice set if they cannot be reached in the time available, it is expected that, <u>on average</u>, both travel time measures will be larger for those alternatives in the full set but not in the restricted set. To account for those more distant alternatives never being chosen, the travel time coefficient should be more negative for the full choice set estimation than for the constrained set. Thus, not only will the full choice set estimation give travel time more weight than it should have, it will assign positive choice probabilities to alternatives which actually have zero probability of choice. The constrained choice set estimation, by first removing those alternatives with zero probability of choice, should result in a better estimate of the travel time coefficient.

<u>Conventional vs. deviation travel time measures:</u>

It is argued in section 8.3.3 that the deviation variable DTT_a is a more appropriate travel time measure for the activity pattern-based

approach than the conventional variable TT_{pa}. Thus, it is expected that models containing DTT_a should possess better goodness-of-fit characteristics (χ^2, ρ^2, % correctly predicted) than those with TT_{pa}. While there is no firm hypothesis with respect to the relative magnitudes of the coefficients of DTT_a and TT_{pa}, the measure TT_{pa} should show more variation vis à vis the chosen alternative than DTT_a. That is, chosen alternatives should tend to have _smaller_ values of DTT_a, but may have small _or_ large values of TT_{pa} depending on whether the destination a is near to p or relatively closer to s. Thus, the coefficient of TT_{pa} might be expected to have a higher estimated standard error (i.e., be more likely to be insignificant), and/or possibly a relatively smaller weight (i.e., be less important to the decision) than the DTT_a coefficient.

8.4.2 Estimation Results

Most discrete choice estimation packages do not treat as many as 25 alternatives. Thus, the usual practice for problems with large choice sets was followed: a (semi-) random sample from each choice set was used for the estimation. Six alternatives were selected for each individual, including the chosen alternative, the two most frequently visited alternatives (nodes 105 and 256), and three (or four, if node 105 or 256 were the chosen alternative) additional randomly picked destinations. For the full choice set models, these additional destinations were picked from the 22 or 23 remaining locations; for the constrained choice set

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models, the destinations were chosen from the set of feasible locations only. If fewer than the three or four needed destinations were feasible, all available alternatives were used. The results presented are based on averaging the outcomes of estimation on five different random samples of destinations for each of the four cases studied.

Table 3 contains the average results for the full sample of 122 trips. In general terms, the four sets of models estimated perform similarly. The χ^2 goodness-of-fit statistics are close to each other and are all significant. The ρ^2 values range from .37 to .39. This is a reasonable range for discrete choice models, particularly considering the simple specification and the number of alternatives involved.

Choices correctly predicted (85-87%) and individuals correctly predicted (53-55%) are again comparable across the four sets of models and are at an acceptable level (53-55% should be compared to the "know-nothing" model, which would predict 1/6 or 17% of the individuals correctly by chance alone). Finally, both the travel time and attractiveness coefficients are highly significant and have the expected signs.

With respect to the two hypotheses offered in Section 8.4.1, there is indirect support for the first (travel time coefficients should be more negative for the full choice set than for the constrained choice set) in th results in Table 8.3. While there is no significant difference in the travel time coefficients themselves between the constrained and full

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Table 8.3

Comparative Estimation Results, Full Data Set*

(n=122)

	constrained choice set		full choice set	
	deviation (DTT_a)	conventional (TT_{pa})	deviation (DTT_a)	conventional (TT_{pa})
χ^2	167.69	159.69	159.64	168.19
ρ^2	.39	.37	.39	.39
Choices correctly predicted	.85	.86	.86	.87
Individuals correctly predicted	.53	.55	.55	.55
mean travel time coefficient	-11.67	-12.70	-11.65	-12.91
(s.e. of the mean)	(.41)	(.26)	(.26)	(.18)
mean standard error of tt. coeff.	1.48	1.54	1.49	1.54
mean attractiveness coefficient	2.77	2.56	2.55	2.34
(s.e. of the mean)	(.03)	(.03)	(.05)	(.05)
mean standard error or attr. coeff.	.46	.44	.47	.44

*Average over five different random subsets of the choice set

choice set estimations, the <u>attractiveness</u> coefficients are significantly <u>smaller</u> in the latter case. This means that travel time is <u>relatively</u> more important for the full choice set than for the constrained choice set, as hypothesized. Since for 82.8% of the sample, the full and "constrained" choice sets are identical, it is not surprising that the differences in the estimations are not more pronounced. It would be desirable to do comparative estimations for the subset of the sample that actually had fewer than the full number of alternatives available, but unfortunately there are not enough such individuals to ensure the statistical reliability of the results.

There is no evidence to support the second hypothesis, that models with the deviation travel time measure should have better goodness-of-fit statistics than models with the conventional measure. The statistics are nearly identical in all cases and do not consistently favor one formulation over the other. However, it should be pointed out that for 63.9% of the sample, the grocery shopping trip was the only activity in the tour, and therefore the two travel time measures were identical. In fact, the correlation between the two measures is .84, so the similarity in performance between the two sets of models is entirely reasonable.

It may be noted that the mean conventional travel time coefficient is (statistically) significantly more negative than the mean deviation coefficient for both the full and constrained choice-set estimations. Also, the mean attractiveness coefficient is statistically smaller in the conventional formulation for both full and constrained cases. While this

result may appear surprising in view of the empirical similarity in the two formulations of travel time, it is actually primarily an artifactual difference, accounting for small differences in scale between the two measures. For example, as shown in Table 8.4, the mean travel times in the constrained case are .35 for the deviation measure and .32 for the conventional measure. When multiplied by the differing coefficients and added to the attractiveness term, the mean utility is the same for the two models. Thus, on average, the different sets of coefficients lead to the same results.

Since the two travel time formulations are identical for 64% of the cases, it is natural to study the 36% of the sample for which the two measures differ, i.e., the 44 cases in which grocery shopping is one stop on a multi-trip tour. Even for the multi-trip tours, the two travel time measures are very highly correlated (.85). Accordingly, it is expected that the estimation results for this sample would not be dramatically different from the previous results.

This is in fact the case, as shown in Table 8.5. The χ^2 statistics are smaller, since the χ^2 measure is sample-size dependent, but they are all still significant. The ρ^2 and percent correctly predicted statistics are slightly higher than before, again due to the smaller sample size. The coefficients all decline in magnitude, but their relative proportions do not change much from the full sample results. Standard errors are higher, as expected with a smaller sample size. The same arguments in support of the first hypothesis may be made here, and there is again no evidence in favor of the second hypothesis.

Table 8.4

Mean Variable and Utility Values for the Different

Travel Time Specifications

(Constrained Choice Set)

	deviation measure	conventional measure
mean travel time	.35	.32
travel time coefficient (β_1)	-11.67	-12.70
mean attractiveness	.08	.08
attractiveness coefficient (β_2)	2.77	2.56
mean utility $(\beta_1\overline{TT} + \beta_2\overline{ATTR})$	-3.86	-3.86

Table 8.5

Comparative Estimation Results, Multitrip Tours Only*

(n=44)

	constrained choice set		full choice set	
	deviation (DTT_a)	conventional (TT_{pa})	deviation (DTT_a)	conventional (TT_{pa})
χ^2	64.16	54.73	56.13	58.62
ρ^2	.42	.35	.40	.37
Choices correctly predicted	.88	.87	.88	.88
Individuals correctly predicted	.64	.65	.64	.65
mean travel time coefficient	-10.29	-12.74	-9.52	-12.35
(s.e. of the mean)	(1.08)	(1.15)	(.31)	(.46)
mean standard error of tt. coeff.	2.15	2.50	2.02	2.37
mean attractiveness coefficient	2.74	2.12	2.17	1.71
(s.e. of the mean)	(.06)	(.03)	(.11)	(.07)
mean standard error or attr. coeff.	.79	.70	.80	.70

*Average over five different random subsets of the choice set

In sum, whatever the conceptual merits of the proposed hypotheses concerning the differences between the activity pattern-based and the conventional approaches to destination choice modeling, the ability to test those hypotheses is limited by the empirical environment at hand. In the present study, the high correlation between the activity pattern-based deviation measure of travel time and the conventional measure precludes the identification of significant differences between the two approaches. Also, the high proportion of individuals with no constraints on their choice sets limits the differences which can be expected between models using the full set and those using the ("true") constrained choice set. In view of this, the differences which did appear in the relative importance of travel time between the two sets of models are all the more significant.

To the extent that the relevant characteristics of this empirical environment are comparable to those found elsewhere, it may be argued that the results obtained here simply indicate that the conventional method of destination choice modeling is an acceptable simplification of a complex choice situation. However, it should be emphasized that this is only true in a static sense. In any situation involving substantial changes in choice sets and/or chaining of trips, it is expected that the conceptually superior activity-based approach will be more responsive to the true choice mechanism being used.

8.5. Summary

This chapter describes and implements an activity pattern-based approach to destination choice modeling. The argument is that only in

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the context of an entire activity pattern can the spatial and temporal constraints on behavior be fully accounted for, and only then can the "true" choice be modeled. The approach presented here is designed to be integrated with the general simulation model of trip-making behavior. Ultimately, choice of locations can be combined with choice of sequence and timing of a set of activities, where the utility of a given pattern is a function of each of those three characteristics.

The major aspect of the activity pattern-based destination choice methodology is defining the choice set for each individual. This step consists of analyzing the spatial-temporal constrains on a given pattern, and then identifying the set of locations that can be reached within the time available.

In addition, an alternative to the conventional measure of travel time is proposed. It is argued that in an activity pattern context, it is only important how much out of the way a location is from the path joining two fixed points, not how far the location is from the site of the previous activity.

In this particular empirical application, little difference was found between the activity pattern-based and the conventional approaches. The two different travel time measures were highly correlated (.85), even for the 36% of the sample which made multi-trip tours. Also, it was found that 83% of the sample had all choices available to them. However, even under these unfavorable circumstances, there was evidence that assuming the full choice set always to be available (as is conventionally done) can distort the importance of travel time to the decision-making

process. Further, it was argued that even if in a static environment there is little difference between the conventional and activity pattern-based approaches, in a situation in which the choice set and/or the trip-chaining behavior of individuals are likely to change, the activity-based approach offers the more realistic depiction of the true choice process.

Ongoing research into activity pattern-based destination choice modeling can take several directions. First, the specification of the utility of a location needs refinement. Conventional destination choice studies (Koppelman and Hauser, 1978; Recker and Kostyniuk, 1978) have identified several perceptual dimensions of attractiveness; variables of this nature should be integrated into an activity-based model.

Second, the conceptual framework discussed in Section 8.2 involves the general case of making several destination choices sequentially. While the theory for this situation is well-developed, the actual application is relatively complex. Nevertheless, to the extent that trip-chaining is or becomes an increasing phenomenon, it is of increasing importance to be able to model more than one destination choice.

Finally, as pointed out by Landau, et al. (1982) and others, there are other constraints on the choice set than spatial and temporal ones. In particular, in a complex urban environment, the amount of information held by the individual is likely to be a significant constraint on the choice set; modeling that aspect of the decision-making process is a research area in its own right.

It is expected that adoption and refinement of the activity pattern-based approach to destination choice modeling will lead to an increased understanding of trip-making behavior and an improved ability to predict changes in that behavior in response to external changes. Continued research in this area is desirable and should be rewarding.

CHAPTER 9

Empirical Results of the Activity/Travel Pattern Model System

9.1 Introduction

The theoretical formulation of complex travel behavior developed in Chapter 3, and operationalized as a simulation model of activity pattern choice in Chapters 4 and 5, was applied to the Windham, Connecticut data set described in Chapter 6. The simulation model (CHAINS) comprises six, separate components, and the application and resulting analysis proceeded sequentially through the following modules:

(1) TROOPER   Generation of Household Activity Programs and Analysis of Household Interaction

(2) SNOOPER   Specification of Feasible Activity Patterns

(3) GROOPER   Reduction of the Feasible Pattern Choice Set to Representative Activity Patterns

(4) SMOOPER   Computation of Pattern Choice Objectives and Identification of the Noninferior Pattern Set

(5) REGROOPER   Reduction of the Noninferior Pattern Choice Set to Representative Activity Patterns

(6) CHOOZER   Activity Pattern Choice Model Prototype

Each module will be discussed in a separate section. In general, the output of a module serves as input to the succeeding module, although certain data is required in several modules. Furthermore, dependent on the results of modules 1 and 2, the utilizing of modules 3, 4, and 5 are optional, each reflecting a method of choice set specification. Finally,

module 6 (CHOOZER) actually comprises several submodels of pattern choice. In this preliminary application, only standard, multinomial logit models have been estimated.

9.2 Generation of Household Activity Programs and Analysis of Household Interaction

The primary function of the first module (TROOPER) of the simulation model (CHAINS) is to specify the activity programs for each individual within a household for subsequent input for the activity pattern simulation module (SNOOPER). The data input consisted of the actual trip diaries reported in the travel survey, and a matrix of travel times developed from the coded network for the Windham region. Individuals may be treated as isolated decision-makers, or alternately as members of a larger, decision-making household. At present, alternate structures of household interaction have not been fully incorporated into the module; thus, the simulation of interaction is temporarily limited to determination of modal availability, specification of planned (and possibly, temporally fixed) home activities, and construction of coupling constraints resulting from joint automobile use among household members (e.g., pickup/drop-off trips, or planned, joint activities).

The intent of the preliminary model estimation was to establish the feasibility of the simulation methodology in the specification of pattern choice sets, and to further investigate those variables which are determinants of actual choice. As such, the initial sample of 99 observations comprises primarily individuals from different households.

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The effects of interaction within their households was incorporated into their activity patterns, although the resultant simulation is individual specific.[1]

There are three primary outputs from the TROOPER module:

(1) Input data for the second module, consisting of the IPD, APD, MAD, CCD and ADD arrays described in Chapter 4.

(2) A file of the observed activity pattern, coded in standard format, for input to subsequent modules.

(3) An array of transition times reflecting arrivals and departures of household members, for utilization in objective specification in the SMOOPER module.

The former output serves the complete data requirement of the simulation model's second module, SNOOPER. An example for a sample individual is provided in Figure 9.1.

9.3 Specification of Feasible Activity Patterns

The constrained, combinatoric simulation algorithm (SNOOPER module) iteratively generates feasible, fully specified activity patterns from the data arrays provided by the TROOPER module. Although the module itself requires only limited computing and core requirements due to its iterative structure, significant output may be produced as the result of flexibility inherent in many activity programs. Output restriction on the computer system used prevented full analysis of all 99 individuals, reducing the sample to 88 observations.

