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Method For Estimating Patronage Of Demand Responsive Transportation Systems

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16. Abstract

This study has developed a method for estimating patronage of demand responsive transportation (DRT) systems. This procedure requires as inputs a description of the intended service area, current work trip patterns, characteristics of the served population, and the major design choices, such as the vehicle fleet size, changes in fleet size over the day, types of vehicles being used (buses or taxis), and the fare level. Using these data, the model predicts patronage and service levels for each user-specified interval during the day. The model system has been developed as a software package which includes a set of disaggregate demand models, a set of analytic supply models, and an equilibration procedure. In addition, a simple sketch planning procedure has been developed which can be used for quick, preliminary analysis of DRT sites.

The models have been estimated on data from existing systems in Rochester NY and Haddonfield NJ and validated on systems currently operating in Davenport IA and LaHabra CA. Comparisons of forecasts and actual ridership levels have also been carried out for six other U.S. DRT systems.

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PREFACE

Public transportation officials have had a tendency to concentrate their planning and design efforts on rail and and fixed route bus systems. However, the combination of shifting residential densities and the desire for public transportation to serve a wider spectrum of travel needs has focused increasing attention on demand responsive transportation (DRT) systems. Demand responsive transportation refers not to one type of system, but encompasses a wide range of possible service options that have one common element: they respond to the demands of passengers both in terms of where and when they wish to travel.

A critical problem local planners face when they attempt to design DRT systems is the difficulty of forecasting future patronage; many of the major decisions on capital outlays such as the number of vehicles purchased depend on expected ridership levels. In response to this need for planning methods, this study, funded under contract DOT-TSC-977, entitled, "A Method for Estimating Patronage of Demand Responsive Transportation Systems," has developed a computer-based procedure which can be used by local planners to predict DRT patronage.

Cambridge Systematics wishes to thank the individuals who contributed to the scope and direction of this study. Howard Simkowitz and Donald Ward of the U.S. Department of Transportation, Transportation Systems Center, deserve special mention for their critical review and helpful comments throughout the course of this study.

The authors personally thank the other members of the staff at Cambridge Systematics who contributed to this project: Moshe E. Ben-Akiva, Charles F. Manski, John R. Sawyer, Carol A. Walb, Christine M. Winquist and Jeanne S. Roberts.

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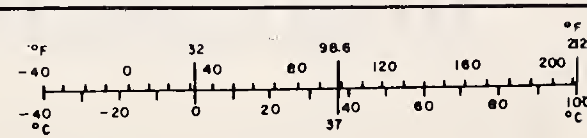
METRIC CONVERSION FACTORS

Approximate Conversions to Metric Meesures

Symbol	When You Know	Multiply by	To Find	Symbol
		LENGTH		
in	inches	2.5	centimeters	cm
ft	feet	30	centimeters	cm
yd	yards	0.9	meters	m
mi	miles	1.6	kilometers	km
		AREA		
in^2	square inches	6.5	square centimeters	cm^2
ft^2	square feet	0.09	square meters	m^2
yd^2	square yards	0.8	square meters	m^2
mi^2	square miles	2.6	square kilometers	km^2
	acres	0.4	hectares	ha
		MASS (weight)		
oz	ounces	28	grams	g
lb	pounds	0.45	kilograms	kg
	short tons (2000 lb)	0.9	tonnes	t
		VOLUME		
tsp	teaspoons	5	milliliters	ml
Tbsp	tablespoons	15	milliliters	ml
fl oz	fluid ounces	30	milliliters	ml
c	cups	0.24	liters	l
pt	pints	0.47	liters	l
qt	quarts	0.95	liters	l
gal	gallons	3.6	liters	l
ft^3	cubic feet	0.03	cubic meters	m^3
yd^3	cubic yards	0.76	cubic meters	m^3
		TEMPERATURE (exact)		
°F	Fahrenheit temperatura	5/9 (after subtracting 32)	Celsius temperature	