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[1]A comprehensive model of household decision-making is being developed and integrated into the TROOPER module.

```
    1    56    1    3   263  10.00  24.00
   1.00  12.30  14.30   2.00 258.00   4.00    .00    .00   0   0   2   2   6
   2.00   7.73  22.00   1.00 256.00   6.00    .00    .00   0   0   1   2   6
   3.00  18.00  19.00   1.00 263.00  16.00    .00    .00   0   0   0   0   0
   0.00  24.00
 0  0  0
 0  0  0
 0  0  0
  56  1  3
 263 258 256
  3.0 10.0  3.0
 10.0  3.0 10.0
  3.0 10.0  3.0
   1   56    1
  1.   1.   1.   2.   1.   0.00  0.00 12.00  2.00  1.  0.  0.00  0.00
  2.   2.   2.   2.   1.   0.00  0.00 13.00  1.00  1.  1.  0.08  1.84
  3.   4.   0.   0.   0.   0.00  0.00 18.00  1.00  1.  0.  0.00  0.00
   56     .00      0       0
 999
```

FIGURE 9.1 SAMPLE OUTPUT FROM TROOPER MODULE

There are many factors which contribute to the range of patterns which are generated by the algorithm, including the number of planned activities, the number of available modes, the degree of fixity of each planned activity, coupling constraints, automobile availability, and the length of the travel day. The specification of these variables is, of course, dependent solely on the characteristics of the household, individual, and reported activities. Since the initial sample was restricted to individuals who made all trips by automobile, mode simulation was unnecessary. All constraints evident in the travel surveys were integrated into the activity program data to limit the resultant pattern opportunity set. Nevertheless, some significantly large pattern sets resulted. Table 9.1 provides some summary statistics illustrating SNOOPER results. Figure 9.2 depicts the actual output for a sample individual.

Table 9.1

Number of Planned Activities	Number of Individuals	Percent	Mean Number of Patterns
2	9	10.2	11
3	41	46.6	53
4	19	21.6	195
5	13	14.8	428
6	6	6.8	226
TOTAL	88		147

```
*****************  SNOOPER  *********************
*                                                *
*    CHAINING BEHAVIOR IN URBAN TRIP MAKING      *
*                                                *
*    SIMULATION OF COMPLEX TRAVEL BEHAVIOR        *
*         (VERSION SNOOP10  SEPT.1,1982)          *
*                                                *
*    ** SNOOPER **              MODULE #2         *
*    SPECIFICATION OF FEASIBLE ACTIVITY          *
*    PATTERNS AND MULTI-OBJECTIVE CRITERIA       *
*                                                *
*      W.W.RECKER   M.G.MCNALLY  G.S.ROOT         *
*                                                *
*****************  SNOOPER  *********************
```

```
------------------------------------------------------------------
       ACTLIST3  *** SNOOPER VERS 0 ***  ACTLIST3
------------------------------------------------------------------
```

FILE OUTPUT:
     FEASOUT - FEASIBLE PATTERN DATA

```
    ----------------------------------------------
    GENERATION OF FEASIBLE ACTIVITY PATTERNS
    ----------------------------------------------

    NUMBER OF INDIVIDUALS ANALYZED. . . .   9
    SPATIAL DISAGGREGATION. . . . . . . ZONE
    TIME/DISTANCE INPUT FILE. . . . . .   14
    NUMBER OF SIMULATED MODES . . . . .    1
    BASIC TIME SIMULATION UNIT. . . .  0.250

    RANDOM SELECTION OF SEQUENCES
     OCCURS FOR ACTIVITY PROGRAM SIZE . .   6
    SEQUENCE SAMPLING RATE (PERCENT). . . 10
```

FIGURE 9.2 SAMPLE SNOOPER OUTPUT

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```
**********************************
* HOUSEHOLD    56               *
**********************************
* INDIVIDUAL    1               *
*   PLANNED ACTIVITIES      3    *
*   HOME LOCATION         263    *
*   TRAVEL DAY START     10.00   *
*   TRAVEL DAY END       24.00   *
**********************************
```

ACTIVITY PROGRAM DATA ARRAY
```
1.00  12.50  14.50   2.00 258.00   4.00   0.00   0.00 0. 0. -2. 2. 8.
2.00   7.75  22.00   1.00 256.00   8.00   0.00   0.00 0. 0. 1. 2. 5.
3.00  18.00  19.00   1.00 263.00  16.00   0.00   0.00 0. 0. 0. 0. 0.
```

TRAVEL TIME ARRAY
```
ZONE              258.   256.    263.    263.
      ACTIVITY   1.000  2.000   3.000   0.000
258.    1.000     .083   .167    .167    .167
256.    2.000     .167   .083    .083    .083
263.    3.000     .167   .083    .083    .083
263.    0.000     .167   .083    .083    .063
```

HOUSEHOLD   56   INDIVIDUAL   1   FEASIBLE PATTERN   1

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS			
	NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	2	6	1	2	6	256	1	.17	14.67	0.00	14.67	1.00	15.67
3	3	16	0	0	0	263	1	.08	15.75	2.25	18.00	1.00	19.00

HOUSEHOLD   56   INDIVIDUAL   1   FEASIBLE PATTERN   2

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS			
	NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	256	1	.17	12.50	0.00	12.50	2.00	14.50
2	3	16	0	0	0	263	1	.17	14.67	3.33	18.00	1.00	19.00
3	2	6	1	2	6	256	1	.08	19.08	0.00	19.08	1.00	20.08
4	0	16	0	0	0	263	1	.08	20.17	0.00	20.17	0.00	0.00

HOUSEHOLD   56   INDIVIDUAL   1   FEASIBLE PATTERN   3

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS			
	NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	6	256	1	.08	10.00	0.00	10.00	1.00	11.00
2	1	4	2	2	8	258	1	.17	11.17	1.33	12.50	2.00	14.50
3	3	16	0	0	0	263	1	.17	14.67	3.33	18.00	1.00	19.00

HOUSEHOLD   56   INDIVIDUAL   1   FEASIBLE PATTERN   4

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS			
	NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	6	256	1	.08	10.33	0.00	10.33	1.00	11.33
2	1	4	2	2	8	258	1	.17	11.50	1.00	12.50	2.00	14.50
3	3	16	0	0	0	263	1	.17	14.67	3.33	18.00	1.00	19.00

HOUSEHOLD   56   INDIVIDUAL   1   FEASIBLE PATTERN   5

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS			
	NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	6	256	1	.08	10.67	0.00	10.67	1.00	11.67
3	1	2	2	2	8	258	1	.17	11.54	.17	12.57	2.17	14.50

FIGURE 9.2 SAMPLE SNOOPER OUTPUT

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```
! 3 ! 3 16  0  0  0 263 ! 1   .17 !  14.67   3.33   18.00   1.00  19.00!
```

HOUSEHOLD 56 INDIVIDUAL   1   FEASIBLE PATTERN   6

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	6 256	1	.08	11.00	0.00	11.00	1.00	12.00
2	1	4	2	2	8 258	1	.17	12.16	.34	12.50	2.00	14.50
3	3	16	0	0	0 263	1	.17	14.67	3.33	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL   1   FEASIBLE PATTERN   7

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	6 256	1	.08	11.33	0.00	11.33	1.00	12.33
2	1	4	2	2	6 258	1	.17	12.50	.00	12.50	2.00	14.50
3	3	16	0	0	0 263	1	.17	14.67	3.33	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL   1   FEASIBLE PATTERN   8

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8 258	1	.17	12.50	0.00	12.50	2.00	14.50
2	0	16	0	0	0 263	1	.17	14.67	0.00	14.67	0.00	14.67
3	2	6	1	2	6 256	1	.08	14.75	0.00	14.75	1.00	15.75
4	3	16	0	0	0 263	1	.08	15.83	2.17	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL   1   FEASIBLE PATTERN   9

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8 258	1	.17	12.50	0.00	12.50	2.00	14.50
2	0	16	0	0	0 263	1	.17	14.67	0.00	14.67	.54	15.21
3	2	6	1	2	6 256	1	.08	15.29	0.00	15.29	1.00	15.29
4	3	16	0	0	0 263	1	.08	16.37	1.63	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL   1   FEASIBLE PATTERN   10

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8 258	1	.17	12.50	0.00	12.50	2.00	14.50
2	0	16	0	0	0 263	1	.17	14.67	0.00	14.67	1.08	15.75
3	2	6	1	2	6 256	1	.08	15.83	0.00	15.83	1.00	16.83
4	3	16	0	0	0 263	1	.08	16.91	1.09	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL   1   FEASIBLE PATTERN   11

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8 258	1	.17	12.50	0.00	12.50	2.00	14.50
2	0	16	0	0	0 263	1	.17	14.67	0.00	14.67	1.66	16.29
3	2	6	1	2	6 256	1	.08	16.37	0.00	16.37	1.00	17.37
4	3	16	0	0	0 263	1	.08	17.45	.55	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL   1   FEASIBLE PATTERN   12

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8 258	1	.17	12.50	0.00	12.50	2.00	14.50
2	0	16	0	0	0 263	1	.17	14.67	0.00	14.67	2.16	16.83
3	2	6	1	2	6 256	1	.08	16.91	0.00	16.91	1.00	17.91
4	3	16	0	0	0 263	1	.08	17.99	.01	18.00	1.00	19.00

FIGURE 9.2 SAMPLE SNOOPER OUTPUT

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 13

		ACTIVITY					TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	2	5	1	2	8	256	1	.17	14.67	0.00	14.67	1.00	15.67
3	0	16	0	0	0	263	1	.08	15.75	0.00	15.75	2.17	17.92
4	3	16	0	0	0	263	1	.08	18.00	0.00	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 14

NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	0	16	0	0	0	263	1	.17	14.67	0.00	14.67	3.25	17.92
3	3	16	0	0	0	263	1	.08	18.00	0.00	18.00	1.00	19.00
4	2	6	1	2	6	256	1	.08	19.08	0.00	19.08	1.00	20.08
5	0	16	0	0	0	263	1	.08	20.17	0.00	20.17	0.00	0.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 15

NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	3	16	0	0	0	263	1	.17	14.67	3.33	18.00	1.00	19.00
3	0	16	0	0	0	263	1	.08	19.08	0.00	19.08	0.00	19.08
4	2	6	1	2	6	256	1	.08	19.17	0.00	19.17	1.00	20.17
5	0	16	0	0	0	263	1	.08	20.25	0.00	20.25	0.00	0.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 16

NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	3	16	0	0	0	263	1	.17	14.67	3.33	18.00	1.00	19.00
3	0	16	0	0	0	263	1	.08	19.08	0.00	19.08	.46	19.54
4	2	6	1	2	6	256	1	.08	19.62	0.00	19.62	1.00	20.62
5	0	16	0	0	0	263	1	.08	20.71	0.00	20.71	0.00	0.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 17

NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	3	16	0	0	0	263	1	.17	14.67	3.33	18.00	1.00	19.00
3	0	16	0	0	0	263	1	.08	19.08	0.00	19.08	.91	20.00
4	2	6	1	2	6	256	1	.08	20.08	0.00	20.08	1.00	21.08
5	0	16	0	0	0	263	1	.08	21.16	0.00	21.16	0.00	0.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 18

NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	3	16	0	0	0	263	1	.17	14.67	3.33	18.00	1.00	19.00
3	0	15	0	0	0	263	1	.08	19.08	0.00	19.08	1.37	20.45
4	2	6	1	2	6	256	1	.08	20.54	0.00	20.54	1.00	21.54
5	0	16	0	0	0	263	1	.08	21.62	0.00	21.62	0.00	0.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 19

NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	3	16	0	0	0	263	1	.17	14.67	3.33	18.00	1.00	19.00

FIGURE 9.2 SAMPLE SNOOPER OUTPUT

```
! 3 ! 0 15 0 0 0 263 ! 1 .08 ! 19.08 0.00 19.08 1.83 20.91!
! 4 ! 2 16 1 2 8 256 ! 1 .08 ! 21.00 0.00 21.00 1.00 22.00!
! 5 ! 0 16 0 0 0 263 ! 1 .08 ! 22.08 0.00 22.08 0.00 0.00!
```

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 20

		ACTIVITY					TRAVEL		TEMPORAL SPECIFICATIONS			
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	8 256	1	.08	10.00	0.00	10.00	1.00	11.00
2	0	16	0	0	0 263	1	.08	11.08	0.00	11.08	1.25	12.33
3	1	4	2	2	8 258	1	.17	12.50	0.00	12.50	2.00	14.50
4	3	16	0	0	0 263	1	.17	14.67	3.33	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 21

		ACTIVITY					TRAVEL		TEMPORAL SPECIFICATIONS			
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	6 256	1	.08	10.00	0.00	10.00	1.00	11.00
2	1	4	2	2	8 258	1	.17	11.17	1.33	12.50	2.00	14.50
3	0	16	0	0	0 263	1	.17	14.67	0.00	14.67	3.25	17.92
4	3	16	0	0	0 263	1	.08	18.00	0.00	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 22

		ACTIVITY					TRAVEL		TEMPORAL SPECIFICATIONS			
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	6 256	1	.08	10.33	0.00	10.33	1.00	11.33
2	1	4	2	2	8 258	1	.17	11.50	1.00	12.50	2.00	14.50
3	0	16	0	0	0 263	1	.17	14.67	0.00	14.67	3.25	17.92
4	3	16	0	0	0 263	1	.08	18.00	0.00	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 23

		ACTIVITY					TRAVEL		TEMPORAL SPECIFICATIONS			
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	6 256	1	.08	10.67	0.00	10.67	1.00	11.67
2	1	4	2	2	8 258	1	.17	11.83	.67	12.50	2.00	14.50
3	0	16	0	0	0 263	1	.17	14.67	0.00	14.67	3.25	17.92
4	3	16	0	0	0 263	1	.08	18.00	0.00	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 24

		ACTIVITY					TRAVEL		TEMPORAL SPECIFICATIONS			
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	8 256	1	.08	11.00	0.00	11.00	1.00	12.00
2	1	4	2	2	8 258	1	.17	12.16	.34	12.50	2.00	14.50
3	0	16	0	0	0 263	1	.17	14.67	0.00	-14.67	3.25	17.92
4	3	16	0	0	0 263	1	.08	18.00	0.00	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 25

		ACTIVITY					TRAVEL		TEMPORAL SPECIFICATIONS			
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	6 256	1	.08	11.33	0.00	11.33	1.00	12.33
2	1	4	2	2	8 258	1	.17	12.50	.00	12.50	2.00	14.50
3	0	16	0	0	0 263	1	.17	14.67	0.00	14.67	3.25	17.92
4	3	16	0	0	0 263	1	.08	18.00	0.00	18.00	1.00	19.00

HOUSEHOLD 56 INDIVIDUAL 1   FEASIBLE PATTERN 26

		ACTIVITY					TRAVEL		TEMPORAL SPECIFICATIONS			
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8 258	1	.17	12.33	0.00	12.33	2.00	14.33
2	0	16	0	0	0 263	1	.17	14.67	0.00	14.67	0.00	14.67

FIGURE 9.2 SAMPLE SNOOPER OUTPUT

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```
! 3 ! 2  6  1  2  6 256 !  1    .08 !  14.75   C.00   14.75   1.00   15.75!
! 4 ! 0 16  0  2  0 263 !  1    .08 !  15.93   0.00   15.93   2.06   17.96!
! 5 ! 0 16  0  0  0 263 !  1    .08 !  18.00   0.00   18.00   1.00   19.00!
```

HOUSEHOLD   56   INDIVIDUAL   1   FEASIBLE PATTERN   27

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	0	16	0	0	0	263	1	.17	14.67	0.00	14.67	3.25	17.92
3	3	16	0	0	0	263	1	.08	18.00	0.00	18.00	1.00	19.00
4	0	16	0	0	0	263	1	.08	19.08	0.00	19.08	0.00	19.08
5	2	6	1	2	6	256	1	.08	19.17	0.00	19.17	1.00	20.17
6	0	16	0	0	0	263	1	.08	20.25	0.00	20.25	0.00	0.00

HOUSEHOLD   56   INDIVIDUAL   1   FEASIBLE PATTERN   28

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	0	16	0	0	0	263	1	.17	14.67	0.00	14.67	3.25	17.92
3	3	16	0	0	0	263	1	.08	18.00	0.00	18.00	1.00	19.00
4	0	16	0	0	0	263	1	.08	19.08	0.00	19.08	.46	19.54
5	2	6	1	2	6	256	1	.08	19.62	0.00	19.62	1.00	20.62
6	0	16	0	0	0	263	1	.08	20.71	0.00	20.71	0.00	0.00

HOUSEHOLD   56   INDIVIDUAL   1   FEASIBLE PATTERN   29

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	0	16	0	0	0	263	1	.17	14.67	0.00	14.67	3.25	17.92
3	3	16	0	0	0	263	1	.08	18.00	0.00	18.00	1.00	19.00
4	0	16	0	0	0	263	1	.08	19.08	0.00	19.08	.91	20.00
5	2	6	1	2	6	256	1	.08	20.08	0.00	20.08	1.00	21.08
6	0	16	0	0	0	263	1	.08	21.16	0.00	21.16	0.00	0.00

HOUSEHOLD   56   INDIVIDUAL   1   FEASIBLE PATTERN   30

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	0	16	0	0	0	263	1	.17	14.67	0.00	14.67	3.25	17.92
3	3	16	0	0	0	263	1	.08	16.00	0.00	16.00	1.00	19.00
4	0	16	0	0	0	263	1	.08	19.08	0.00	19.08	1.37	20.45
5	2	6	1	2	6	256	1	.08	20.54	0.00	20.54	1.00	21.54
6	0	16	0	0	0	263	1	.08	21.62	0.00	21.62	0.00	0.00

HOUSEHOLD   56   INDIVIDUAL   1   FEASIBLE PATTERN   31

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
2	0	16	0	0	0	263	1	.17	14.67	0.00	14.67	3.25	17.92
3	3	16	0	0	0	263	1	.08	18.00	0.00	18.00	1.00	19.00
4	0	16	0	0	0	263	1	.08	19.08	0.00	19.08	1.83	20.91
5	2	6	1	2	6	256	1	.08	21.00	0.00	21.00	1.00	22.00
6	0	16	0	0	0	263	1	.08	22.08	0.00	22.08	0.00	0.00

HOUSEHOLD   56   INDIVIDUAL   1   FEASIBLE PATTERN   32

	ACTIVITY						TRAVEL		TEMPORAL SPECIFICATIONS				
NO	TP	IM	FR	KN	ZONE	MODE	TIME	ARRIVAL	IDLE	START	LENGTH	FINISH
1	2	6	1	2	6	256	1	.08	10.00	0.00	10.00	1.00	11.00
2	0	16	0	0	0	263	1	.08	11.08	0.00	11.08	1.42	12.33
3	1	4	2	2	8	258	1	.17	12.50	0.00	12.50	2.00	14.50
4	0	16	0	0	0	263	1	.17	14.67	0.00	14.67	3.25	17.92

FIGURE 9.2   SAMPLE SNOOPER OUTPUT

228e

```
! 5 ! 3 15  0  0  0 263 !  1   .03 !  18.00    0.00   16.00   1.00   19.00!
-------------------------------------------------------------------------------

---------------------------------------------------------------
 SIMULATED FEASIBLE PATTERNS
---------------------------------------------------------------

HOUSEHOLD NUMBER       56        IOBS      1
INDIVIDUAL    1 HAS  32 FEASIBLE PATTERNS
(PROGRAM HAS 3 PLANNED ACTIVITIES)
---------------------------------------------------------------
```

FIGURE 9.2   SAMPLE SNOOPER OUTPUT

228f

Due to computer limitations restricting the core available to execute the third module, GROOPER, the sample was reduced to 79 individuals. The corresponding summary results are depicted in Table 9.2

Table 9.2

Number of Planned Activities	Number of Individuals	Percent	Mean Number of Patterns
2	9	11.4	11
3	41	51.9	53
4	17	21.5	112
5	8	10.1	127
6	4	5.1	145
TOTAL	79		73

Table 9.1 illustrated an increase in patterns with an increase in planned activities except for those individuals who planned six activities. The SNOOPER module provides for various sampling schemes to reduce the number of patterns simulated. Preliminary tests revealed that six planned activities would, in general, produce an excessive number of feasible patterns, thus, for this category only, potential sequences of activities were sampled in proportion to the absolute number of sequences possible. The results of this approximation are present in Table 9.2. When individuals whose patterns exceeded the GROOPER restriction were removed, a greater proportion came from the five planned activity category due to the selection specification, as shown in Table 9.2.

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9.4 Reduction of the Feasible Pattern Choice Set to Representative Activity Patterns

In general, there is no assurance that individuals perceive each feasible activity pattern as a unique alternative. The iterative nature of the constrained, coimbinatoric simulation algorithm virtually guarantees that similar patterns will be produced, particularly for extremely flexible activity programs. The number of feasible patterns produced across all individuals illustrates the problem of utilizing the feasible patterns, or the opportunity set, as a true set of choice alternatives.

The potential for significant pattern similarity suggests a classification approach which transforms the feasible pattern set into a set of repreentative activity patterns. The third module of the simulation model, GROOPER, employs pattern recognition and classification techniques to

(1) identity groups of representative patterns,

(2) select the "best" grouping based on the variance maintained by the classification, and

(3) assign the observed activity pattern to the representative pattern to which it is most similar.

The pattern recognition component is achieved by transforming the pattern set in standard format into a listing by planned activities, each in identical order. The characteristics identified in Chapter 4 are then examined to establish pattern similarity based on the nature of the variable in question (e.g., discrete, nominally scaled versus continuous and ordinal).

The classification component constructs representative patterns with random initialization, and proceeds to reassign patterns in an iterative fashion. Reinitialization is attempted if unstability of groupings is evident, and if an assigned recursive limit is exceeded, the module will attempt a lower level of pattern segmentation.

A major problem associated with many classification procedures involves the decision on how many distinct categories, or representative patterns, do indeed exist. The initial range of classification for preliminary estimation was restricted to from four to seven categories, with the lower limit flexible, as previously described. Although a greater number of representative patterns appeared appropriate for several individuals (primarily those with extremely flexible activity programs which resulted in very large feasible pattern sets), the majority of the sample seemed to fall naturally into the proposed range.

The selection of the "best" classification result was based on a pseudo F-ratio and examination of the variance within each representative pattern identified. The classification algorithm was reentered with the "best" groupings, and the observed choice was classified as simply an additional pattern.

The representative activity patterns can be compared to centroids resulting from conventional cluster analysis. However, although comparable on a planned activity by planned activity basis, internal inconsistencies may arise in these RAPs. An example would be an activity start time occurring before the preceding activity's ending time, attributed to the compaction of several patterns into a single

representative pattern. Two alternatives are available, the first being selection of that feasible pattern closest to the representative pattern as the representative pattern itself, and the second being synthesis of an explicit representative pattern, which is internally consistent, based on a reconstruction of the pattern from its characteristics.[2] The former approach was selected for the preliminary model estimation, and is consistent with past similar research. A brief summary of the representative results is given in Table 9.3.

Table 9.3

Number of Representative Patterns	Number of Individuals (Total = 79)	Percent	Cumulative Percent
2	1	1.3	1.3
3	2	2.5	3.8
4	5	6.3	10.1
5	9	11.4	21.5
6	10	12.7	34.2
7	52	65.8	100

Figure 9.3 provides a partial output of this module, illustratintg classification results and assignment of the observed choice. GROOPER also produces the representative activity patterns in standard format for input to subsequent modules, in addition to a comprehensive file

---

[2] In prior research (Recker, et al, 1980), transform techniques were used for pattern recognition, and explicit representative patterns were obtained by inverting the classified, transformed coefficients.

232

```
****************** GROOPER ******************
*                                            *
*      CHAINING BEHAVIOR IN URBAN TRIP MAKING  *
*                                            *
*              C H A I N S                     *
*                                            *
*  COMPLEX HOUSEHOLD ACTIVITY INTERACTION SIMULATOR *
*                                            *
*           MODULE # 1  --  GROOPER           *
*           (VERSION GROOP:C  SEPT.6,1982)     *
*                                            *
*    SPECIFICATION OF PATTERN CHOICE SET THROUGH *
*    IDENTIFICATION OF REPRESENTATIVE PATTERNS *
*                                            *
*        W.W.RECKER   M.G.MCNALLY   G.S.ROOT   *
*                                            *
****************** GROOPER ******************
```

```
----------------------------------------------------------
    GROOPER - GENERATION OF RAPS (WINDHAM) PDATA3
----------------------------------------------------------
```

```
FILE OUTPUT:
     RAPS     - PATTERN CENTROIDS FOR THE CHOICE SET (F:50)
     RAPSSYN  - SYNTHESIZED REPRESENTATIVE PATTERNS  (F:51)
     RAPSMIN  - CLOSEST ACTIVITY PATTERNS            (F:52)
     RAPSOBJ  - PATTERN CHOICE SET OBJECTIVE VALUES  (F:53)
     RAPSASS  - OBSERVED CHOICE ASSIGNMENT SUMMARY   (F:54)
```

```
          ------------------------------------------
          DIRECT ANALYSIS OF PATTERN CHARACTERISTICS
          ------------------------------------------

          NUMBER OF INDIVIDUALS ANALYZED. . . . . . 8
          NUMBER OF PATTERN CHARACTERISTICS . . . . 12
          MINIMUM NUMBER OF RAP CLUSTERS. . . . . . 5
          MAXIMUM NUMBER OF RAP CLUSTERS. . . . . . 7
          MAXIMUM REASSIGNMENT ITERATIONS . . . . . 10

          RANDOM INITIALIZATION OF CLUSTERS . . . .YES
          ITERATIONS FOR CLUSTER STABILITY. . . . . 3
          PATTERN DATA INPUT FILE . . . . . . . . . 15
          INPUT ACTIVITY PATTERNS ARE . . . . FEASIBLE
```

FIGURE 9.3 SAMPLE GROOPER OUTPUT

232a

```
***********************************
* HOUSEHOLD    56                 *
***********************************
* INDIVIDUAL    1                 *
*   PLANNED ACTIVITIES      3     *
*   HOME LOCATION         263     *
*   TRAVEL DAY START     10.00    *
*   TRAVEL DAY END       24.00    *
***********************************


  *** DATA PREPARATION COMPLETE ***
  (AFTER PROCESSING 32  FEASIBLE  PATTERNS ON FILE 15)



                    ***************************
********* GROOPER ********* BEGINNING OF ANALYSIS ********* GROOPER ********
                    ***************************
              424


              -----------------------------
              ! RANDOM INITIALIZATION !
              !-----------------------------!
              !   RAP   HAP  LABEL          !
              !   -----------------         !
              !    1    18    18            !
              !    2    30    30            !
              !    3    25    25            !
              !    4    10    10            !
              !    5    15    15            !
              -----------------------------


                          hos


  ***********************************************************************
  *                                                                     *
  *   PATTERN RECOGNITION AND CLASSIFICATION              5 GROUPS      *
  *                                                                     *
  *   CONVERGENCE AFTER  3 ITERATIONS ON  32 PATTERNS.                  *
  *   PATTERN DEFINED BY  3 PLANNED ACTIVITIES AND  12 CHARACTERISTICS  *
  ***********************************************************************


  REPRESENTATIVE PATTERN   1  (INCORPORATES   2   FEASIBLE   PATTERNS)
  ---------------------------------------------------------------------
      1 -     1   13 -    13
  ---------------------------------------------------------------------

  REPRESENTATIVE PATTERN   2  (INCORPORATES   6   FEASIBLE   PATTERNS)
  ---------------------------------------------------------------------
     14 -    14   27 -    27   26 -    26   29 -    29   30 -    30
     31 -    31
  ---------------------------------------------------------------------

  REPRESENTATIVE PATTERN   3  (INCORPORATES  10   FEASIBLE   PATTERNS)
  ---------------------------------------------------------------------
      3 -     3    4 -     4    5 -     5    6 -     6    7 -     7
```

FIGURE 9.3 SAMPLE GROOPER OUTPUT

```
-----------------------------------------------------------------------
REPRESENTATIVE PATTERN   4  (INCORPORATES   7   FEASIBLE   PATTERNS)
-----------------------------------------------------------------------
    8 -     8    9 -     9   10 -    10   11 -    11   12 -    12
   26 -    26   32 -    32
-----------------------------------------------------------------------


-----------------------------------------------------------------------
REPRESENTATIVE PATTERN   5  (INCORPORATES   7   FEASIBLE   PATTERNS)
-----------------------------------------------------------------------
    2 -     2   15 -    15   16 -    16   17 -    17   18 -    18
   19 -    19   20 -    20
-----------------------------------------------------------------------
```

```
------------------------------------------
POOLED SUM OF SQUARED DISTANCES
------------------------------------------
```

REPRESENTATIVE PATTERN

	1	2	3	4	5
1	.3568E+01				
2	.1500E+03	.1545E+02			
3	.1554E+03	.7681E+03	.1404E+03		
4	.1297E+03	.2272E+03	.5708E+03	.5744E+02	
5	.1473E+03	.2901E+03	.2516E+03	.4341E+03	.5794E+02

```
-----------------------------------
SUMMARY OF STATISTICS
-----------------------------------
```

```
    TOTAL SSD                    =    .3999E+04
    WITHIN SSD                   =    .2748E+03
    TOTAL VARIANCE IN PATTERNS   =    .1250E+03
    POOLED WITHIN GROUP VARIANCE =    .3438E+02
    BETWEEN GROUP VARIANCE       =    .9009E+02
    PSUEDO F-RATIO :          F  =    .2249E+01
```

```
        --------------------------
        ! RANDOM INITIALIZATION  !
        !------------------------!
        !   RAP   HAP  LABEL     !
        !   -------------------  !
        !    1     1     1       !
        !    2     9     9       !
        !    3    10    10       !
        !    4    22    22       !
        !    5    12    12       !
        !    6     5     5       !
        --------------------------
```

```
**********************************************************************
*                                                                    *
*  PATTERN RECOGNITION AND CLASSIFICATION               6 GROUPS     *
*                                                                    *
*  CONVERGENCE AFTER  3 ITERATIONS ON  32 PATTERNS.                  *
*                                                                    *
```

FIGURE 9.3 SAMPLE GROOPER OUTPUT

****

```
REPRESENTATIVE PATTERN   1  (INCORPORATES   2    FEASIBLE   PATTERNS)
----------------------------------------------------------------------
     1 -      1   13 -     13
----------------------------------------------------------------------


REPRESENTATIVE PATTERN   2  (INCORPORATES   6    FEASIBLE   PATTERNS)
----------------------------------------------------------------------
     2 -      2   15 -     15   16 -      16   17 -     17   18 -     18
    19 -     19
----------------------------------------------------------------------


REPRESENTATIVE PATTERN   3  (INCORPORATES   7    FEASIBLE   PATTERNS)
----------------------------------------------------------------------
     3 -      8    9 -      9   10 -      10   11 -     11   12 -     12
    26 -     26   32 -     32
----------------------------------------------------------------------


REPRESENTATIVE PATTERN   4  (INCORPORATES   5    FEASIBLE   PATTERNS)
----------------------------------------------------------------------
    21 -     21   22 -     22   23 -      23   24 -     24   25 -     25
----------------------------------------------------------------------


REPRESENTATIVE PATTERN   5  (INCORPORATES   6    FEASIBLE   PATTERNS)
----------------------------------------------------------------------
    14 -     14   27 -     27   28 -      28   29 -     29   30 -     30
    31 -     31
----------------------------------------------------------------------


REPRESENTATIVE PATTERN   6  (INCORPORATES   6    FEASIBLE   PATTERNS)
----------------------------------------------------------------------
     3 -      3    4 -      4    5 -       5    6 -      6    7 -      7
    20 -     20
----------------------------------------------------------------------
```

POOLED SUM OF SQUARED DISTANCES

REPRESENTATIVE PATTERN

	1	2	3	4	5	6
1	.3562E+01					
2	.1291E+03	.1545E+02				
3	.1297E+03	.3736E+03	.5744E+02			
4	.3606E+02	.4592E+03	.2247E+03	.3162E+01		
5	.1500E+03	.2171E+03	.2272E+03	.3107E+03	.1545E+02	
6	.3753E+02	.3407E+03	.4056E+03	.1939E+03	.5303E+03	.3854E+02

SUMMARY OF STATISTICS

```
    TOTAL SSD                 =    .3999E+04
    WITHIN SSD                =    .1336E+03
    TOTAL VARIANCE IN PATTERN  =    .1290E+07
```

FIGURE 9.3 SAMPLE GROOPER OUTPUT

232d

```
BETWEEN GROUP VARIANCE              *    .1023E+03
PSUEDO F-RATIO :             F  *    .3834E+C1
```

```
!-------------------------------!
!  RANDOM INITIALIZATION !
!-------------------------------!
!   RAP   HAP  LABEL         !
!      ------------------    !
!     1     25    26         !
!     2     19    19         !
!     3      4     4         !
!     4      9     9         !
!     5     20    20         !
!     6      3     3         !
!     7     31    31         !
!-------------------------------!
```

```
****************************************************************************
*                                                                          *
*   PATTERN RECOGNITION AND CLASSIFICATION                    7 GROUPS     *
*                                                                          *
*   CONVERGENCE AFTER  54 ITERATIONS ON  32 PATTERNS.                      *
*   PATTERN DEFINED BY  3 PLANNED ACTIVITIES AND   12 CHARACTERISTICS     *
****************************************************************************
```

```
REPRESENTATIVE PATTERN   1  (INCORPORATES   2   FEASIBLE   PATTERNS)
--------------------------------------------------------------------
   25 -   26   32 -   32
--------------------------------------------------------------------

REPRESENTATIVE PATTERN   2  (INCORPORATES   6   FEASIBLE   PATTERNS)
--------------------------------------------------------------------
    2 -    2   15 -   15   15 -   16   17 -   17   18 -   18
   19 -   19
--------------------------------------------------------------------

REPRESENTATIVE PATTERN   3  (INCORPORATES   6   FEASIBLE   PATTERNS)
--------------------------------------------------------------------
    1 -    1    3 -    3    4 -    4    5 -    5    6 -    6
    7 -    7
--------------------------------------------------------------------

REPRESENTATIVE PATTERN   4  (INCORPORATES   5   FEASIBLE   PATTERNS)
--------------------------------------------------------------------
    8 -    8    9 -    9   10 -   10   11 -   11   12 -   12
--------------------------------------------------------------------

REPRESENTATIVE PATTERN   5  (INCORPORATES   2   FEASIBLE   PATTERNS)
--------------------------------------------------------------------
   13 -   13   20 -   20
--------------------------------------------------------------------

REPRESENTATIVE PATTERN   6  (INCORPORATES   5   FEASIBLE   PATTERNS)
--------------------------------------------------------------------
   21 -   21   22 -   22   23 -   23   24 -   24   25 -   25
--------------------------------------------------------------------

REPRESENTATIVE PATTERN   7  (INCORPORATES   6   FEASIBLE   PATTERNS)
--------------------------------------------------------------------
```

FIGURE 9.3   SAMPLE GROOPER OUTPUT

232e

31 - 31

POOLED SUM OF SQUARED DISTANCES

REPRESENTATIVE PATTERN

	1	2	3	4	5	6
	7					
1	.4583E+01					
2	.1249E+03	.1545E+02				
3	.1473E+03	.3621E+03	.2791E+02			
4	.5005E+02	.2488E+03	.2598E+03	.2816E+01		
5	.2951E+02	.1077E+03	.9341E+02	.9971E+02	.8422E+01	
6	.8061E+02	.4582E+03	.1711E+03	.1441E+03	.1089E+03	.3162E+01
7	.7370E+02	.2171E+03	.5364E+03	.1535E+03	.1440E+03	.3107E+03
	.1545E+02					

SUMMARY OF STATISTICS

TOTAL SSD	=	.3999E+04
WITHIN SSD	=	.7768E+02
TOTAL VARIANCE IN PATTERNS	=	.1250E+03
POOLED WITHIN GROUP VARIANCE	=	.1748E+02
BETWEEN GROUP VARIANCE	=	.1075E+03
PSUEDO F-RATIO : F	=	.4959E+01

HAP ASSIGNMENT TABLE
---

* IDENTIFICATION OF PATTERN CLOSEST TO EACH CENTROID *

	REPRESENTATIVE PATTERNS					
GROUPS	1	2	3	4	5	6
5	(13, 13)	(29, 29)	(23, 23)	(10, 10)	(17, 17)	(
6	(13, 13)	(17, 17)	(10, 10)	(23, 23)	(29, 29)	(5,
7	(32, 32)	(17, 17)	(5, 5)	(10, 10)	(13, 13)	(23,

	REPRESENTATIVE PATTERNS
GROUPS	7
7	(29, 29) (

CHOICE SET SELECTION

FIGURE 9.3 SAMPLE GROOPER OUTPUT

232f

```
  PATTERN      PSEUDO    WITHIN GROUP
   GROUP       F-RATIO    VARIANCE
  ------------------------------------------------------------
      5        .2249E+C1   .3468E+02
      6        .3884F+01   .2219E+02
      7        .4959E+C1   .1748E+02   ** CHOICE SET **
  ------------------------------------------------------------

 ***  7 GROUP CHOICE SET SELECTED FCR OBSERVATION  1 ***


** OBSERVED ACTIVITY PROGRAM **

  1   55    1
   1.   1.  .2.  1.    .50  0.00 12.50  2.00  1.  0.  0.00  0.00
   2.   2.  2.   1.    .50  0.00 15.00  1.00  1.  1.   .08  1.84
   4.   0.  0.   0.    .C8  C.00 18.00  1.00  1.  0.  0.00  0.00


  ------------------------------
OBSERVED CHOICE ASSIGNMENT
  ------------------------------

    * FOR  7 RHAP CHOICE SET *
    --------------------------------------------------------
               CLOSEST PATTERN    OBSERVED
       RHAP    ----------------    CHOICE
               HAP    LABEL       ASSIGNMENT
    --------------------------------------------------------
        1       32      32        * RHAP  1 *
        2       17      17
        3        5       5
        4       10      1C
        5       13      13
        6       23      23
        7       29      29  .
    --------------------------------------------------------
```

```
          ****************************************
***************** END OF ANALYSIS -- OBSERVATION   1 *****************
          ****************************************
```

FIGURE 9.3 SAMPLE GROOPER OUTPUT

identifying the representative pattern set and summarizing the feasible pattern set reduction process.

9.5 Computation of Pattern Choice Objectives and Identification of the Noninferior Pattern Set

The pattern objectives defined in Chapter 5 were computed for each representative activity pattern identified in the GROOPER module. These objectives included:

1. travel time - very important activities

2. travel time - important activities

3. travel time - relatively unimportant activities

4. travel time - unimportant activities

5. travel time - return home activities

6. waiting time

7. time at home - no household members present

8. time at home - some household members present

9. time at home - all household members present

10. unplanned activity potential

11. unplanned travel potential

12. risk - very important activities

13. risk - important activities

14. risk - relatively unimportant activities

15. risk - unimportant activities

Since the pattern choice sets were restricted to a maximum of seven representative patterns, the second function of the SMOOPER module--the

establishment of pattern noninferiority--was not executed. The module produced two output files: (1) objective results in a form directly usable in the model's choice module, and (2) pattern specification for input to the module's plotting routine, where each representative pattern is plotted over travel time from home and time of day. Figure 9.4 illustrates sample SMOOPER output. Figure 9.5 depicts the plotted results for a sample individual. A more complete sample of the SMOOPER output for several individuals in the sample is contained in Appendix C.

9.6 Reduction of the Noninferior Pattern Choice Set to Representative Activity Patterns

The results of the application of the third module, GROOPER, and the fourth module, SMOOPER, produced a reasonable specification of activity pattern alternatives for the Windham sample. As such, application of the fifth module was not necessary in this preliminary estimation, and the simulation proceeded, with the existing specification, directly to the sixth and final module, the pattern choice model.

9.7 Results of Preliminary Estimation of Prototype Choice Model

Initial testing of the model structure was accomplished by means of a preliminary estimation of the activity/travel pattern choice model. Utility measures consistent with those components outlined in Chapter 5 were computed for each representative activity pattern (RAP) contained in the deprived choice set of each of the 79 individuals in the sample. The actual variables used in the prototype model specification are identified in Table 9.4.

234

```
*********************** BLOOPER ***********************
*                                                     *
*       CHAINING BEHAVIOR IN URBAN TRIP MAKING         *
*                                                     *
*               C H A I N S                            *
*                                                     *
* Complex Household Activity INteraction Simulator    *
*                                                     *
*             Module # 3B --   BLOOPER                 *
*          (Version BLOOP:B    Jan.,1983)              *
*                                                     *
*        Computation of Individual Choice Set          *
*        Activity Pattern Decision Objectives          *
*                                                     *
*          W.W.RECKER  M.G.MCNALLY  G.S.ROOT           *
*                                                     *
*********************** BLOOPER ***********************


***********************************
* HOUSEHOLD    56                  *
***********************************
* INDIVIDUAL    1                  *
*   PLANNED ACTIVITIES       3     *
*   HOME LOCATION          263     *
*   TRAVEL DAY START      10.00    *
*   TRAVEL DAY END        24.00    *
***********************************


   ** OBJECTIVES WILL BE COMPUTED FOR   7  REPRESENTATIVE PATTERNS
      (BASED ON   32  FEASIBLE PATTERNS)


   HOUSEHOLD   56  INDIVIDUAL    1           RAP    1  FEASIBLE PATTERN    5
   -------------------------------------------------------------------------
   !   !    ACTIVITY      !  TRAVEL  !    TEMPORAL SPECIFICATIONS     ! TIME!
   !   !------------------!----------!-------------------------------! FROM!
   !   !NO TP IM FR KN ZONE!MODE  TIME!ARRIVAL   IDLE   START LENGTH FINISH! HOME!
   !------------------------------------------------------------------------!
   ! 1 ! 2  6  1  2  6 256 !  1   .08 !  10.67    .00   10.67  1.00  11.67! 5.00!
   ! 2 ! 1  4  2  2  8 258 !  1   .17 !  11.83    .67   12.50  2.00  14.50!10.00!
   ! 3 ! 3 16  0  0  0 263 !  1   .17 !  14.67   3.33   18.00  1.00  19.00!  .00!
   -------------------------------------------------------------------------


   PATTERN   5  OBJECTIVES
   ------------------------

     TRAVEL TIME     .2500E+00    .1700E+00    .0000E+00    .0000E+00    .0000E+00
     WAIT TIME       .6700E+00
     TIME AT HOME    .1792E+02    .0000E+00    .0000E+00
     POTENTIAL       .7140E+00    .2073E+00
     PATTERN RISK    .0000E+00    .2000E+01    .0000E+00    .0000E+00


   HOUSEHOLD   56  INDIVIDUAL    1           RAP    2  FEASIBLE PATTERN   10
   -------------------------------------------------------------------------
   !   !    ACTIVITY      !  TRAVEL  !    TEMPORAL SPECIFICATIONS     ! TIME!
   !   !------------------!----------!-------------------------------! FROM!
   !   !NO TP IM FR KN ZONE!MODE  TIME!ARRIVAL   IDLE   START LENGTH FINISH! HOME!
```

FIGURE 9.4 SAMPLE SMOOPER OUTPUT

235a

```
  1 ! 1   4   2   2   8 258 !   1    .17 !   12.50     .00   12.50    2.00   14.50!10.00!
! 2 ! 0  16   0   0   0 263 !   1    .17 !   14.67     .00   14.67    1.08   15.75!   .00!
! 3 ! 2   6   1   2   6 256 !   1    .08 !   15.83     .00   15.83    1.00   16.83! 5.00!
! 4 ! 3  16   0   0   0 263 !   1    .08 !   16.91    1.09   18.00    1.00   19.00!   .00!
-----------------------------------------------------------------------------------------

   PATTERN  10  OBJECTIVES
   --------------------------
     TRAVEL TIME      .1600E+00    .1700E+00    .0000E+00    .0000E+00    .1700E+00
     WAIT TIME        .0000E+00
     TIME AT HOME     .2050E+02    .0000E+00    .0000E+00
     POTENTIAL        .1571E+01    .4614E+00
     PATTERN RISK     .1000E+01    .1000E+01    .0000E+00    .0000E+00


   HOUSEHOLD   56  INDIVIDUAL    1           RAP    3  FEASIBLE PATTERN    13
-----------------------------------------------------------------------------------------
!    !       ACTIVITY         !  TRAVEL  !      TEMPORAL SPECIFICATIONS      ! TIME!
!    !-------------------------!----------!----------------------------------! FROM!
!    !NO TP IM FR KN ZONE!MODE  TIME!ARRIVAL   IDLE   START LENGTH FINISH! HOME!
!-----------------------------------------------------------------------------------------!
! 1 ! 1   4   2   2   8 258 !   1    .17 !   12.50     .00   12.50    2.00   14.50!10.00!
! 2 ! 2   6   1   2   6 256 !   1    .17 !   14.67     .00   14.67    1.00   15.67! 5.00!
! 3 ! 0  16   0   0   0 263 !   1    .08 !   15.75     .00   15.75    2.17   17.92!   .00!
! 4 ! 3  16   0   0   0 263 !   1    .08 !   18.00     .00   18.00    1.00   19.00!   .00!
-----------------------------------------------------------------------------------------

   PATTERN  13  OBJECTIVES
   --------------------------
     TRAVEL TIME      .2500E+00    .1700E+00    .0000E+00    .0000E+00    .8000E-01
     WAIT TIME        .0000E+00
     TIME AT HOME     .2050E+02    .0000E+00    .0000E+00
     POTENTIAL        .1142E+01    .3344E+00
     PATTERN RISK     .1000E+01    .0000E+00    .0000E+00    .0000E+00


   HOUSEHOLD  .56  INDIVIDUAL    1           RAP    4  FEASIBLE PATTERN    17
-----------------------------------------------------------------------------------------
!    !       ACTIVITY         !  TRAVEL  !      TEMPORAL SPECIFICATIONS      ! TIME!
!    !-------------------------!----------!----------------------------------! FROM!
!    !NO TP IM FR KN ZONE!MODE  TIME!ARRIVAL   IDLE   START LENGTH FINISH! HOME!
!-----------------------------------------------------------------------------------------!
! 1 ! 1   4   2   2   8 258 !   1    .17 !   12.50     .00   12.50    2.00   14.50!10.00!
! 2 ! 3  16   0   0   0 263 !   1    .17 !   14.67    3.33   18.00    1.00   19.00!   .00!
! 3 ! 0  16   0   0   0 263 !   1    .08 !   19.08     .00   19.08     .91   20.00!   .00!
! 4 ! 2   6   1   2   6 256 !   1    .08 !   20.08     .00   20.08    1.00   21.08! 5.00!
! 5 ! 0  16   0   0   0 263 !   1    .08 !   21.16     .00   21.16-     .00     .00!   .00!
-----------------------------------------------------------------------------------------

   PATTERN  17  OBJECTIVES
   --------------------------
     TRAVEL TIME      .3300E+00    .1700E+00    .0000E+00    .0000E+00    .8000E-01
     WAIT TIME        .0000E+00
     TIME AT HOME     .2042E+02    .0000E+00    .0000E+00
     POTENTIAL        .1439E+01    .4041E+00
     PATTERN RISK     .1000E+01    .1000E+01    .0000E+00    .0000E+00


   HOUSEHOLD   56  INDIVIDUAL    1           RAP    5  FEASIBLE PATTERN    23
-----------------------------------------------------------------------------------------
!    !       ACTIVITY         !  TRAVEL  !      TEMPORAL SPECIFICATIONS      ! TIME!
!    !-------------------------!----------!----------------------------------! FROM!
!    !NO TP IM FR KN ZONE!MODE  TIME!ARRIVAL   IDLE   START LENGTH FINISH! HOME!
!-----------------------------------------------------------------------------------------!
```

FIGURE 9.4 SAMPLE SMOOPER OUTPUT

235b

```
  ʹ  ̤ I 1   4  2  2  8 258 I  1    .17 I   11.83     .67   12.50    2.00   14.50I10.00I
I 3 I 0 16  0  0  0 263 I  1    .17 I   14.67     .00   14.67    3.25   17.92I  .00I
I 4 I 3 16  0  0  0 263 I  1    .08 I   18.00     .00   18.00    1.00   19.00I  .00I
```

PATTERN 23 OBJECTIVES

TRAVEL TIME	.1600E+00	.1700E+00	.0000E+00	.0000E+00	.1700E+00
WAIT TIME	.6700E+00				
TIME AT HOME	.1984E+02	.0000E+00	.0000E+00		
POTENTIAL	.7140E+00	.2073E+00			
PATTERN RISK	.0000E+00	.1000E+01	.0000E+00	.0000E+00	

HOUSEHOLD   56 INDIVIDUAL   1   RAP   6 FEASIBLE PATTERN   29

```
I   I       ACTIVITY      I  TRAVEL  I       TEMPORAL SPECIFICATIONS      I TIMEI
I   I-----------------------I----------I---------------------------------------I FROMI
I   INO TP IM FR KN ZONEIMODE  TIMEIARRIVAL   IDLE   START LENGTH FINISHI HOMEI
I----------------------------------------------------------------------------I
I 1 I 1  4  2  2  8 258 I  1    .17 I   12.50     .00   12.50    2.00   14.50I10.00I
I 2 I 0 16  0  0  0 263 I  1    .17 I   14.67     .00   14.67    3.25   17.92I  .00I
I 3 I 3 16  0  0  0 263 I  1    .08 I   18.00     .00   18.00    1.00   19.00I  .00I
I 4 I 0 16  0  0  0 263 I  1    .08 I   19.08     .00   19.08     .91   20.00I  .00I
I 5 I 2  6  1  2  6 256 I  1    .08 I   20.08     .00   20.08    1.00   21.08I 5.00I
I 6 I 0 16  0  0  0 263 I  1    .08 I   21.16     .00   21.16     .00     .00I  .00I
```

PATTERN 29 OBJECTIVES

TRAVEL TIME	.2400E+00	.1700E+00	.0000E+00	.0000E+00	.2500E+00
WAIT TIME	.0000E+00				
TIME AT HOME	.2034E+02	.0000E+00	.0000E+00		
POTENTIAL	.1439E+01	.4041E+00			
PATTERN RISK	.1000E+01	.0000E+00	.0000E+00	.0000E+00	

*** PATTERN 32 CLOSEST TO OBSERVED ***

HOUSEHOLD 56 INDIVIDUAL   1   RAP 73 FEASIBLE PATTERN   32

```
I   I       ACTIVITY      I  TRAVEL  I       TEMPORAL SPECIFICATIONS      I TIMEI
I   I-----------------------I----------I---------------------------------------I FROMI
I   INO TP IM FR KN ZONEIMODE  TIMEIARRIVAL   IDLE   START LENGTH FINISHI HOMEI
I----------------------------------------------------------------------------I
I 1 I 2  6  1  2  6 256 I  1    .09 I   10.00     .00   10.00    1.00   11.00I 5.00I
I 2 I 0 16  0  0  0 263 I  1    .09 I   11.08     .00   11.08    1.25   12.33I  .00I
I 3 I 1  4  2  2  8 258 I  1    .17 I   12.50     .00   12.50    2.00   14.50I10.00I
I 4 I 0 16  0  0  0 263 I  1    .17 I   14.67     .00   14.67    3.25   17.92I  .00I
I 5 I 3 16  0  0  0 263 I  1    .08 I   18.00     .00   18.00    1.00   19.00I  .00I
```

PATTERN 32 OBJECTIVES

TRAVEL TIME	.1600E+00	.1700E+00	.0000E+00	.0000E+00	.2500E+00
WAIT TIME	.0000E+00				
TIME AT HOME	.2043E+02	.0000E+00	.0000E+00		
POTENTIAL	.1142E+01	.3344E+00			
PATTERN RISK	.0000E+00	.2000E-01	.0000E+00	.0000E+00	

****
⌄ HOUSEHOLD 57

FIGURE 9.4 SAMPLE SMOOPER OUTPUT

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FIGURE 9.5 SAMPLE PLOTTED OUTPUT OF RAPS

235d
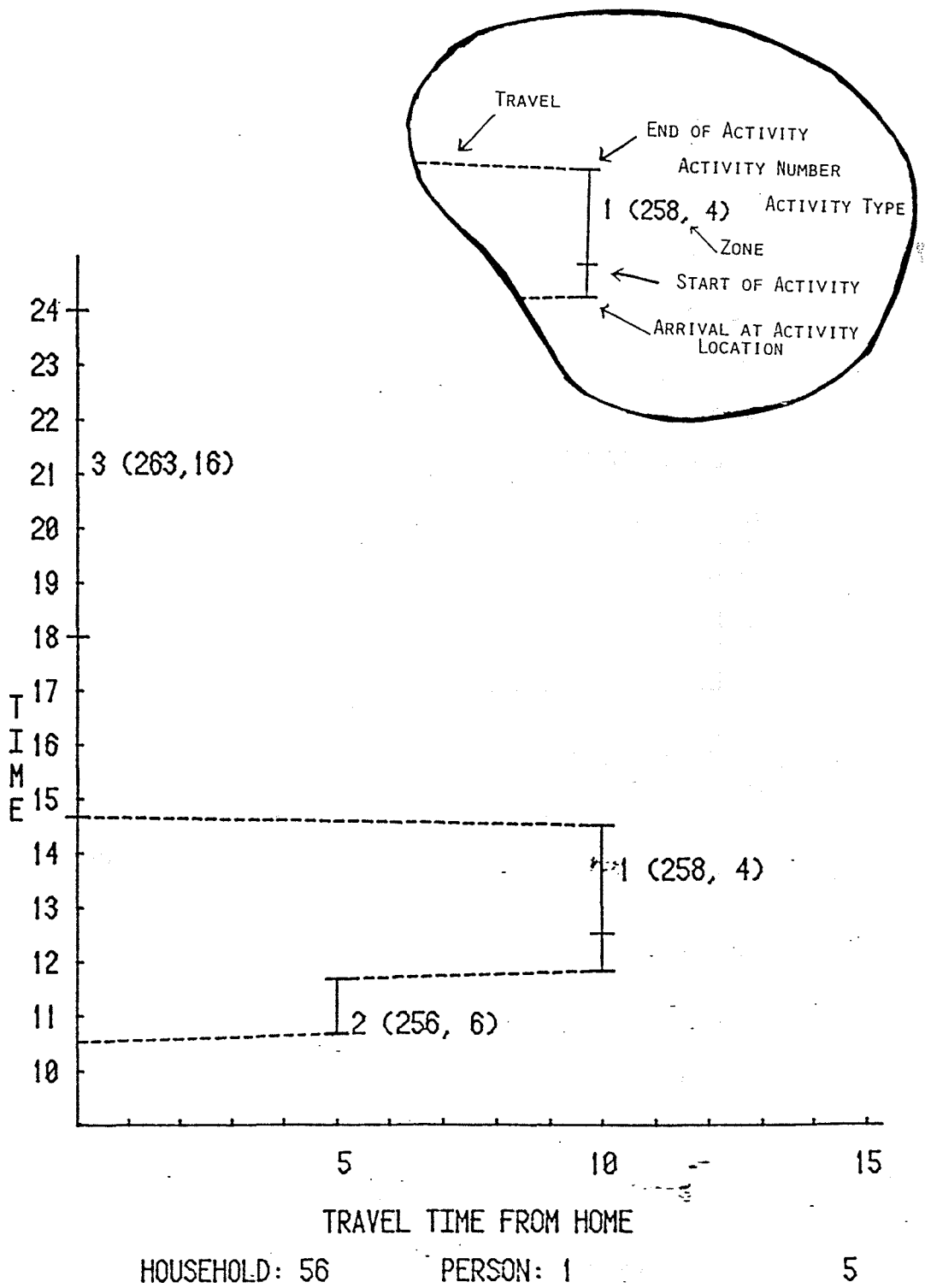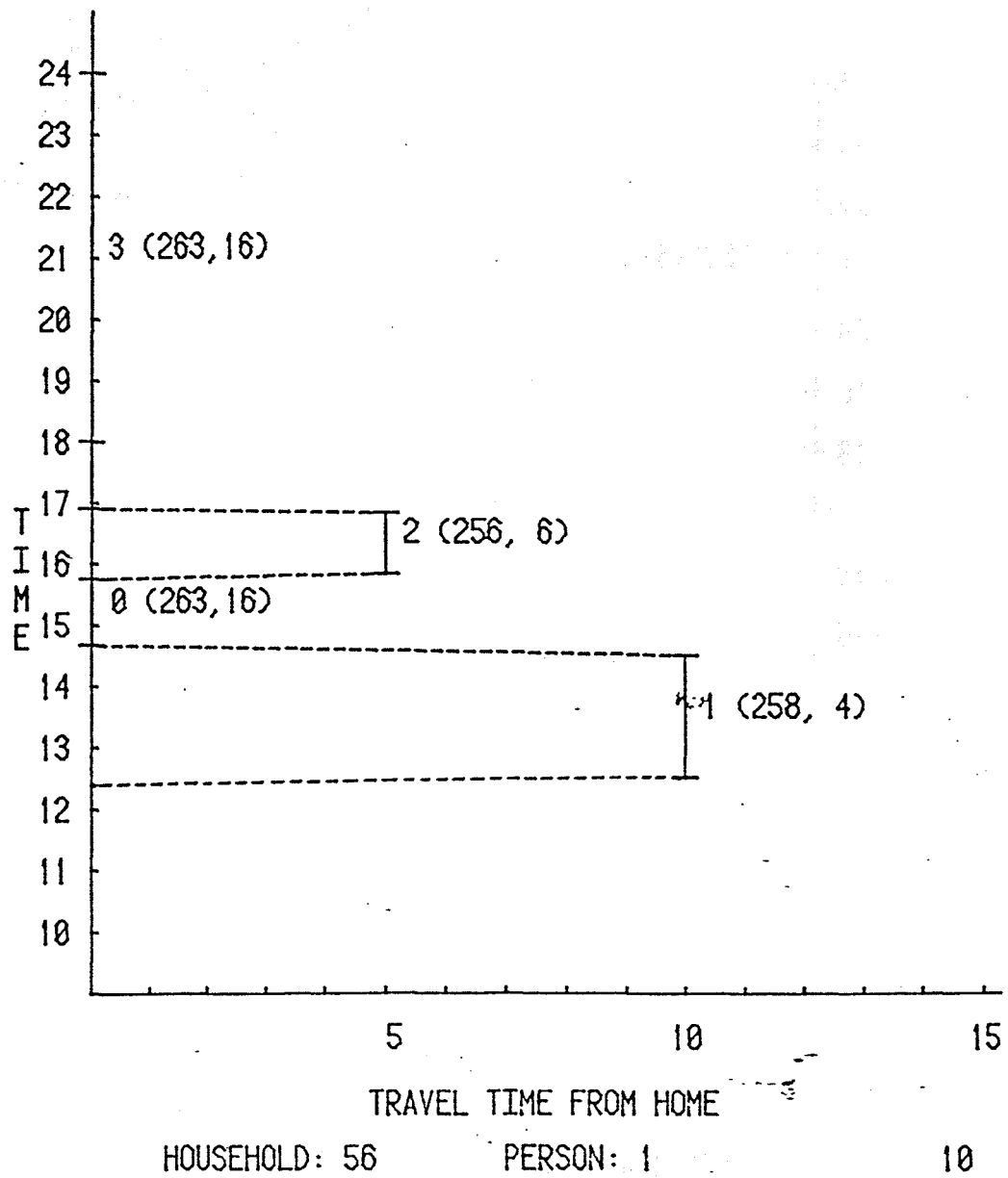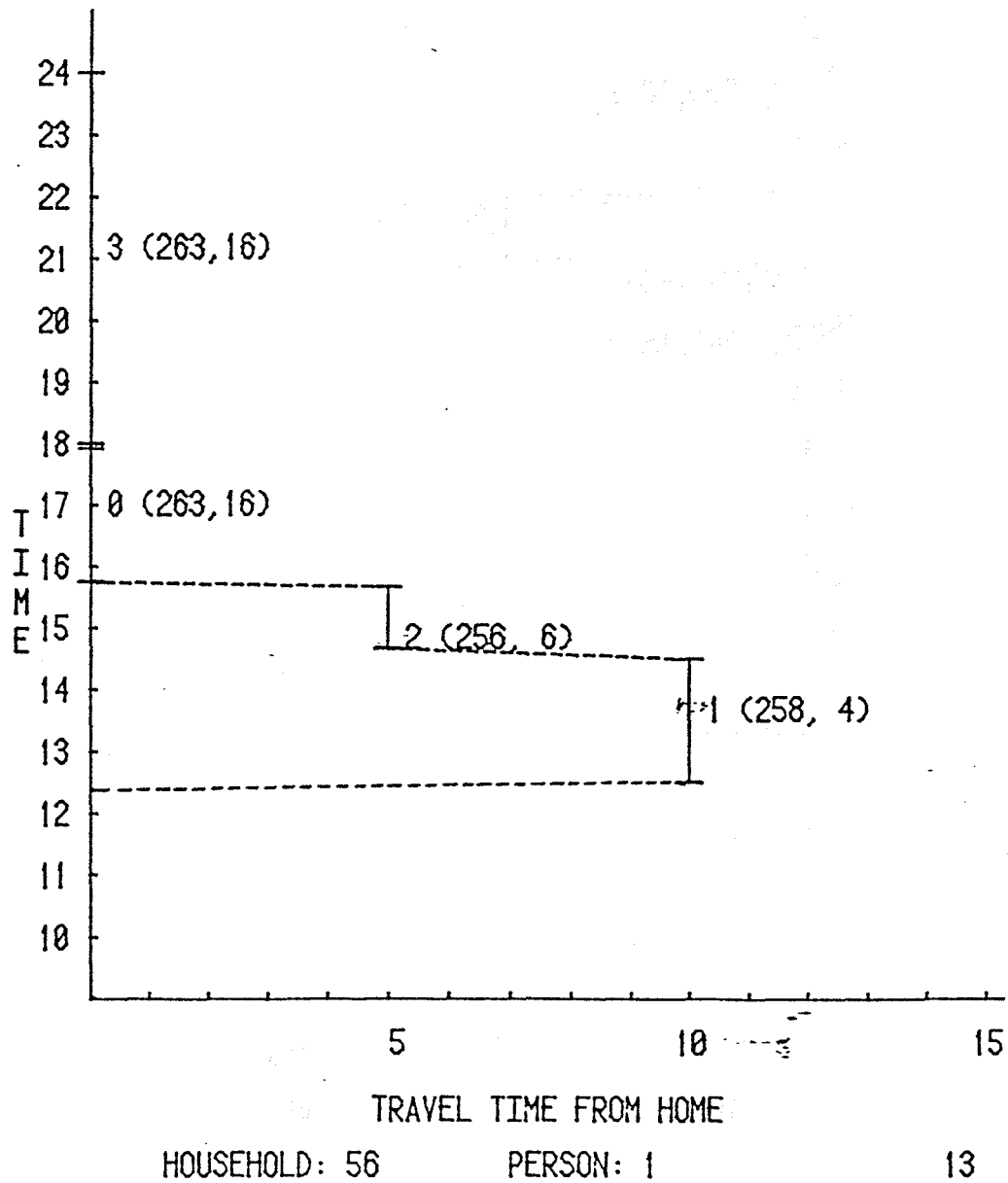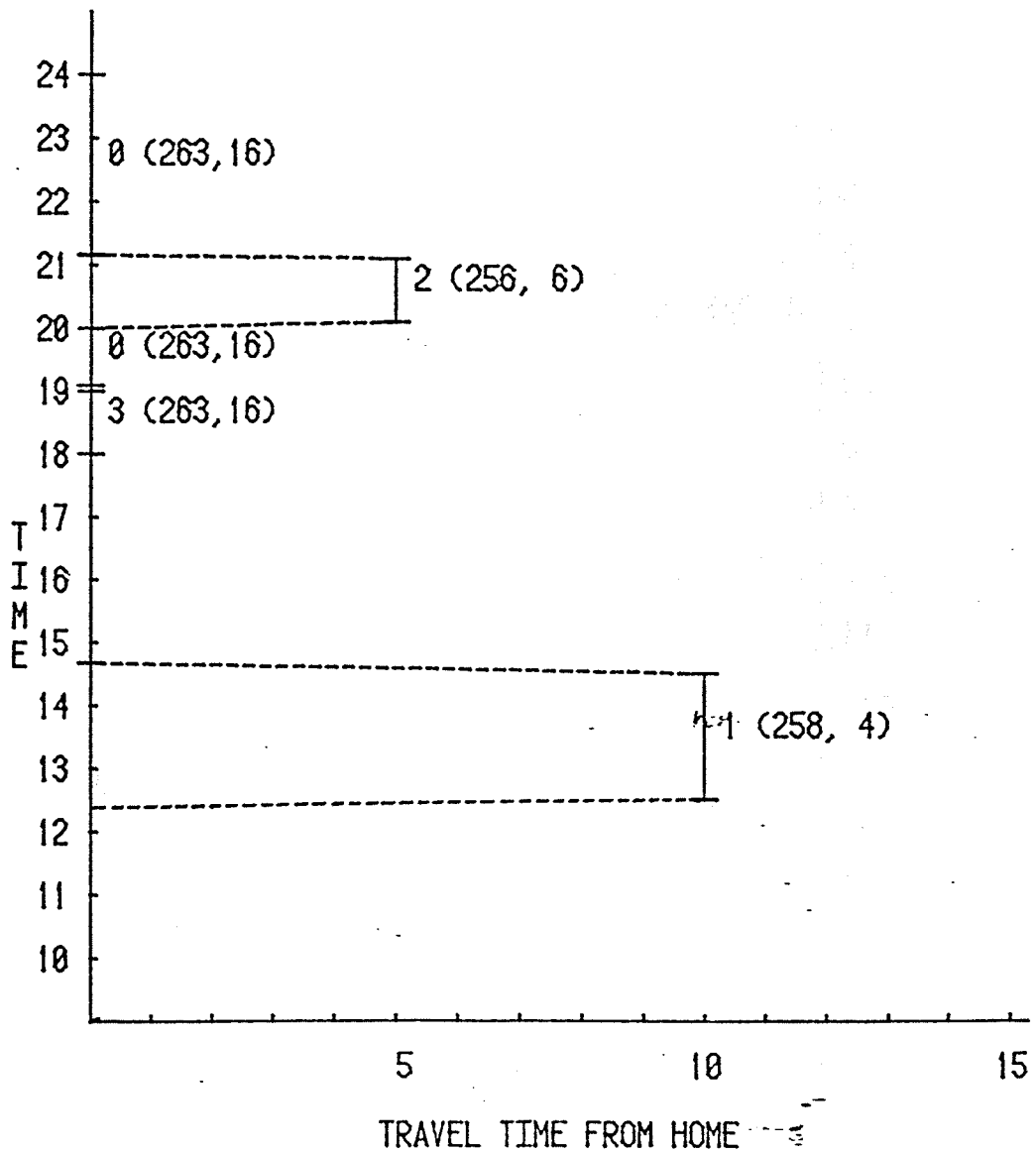
FIGURE 9.5 SAMPLE PLOTTED OUTPUT OF RAPS

235e

FIGURE 9.5   SAMPLE PLOTTED OUTPUT OF RAPS
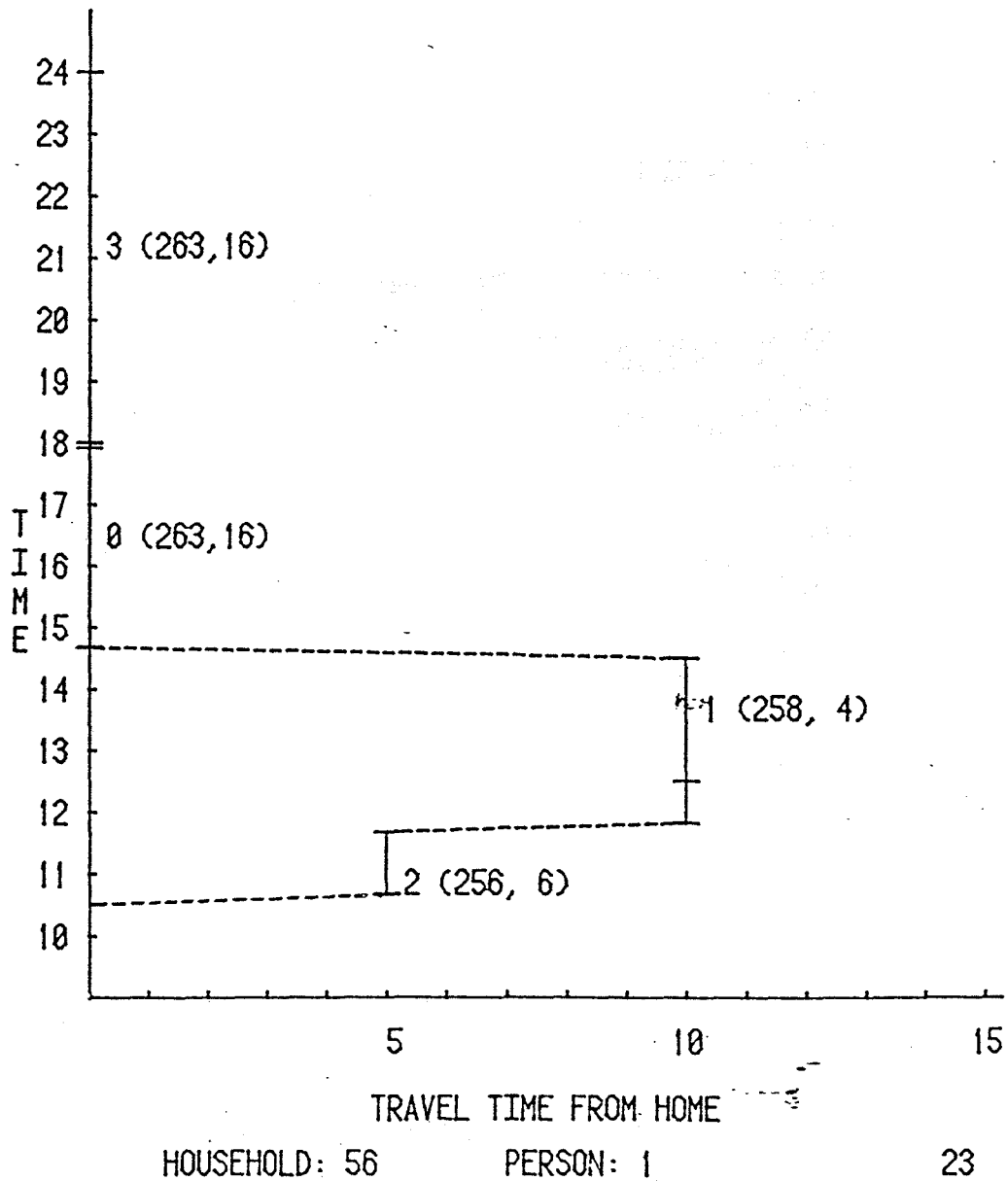
FIGURE 9.5 SAMPLE PLOTTED OUTPUT OF RAPS
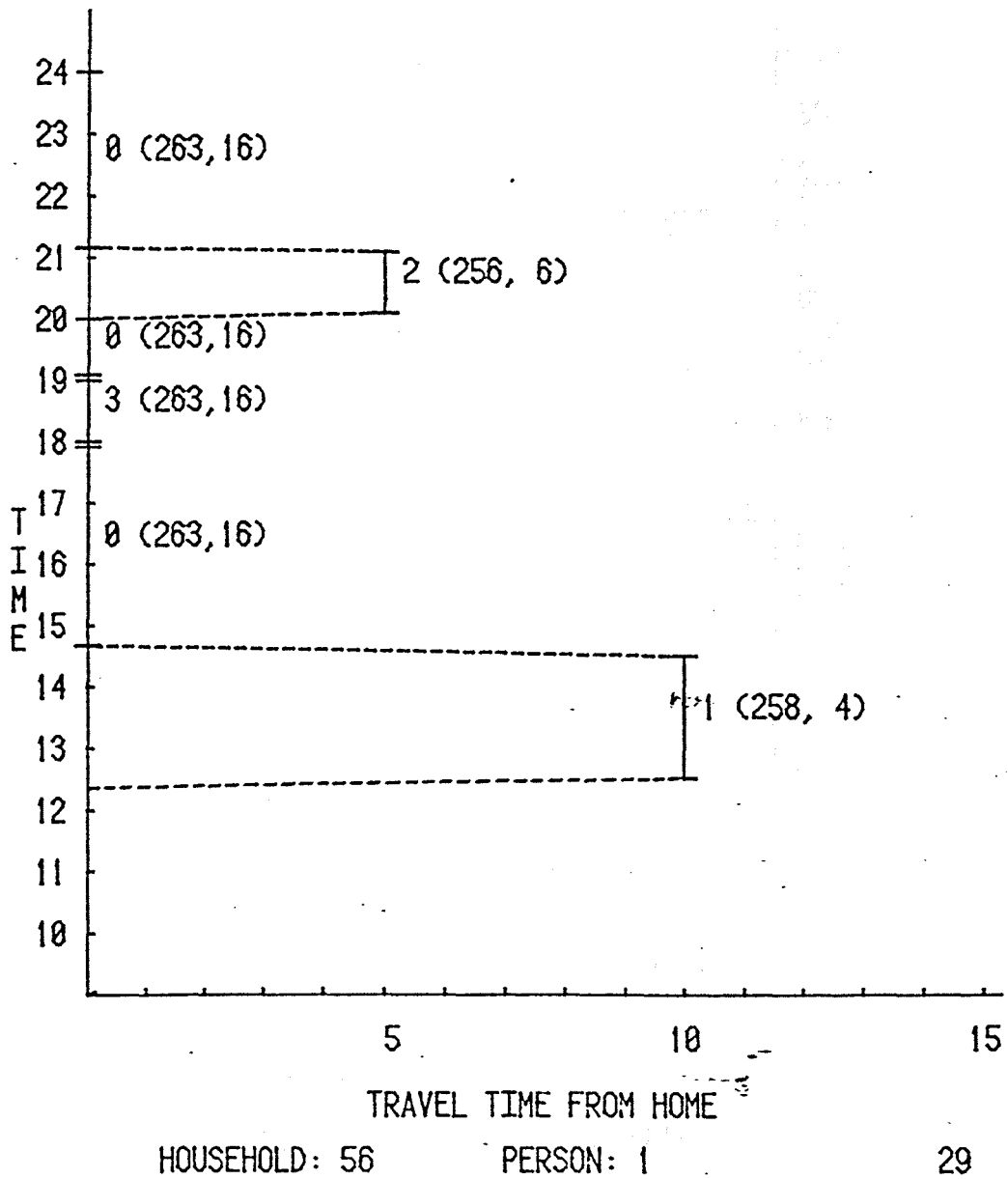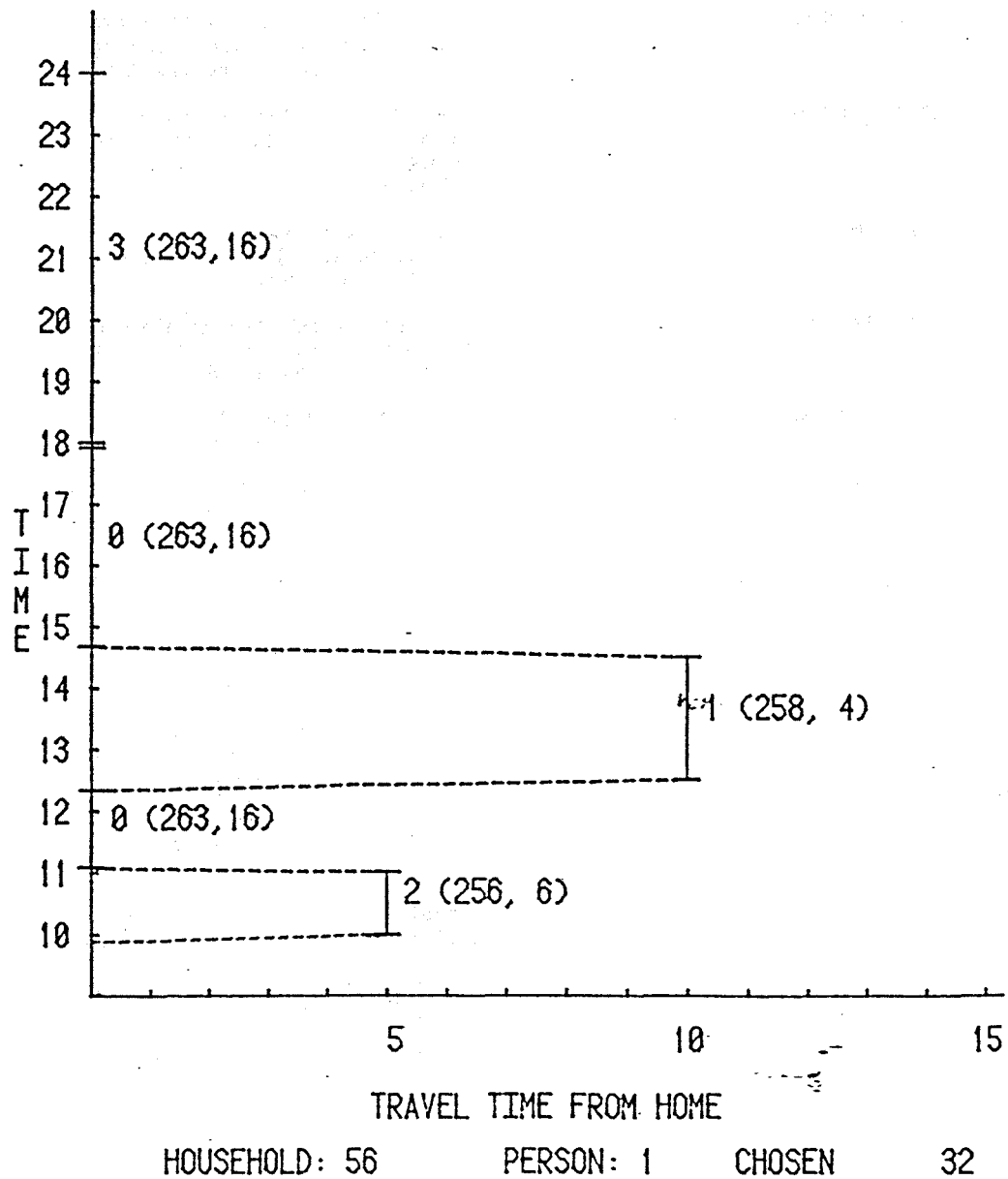
235g

FIGURE 9.5 SAMPLE PLOTTED OUTPUT OF RAPS

FIGURE 9.5 SAMPLE PLOTTED OUTPUT OF RAPS

FIGURE 9.5   SAMPLE PLOTTED OUTPUT OF RAPS

TABLE 9.4

VARIABLE DEFINITIONS

VARIABLE	DEFINITION
TRAVEL TIME:RU&U	Travel time to activities deemed either unimportant or relatively unimportant to the well being of the household
TRAVEL TIME:VI&I	Travel time to activities deemed either important or very important to the well being of the household
TRAVEL TIME:HM	Travel time to discretionary in-home activities that occur between trips to out-of-home activities
WAIT TIME	Time spent waiting (at the activity location) for a scheduled activity to commence
HOME TIME:S&N	Time spent at home either alone or with some (but not all) other members of the household
HOME TIME:ALL	Time spent at home with all other members of the household
POTENTIAL:ACT	A measure (see Chapter 5) of the potential to meet unplanned activities should such need arise
POTENTIAL:TRAV	A measure (see Chapter 5) of the expected travel time to meet unplanned activity needs
RISK:RU&U	A measure (see Chapter 5) of the probability of not being able to participate in a planned activity, that is deemed either unimportant or relatively unimportant to the well being of the household, due to stochastic variations in travel time and/or activity duration
RISK:VI&I	A measure (see Chapter 5) of the probability of not being able to participate in a planned activity, that is deemed either important or very important to the well being of the household, due to stochastic variations in travel time and/or activity duration

A multinomial logit model of selection of activity/travel pattern was then estimated using <u>only</u> these variables, i.e., those which arise directly from the theoretical development. The results of the estimation are displayed in Table 9.5. The model ws able to predict 63% of the observed activity/travel patterns correctly. ("Correct" in this sense is taken to mean that the predicted probability of the observed choice is greater than that of a nonobserved alternative.) For the degrees of freedom associated with the estimation a t value of approximately 1.66 is required for statistical significance at the 0.05 level. The estimated coefficients of the variables are all plausibly signed and offer some interesting preliminary conclusions regarding trip chaining and complex travel behavior in general.

Travel time associated with activities in an individual's program that are judged as unimportant to the well being of the household was found to be insignificant in the choice of activity/travel pattern. The explanation of this result is rooted in an understanding of the nature of the types of activities which typically fall within this category (i.e., "unimportant") in the sample. Such activities typically were of the nonrepetitive, sporadic variety (e.g., spectator sports, movies and theatre, restaurant, etc.). The implication is that, because these are "rare" events, not much attention is devoted to "fine tuning" the repetitive portion of the activity/travel pattern to minimize travel to these activities. A second feature typical to these activities is that they tend to involve more than one member of the household. Since for the sample there was only one mode of travel considered (automobile), all

TABLE 9.5

ESTIMATION RESULTS CHOICE OF ACTIVITY/TRAVEL PATTERN

VARIABLE	COEFFICIENT	STD. ERROR	t
TRAVEL TIME:RU&U	-.13302E 01	.22048E 01	-.603
TRAVEL TIME:VI&I	-.13495E 01	.65779E 00	-2.052
TRAVEL TIME:HM	-.11002E 01	.58350E 00	-1.885
WAIT TIME	-.44620E 00	.28281E 00	-1.578
HOME TIME:S&N	.30058E-01	.16110E-01	1.866
HOME TIME:ALL	-.11369E 00	.53885E-01	-2.110
POTENTIAL:ACT	-.70914E 00	.77945E 00	-.910
POTENTIAL:TRAV	.32048E 00	.15835E 01	.202
RISK:RU&U	.72933E 00	.56425E 00	1.293
RISK:VI&I	-.54147E 00	.24722E 00	-2.190

PERCENT OF CHOICES PREDICTED CORRECTLY = 63%

potential travel time savings associated with the activity/travel pattern choice alternatives involved complex travel behavior (i.e., trip chaining) of one form or another. The implication is (expectedly) that trip chaining is not conducive to activities involving coordination among several individuals.

Conversely, travel time associated with important activities was found to be a significant determinant of the choice of patterns involving trip chaining behavior. These activities tend to be repetitive and involving only the traveler.

The variable TRAVELTIME:HM measures the time required to return home following an out-of-home activity rather than continuing on to the out-of-home activity scheduled next in the activity program. As such, it reflects the additional travel time associated with non-trip-chaining behavior. The results indicate that idividuals indeed are sensitive to this additional time commitment associated with nonoptimal (in the travel sense) travel behavior.

Time spent waiting for scheduled activities to commence was found to be only marginally significant in the choice process. However, in that waiting time in this estimation is principally a product of chaining behavior, there is a weak conclusion that limited temporal availability of activities tends to divert choice from patterns which involve extensive trip chaining.

The results on the HOMETIME variables indicate a tendency among individuals to choose activity/travel patterns which allow them to be home at times when either no or only some other memebers of the household

are there while permitting them to be away from home when all other members of the household are home. A potential explanation of this result is that the fewer the household members at home the more likely that an in-home need that arises must be met by the traveler. A clear example of this explanation is exhibited by a household with small children in which both spouses work. The need for one spouse to return home directly following work may be removed by virtue of the other spouse being home.

The estimated coefficients associated with both POTENTIAL variables tested insignificant. Although considerable additional investigation of alternate constructs of these measures is warranted, the preliminary indication is that individuals are not sensitive to the possibility of unforeseen events arising when constructing their planned activity/travel pattern.

Finally, the results associated with the RISK variables indicate that the additional travel time to home while between activities, which biases choice toward patterns which involve trip chaining, may be counterbalanced by the risk involved in stringing (i.e., chaining) activities together. This risk is due to stochastic variations in duration and/or travel time which may cause participation in one or more of the activities to become infeasible. This effect, according to the model results, is pronounced in cases involving activities deemed important to the household. Although insignificant, the sign of the coefficient of the RISK:RU&U variable tends to indicate that trip chaining behavior may be favored in accessing activities which are of a discretionary nature.

It must be emphasized that these results are preliminary, and represent only one specification of a complex model system which is itself in prototype form. While encouraging, the results also open many aspects of the model system to further investigation and refinement.
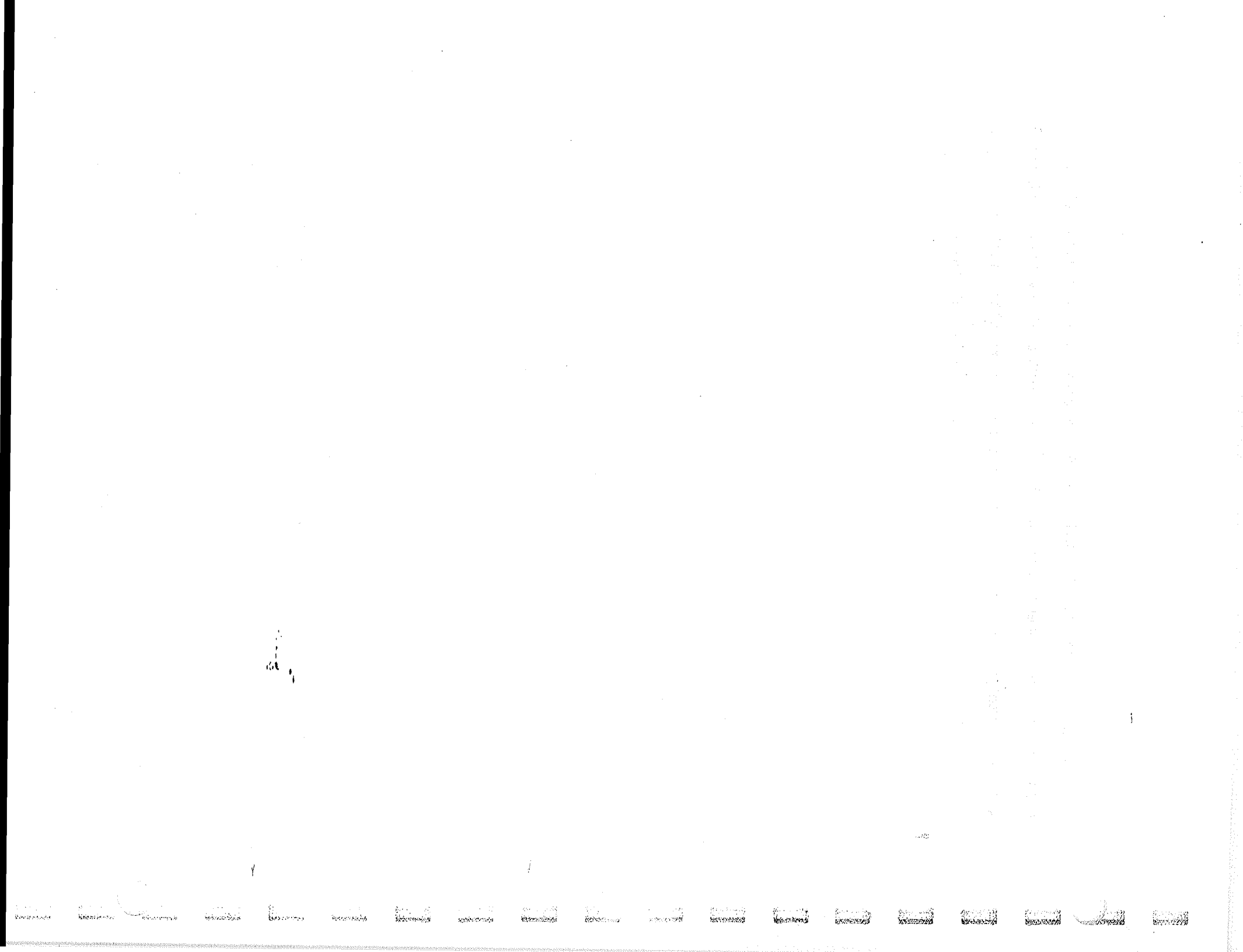
CHAPTER TEN

Conclusions and Directions for Future Research

10.1 Conclusions

The work accomplished during this first phase of the "Chaining Behavior in Urban Tripmaking" project makes several contributions to understanding complex travel behavior. In contrast to most studies of travel behavior, activities are treated explicitly. Travel "demand" is specified in terms of a set of desired activities (an activity program) and travel is viewed as arising from a more fundamental process of scheduling the activities within an available period of time. By focusing on the individual's entire activity pattern (as opposed to individual trips or tours) the theory developed here incorporates the interrelation among individual activity scheduling decisions. The effect of the spatial and temporal characteristics of the transportation and activity systems on travel behavior are explicitly incorporated in the theory--a feature that allows a much wider range of transportation related policies to be analyzed. The interdependencies among individual members of a household are introduced through the use of several household-based constraints. A choice set estimation procedure that recognizes individual's perceptual thresholds and limited evaluative capabilities is employed to reduce the choice set to a size that can be handled by existing choice models.

Finally, the prototype model system has been applied to a sample data set and a model of choice of activity/travel pattern has been estimated.

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The results of the estimation offer encouragement to the continued development and testing of the proposed model system.

10.2 Directions for Future Research

Directions for future research fall generally into two categories: 1) refinement and testing of the model system and 2) application of the model system to policy issues.

Much work is needed in the continued refinement and testing of the model system. Rather than attempt to identify areas of potential concern (they are both too many and too specific), it suffices to state that the model system proposed is a first draft of an extremely complex system (both from theoretical as well as operational viewpoints) that remains virtually untested. And, although initial empirical results are encouraging, they should in no way constitute final validation of either the model process or the theory advanced.

From a policy perspective, the research provides a potential methodology whereby the impact of various transportation-related policy options on the travel/activity behavior of individuals can be assessed. Consistent with the theory advanced in this research, travel behavior is seen as resulting from activity scheduling behavior. This activity scheduling behavior is subject to constraints imposed by the specific characteristics of the transportation, activity and household systems (i.e., the spatial/temporal connectivity of activity locations by travel modes and the interaction between household members). Any policy that changes the characteristics of the transportation, activity or household

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system will therefore change the nature of the constraints imposed on the individual, which in turn, will alter the individual's set of alternatives. Policies that may be investigated based on this framework include:

(1) Changes in operating hours of activity locations (e.g., stores, banks, schools)

(2) Flexible work hours (flex time)

(3) Restrictions o total daily auto vehicle miles of travel (VMT)

(4) Changes in the spatial distribution of activity locations

To estimate the impact that these various policies have on activity scheduling behavior (and hence, on travel behavior) the following procedure could be employed:

(1) The new set of constraints imposed on the individual by the proposed policy is specified and input to the simulation model,

(2) The set of feasible activity patterns resulting from the new constraints is calculated,

(3) The new feasible activity patterns are classified to construct the new choice set, and

(4) Using the choice model parameters estimated previously, choice probabilities for the new pattern alternatives are obtained.

Any policy involving a change in the operating hours of a specific activity type can be incorporated by simply changing the temporal availability parameter associated with that activity type. For example, flex time can be introduced into the model by increasing the temporal availability of the "work" activity and allowing the start time of the

"work" activity to occur over some period of time (as opposed to being constrained to occur at a particular point in time). The duration of the work activity, however, would remain unchanged. To estimate the impacts of a restriction on total automobile travel, the total daily automobile VMT associated with each feasible activity pattern could be calculated and all those patterns having VMT in excess of the limit are eliminated from the individual's opportunity set prior to the implementation of the classification and choice models. The impacts of changes in the spatial distribution of activities could be estimated by changing the observed locations of the activities contained in the individual's activity program. In addition to these transportation-related policies, the impacts of the introduction and utilization of new modes of travel (e.g., electric vehicles) could also be estimated, by specifying the following vehicle design parameters:

- speed
- range (the amount of time that the vehicle can be used before it needs recharging)
- recharge time (the amount of time before the vehicle can be used again)

As with the other policies discussed above, these design characteristics impose a new set of constraints on the individual which would be used to generate a new set of feasible activity patterns. Once these new opportunities are generated, the choice set is created and new choice probabilities can be estimated.

In addition to forecasting an individual's activity pattern changes in response to policy-induced alterations in the transportation and

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activity systems, the proposed methodology may also be used to provide information regarding the range of potential opportunities (and hence, possible choices) available to individuals. This information can then be used to identify segments of the population most impacted by policy alternatives.

These and a wide range of other policy issues may be analyzed using the model system developed in this phase of the research, contingent, of course, on final validation of the model.

REFERENCES

Adler, Thomas J. and Moshe Ben-Akiva (1979). "A Theoretical and Empirical Model of Trip-Chaining Behavior," Transportation Research, Vol. 13B, No. 3, pp. 243-257.

Adler, T. and M. Ben-Akiva (1976). Joint Choice Model for Frequency, Destination, and Travel Mode for Shopping Trips. Transportation Research Record 569.

Bain, Joseph H. (1976). Activity Choice Analysis, Time Allocation and Disaggregate Travel Demand Modeling, unpublished M.S. Thesis, Department of Civil Engineering, MIT.

Ben-Akiva, Moshe, Len Sherman and Brian Kullman (1978). "Non-Home Based Models," Transportation Research Record 673, pp. 128-133.

Bentley, Gillian A., Alex Bruce and David R. Jones (1977). "Intra-Urban Journeys and Activity Linkages," Socio-Economic Planning Science, Vol. 11, pp. 213-220.

Burnett, K. Patricia (1976). "Toward Dynamic Models of Traveller Behavior and Point Patterns of Traveller Origins," Economic Geography, Vol. 52, No. 1, pp. 30-47.

Burnett, K. Patricia (1978). "Markovian Models of Movement Within Urban Spatial Structures," Geographical Analysis, Vol. 10, No. 2, pp. 142-153.

Burnett, P. and S. Hanson (1979). Rationale for an Alternative Mathematical Approach to Movement as Complex Human Behavior. Transportation Research Record 723, 11-24.

Burns, Lawrence D. (1978). Transportation, Temporal and Spatial Components of Accessibility, D.C. Heath, Lexington, Ma.

Clarke, Michael I. and Martin C. Dix (1980). "An Activity Scheduling Model for Generating Feasible Travel Choice Sets," paper presented at the International Conference on Research and Applications of Disaggregate Demand Models, University of Leeds, England.

Clarke, Michael I., Martin C. Dix, Peter M. Jones and Ian G. Heggie (1981). "Recent Advances in Activity-Travel Analysis," paper presented at the 60th Annual Meeting of the Transportation Research Board, Washington, D.C.

Cochran, W. G. (1950). "The Comparison of Percentages in Matched Samples," Biometrika, Vol. 37, pp. 256-266.

Cullen, Ian and Vida Godson (1975). "Urban Networks: The Structure of Activity Patterns," Vol. 4, Part 1 in D. Diamond and J.B. McLoughlin (eds.), Progress in Planning, Pergamon Press.

Damm, David (1979). Toward a Model of Activity Scheduling Behavior, unpublished Ph.D. Dissertation, Department of Civil Engineering, MIT.

Davis, Christian F., William H. Groff and Thomas E. Steahr (1981). An Analysis of the Potential for Dynamic Ridesharing in a Low-Density Area, Final Report to U.S. Department of Transportation, Washington, D.C.

Foerster, James G. (1979). "Mode Choice Decision Process Models: A Comparison of Compensatory and Non-Compensatory Structures," Transportation Research, Vol. 13A, pp. 17-28.

Gilbert, G., G.L. Peterson, and J.L. Schefer (1972). "Markov Renewal Model of Linked Trip Travel Behavior," Transportation Engineering Journal 98, pp. 691-704.

Ginn, James Royce (1969). Transportation Considerations in an Individual's Activity System, unpublished Ph.D. Dissertation, Department of Civil Engineering, Northwestern University.

Hagerstrand, Torsten (1974). The Impact of Transport on the Quality of Life, Report No. 13 in Rapporter och Notiser series, Department of Geography, University of Lund, Sweden.

Hanson, Susan E. and Duane F. Marble (1971). "A Preliminary Typology of Urban Travel Linkages," East Lakes Geographer, Vol. 7, pp. 49-59.

Hanson, Susan E. (1980). "The Importance of the Multi-Purpose Journey to Work in Urban Travel Behavior," Transportation, Vol. 9, pp. 229-247.

Heggie, Ian G. (1977). "Putting Behavior Into Behavioral Models of Travel Choice," Working Paper 22, Transport Studies Unit, Oxford University, England.

Hemmens, George C. (1970). "Analysis and Simulation of Urban Activity Patterns," Socio-Economic Planning Science, Vol. 4, pp. 53-66.

Horowitz, Joel (1976). "The Effect of Travel Time and Cost on the Frequency and Structure of Automobile Travel," Transportation Research Record 592, pp. 1-5.

Horowitz, Joel (1978). "Disaggregate Demand Model for Non-Work Travel," Transportation Research Record 673, pp. 65-71.

Horowitz, Joel (1981). "Modeling Traveler Responses to Alternative Gasoline Allocation Plans," paper presented at the 60th Annual Meeting of the Transportation Research Board, Washington, D.C.

Horton, Frank E. and P.W. Shuldiner (1967). "The Analysis of Land Use Linkages," Highway Research Record 165, pp. 96-107.

Jacobson, Jesse (1978). Models of Non-Work Activity Duration, unpublished Ph.D. Dissertation, Department of Civil Engineering, MIT.

Jones, Peter M. (1977). "Identifying the Determinants of Destination Choice," Chapter 9 in Hensher, D.A. (ed.) Identification and Evaluation of the Determinants of Travel Choice, Saxon House.

Jones, Peter M. (1979). "HATS: A Technique for Investigating Household Decisions," Environment and Planning (A), Vol. 11, No. 1.

Jones, P.M., M.C. Dix, M.I. Clarke and I.G. Heggie (1980). Understanding Travel Behavior, Final Report to the Social Science Research Council, Transport Studies Unit, Oxford University.

Koppelman, F.S. and J.R. Hauser (1978). Destination Choice Behavior for Non-Grocery-Shopping Trips. Transportation Research Record 673, 157-165.

Kitamura, Ryuichi, Lidia P. Kostyniuk and Michael J. Uyeno (1981). "Basic Properties of Urban Space Time-Paths: Empirical Tests," paper presented at the 60th Annual Meeting of the Transportation Research Board, Washington, D.C.

Kobayashi, Kenzo (1976). "An Activity Model: A Demand Model for Transportation," Transportation Research, Vol. 10, pp. 105-110.

Landau, U., J.N. Prashker and B. Alpern (1982). Evaluation of Activity Constrained Choice Sets to Shopping Destination Choice Modelling. Transportation Research 16A(3), 199-207.

Landau, Uzi, J.N. Prashker, B. Alpern and Moshe Ben-Akiva (1980). The Application of Space-Time Budgeting Concepts to Shopping Destination Choice Modeling, Research Report No. 80-24, Transportation Research Institute, Technion-Israel Institute of Technology, Haifa, Israel.

Landau, Uzi, J.N. Prasker and M. Hirsh (1980). The Effect of Temporal Constraints on Household Travel Behavior, Transportation Research Institute, Technion-Israel Institute of Technology, Haifa, Israel.

Lenntorp, Bo (1976a). Paths in Space-Time Environments, Lund Series in Geography, Series B., No. 44, Lund: CWK Gleerup.

Lenntorp, Bo (1976b). A Time-Space Structured Study of the Travel Possibilities of the Public Transport Passenger, No. 24 in Rapporter och Notiser series, Department of Geography, University of Lund, Sweden.

Lerman, Steven R. (1979). "The Use of Disaggregate Choice Models in Semi-Markov Process Models of Trip Chaining Behavior," _Transportation Science_, Vol. 13, No. 4, pp. 273-291.

MacKay, David B. (1971). _Consumer Movement and Store Location Analysis_, unpublished Ph.D. Dissertation, School of Business Administration, Northwestern University.

McFadden, D. (1968). _The Revealed Preferences of a Government Bureaucracy_, Technical Report No. 17, Institute of International Studies, University of California at Berkeley.

Nystuen, John D. (1967). "A Theory and Simulation of Intraurban Travel" in W.L. Garrison and D.F. Marble (eds.), _Quantitative Geography Part I: Economics and Cultural Topics_, Northwestern University Studies in Geography #13, pp. 54-85.

Oster, Clinton V., Jr. (1978a). "The Importance of Multiple Destination Tours in Intra-Urban Household Travel," Harvard University Department of City and Regional Planning, Discussion Paper D78-2.

Oster, Clinton V., Jr. (1978b). "The Second Role of the Work Trip - Visiting Non-Work Destinations," Harvard University Graduate School of Business Administration, Discussion Paper 78-16.

Park, C. W. (1976). "The Effects of Individual and Situation Related Factors on Consumer Selection of Judgment Models," _Journal of Marketing Research_, Vol. 13, pp. 141-155.

Pas, Eric I. (1981). "A Methodology for Analyzing Daily Travel/Activity Patterns," manuscript submitted for review to the Transportation Research Board.

Payne, J. (1977). "Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis," _Organizational Behavior and Human Performance_, Vol. 16, pp. 336-387.

Recker, W.W. and L.P. Kostyniuk (1978). Factors Influencing Destination Choice for the Urban Grocery Shopping Trip. _Transportation_ 7, 19-33.

Recker, Wilfred W., Gregory S. Root, Michael G. McNally, Michael J. Cirrincione and Harry J. Schuler (1980). _An Empirical Analysis of Household Activity Patterns_, Final Report to U.S. Department of Transportation, Washington, D.C.

Recker, Wilfred W., Michael G. McNally, Gregory S. Root, and Mark Smiley (1981). "Chaining Behavior in Urban Trip Making: The Theoretical Model," Working Paper CB-2, Institute of Transportation Studies and School of Engineering, University of California at Irvine.

Richardson, A.J. and W. Young (1982). A Measure of Linked-Trip
    Accessibility. Transportation Planning and Technology 7, 73-82.

Salomon, Ilan (1981). "Life Styles-A Broader Perspective on Travel
    Behavior," paper presented at the International Conference on Travel
    Demand Analysis: Activity-Based and Other New Approaches, St.
    Catherine's University, Oxford, England.

Stephens, John D. (1975). Daily Activity Patterns and Time-Space
    Constraints. Unpublished Ph.D. Dissertation, Michigan State
    University, East Lansing, Michigan.

Swiderski, Detlef (1981). "A Model for Simulating Spatially and
    Temporally Coordinated Activity Sequences on the Basis of Mental
    Maps," paper presented at the International Conference on Travel
    Demand Analysis: Activity Based and other New Approaches, Oxford
    University, England.

Tomlinson, Janet, N. Bullock, P. Dickens, P. Steadman and E. Taylor
    (1973). "A Model of Student's Daily Activity Patterns," Environment
    and Planning, Vol. 5, pp. 231-266.

Van der Hoorn, Toon (1981). "Development of an Activity Model," paper
    presented at the International Conference on Travel Demand Analysis:
    Activity Based and other New Approaches, Oxford University, England.

Vidakovic, Velibor (1974). "A Harmonic Series Model of the Trip Chain,"
    in Buckley, D.J. (ed.), Transportation and Traffic Theory, Elsevier,
    New York, pp. 375-386.

Vidakovic, Velibor (1977). "A Distance Parameter of the Trip Chain
    Process," in Transportation and Traffic Theory, International
    Conference, Kyoto, Japan.

Westelius, Ovar (1973). The Individual's Way of Choosing Between
    Alternative Outlets, National Swedish Council for Building Research,
    Document D17, Stockholm, Sweden.

Wheeler, James O. (1972). "Trip Purposes and Urban Activity Linkages,"
    Annals of the Association of American Geographers, Vol. 62, No. 4,
    pp. 641-654.