Approximate Conversions from Metric Meesures

Symbol	When You Know	Multiply by	To Find	Symbol
		LENGTH		
mm	millimeters	0.04	inches	in
cm	centimeters	0.4	inches	in
m	meters	3.3	feet	ft
m	meters	1.1	yards	yd
km	kilometers	0.6	miles	mi
		AREA		
cm^2	square centimeters	0.16	square inches	in^2
m^2	square meters	1.2	square yards	yd^2
km^2	square kilometers	0.4	square milas	mi^2
ha	hectares (10,000 m^2)	2.5	acres	
		MASS (weight)		
g	grams	0.036	ounces	oz
kg	kilograms	2.2	pounds	lb
t	tonnes (1000 kg)	1.1	short tons	
		VOLUME		
ml	milliliters	0.03	fluid ounces	fl oz
l	liters	2.1	pints	pt
l	liters	1.06	quarts	qt
l	liters	0.26	gallons	gal
m^3	cubic meters	35	cubic feet	ft^3
m^3	cubic meters	1.3	cubic yards	yd^3
		TEMPERATURE (exact)		
°C	Celsius temperature	9/5 (then add 32)	Fahrenheit temperature	°F



EXECUTIVE SUMMARY

The demand responsive patronage forecasting procedure consists of three basic modules: work trip demand; non-work trip demand; and level of service prediction. The model explicitly treats the quality of service provided by the DRT system as a determinant of expected patronage. Conversely, the model also represents the supply relationship, which recognizes that the quality of service provided by the DRT system itself depends on the ridership. The final forecast is therefore the ridership level and service level which simultaneously satisfy these two basic relationships.

The patronage prediction procedure requires as inputs a description of the intended service area, current work trip patterns, the characteristics of the population served and the major design parameters such as the vehicle fleet size, the type of vehicles being used (buses or taxis) and the fare level. Using this data, the model predicts patronage and service levels for each user-specified interval during the day. By testing alternative configurations of fleet size, vehicle type, service area and fare level, the planner can explore the impacts of a range of alternative designs and determine the key sensitivities.

The work and non-work travel demand models rely on disaggregate choice theory, a relatively new methodology which considers the decisions individual travellers make when confronted with a set of possible trip-making alternatives, one and only one of which is selected. These models represent the current state-of-the-art in travel demand modelling and provide for a much more complete and realistic description of trip-making behavior than more traditional procedures.

One of the unique features of the model system involves a procedure to model complex tours of non-work trips by simulating a passenger's choice pattern (including both destination and mode) over the course of the day.

Both the work and non-work travel prediction submodels were developed using data from two urban areas, Haddonfield, New Jersey, and Rochester, New York, which had operational DRT systems. Due to a small data sample and coding problems associated with the Haddonfield home interview survey, only the Rochester data were used to calibrate the final set of models. The Haddonfield information did, however, provide an important starting point for the demand model development, since the data set was readily available. Model specifications tested on the Haddonfield data permitted later efforts with the more complete Rochester data to be better focused.

The level of service prediction component of the model (i.e., given a demand level and distribution pattern over an area, and a number of vehicles, what will the wait and ride times be?) was developed by using information from a computer simulation of DRT operations. This simulation was developed at M.I.T. and was previously validated with data from the Haddonfield, New Jersey DRT system. Using data generated by executing the simulation to forecast DRT service quality under a wide range of operating conditions, sets of equations for predicting expected wait time and travel time were developed, given the demand level and the number of vehicles. These equations can be used separately from the computer-based procedure as independent planning tools.

The entire patronage prediction procedure was validated by applying it to two other urban areas with DRT systems: LaHabra, California, and Davenport, Iowa. These cities were quite different from the cities used for calibrating the model, and therefore present a major test for the forecasting procedure. For example, the Davenport system uses taxis and charges fares that are about a factor of two higher than those charged in Rochester, which relies on minibuses.

Comparison of observed ridership levels for these two cities with levels predicted by the model resulted in errors of 26% and 33% respectively, for Davenport and LaHabra. Comparison of observed and predicted ride and wait times for these two cities resulted in errors of 6% and 30% for Davenport (with 21% error in total time) and 9% and 14% for La Habra (with 15% error in total time).

Recognizing that many agencies will not have the staff and resources to implement and use the above detailed model, a simplified sketch planning model was also developed. This procedure was developed from the more complex computerized model system but requires only simple descriptions of the service area and DRT system to use.

Use of this procedure for six additional existing DRT systems confirmed that the model system produces estimates with a maximum error of approximately $\pm 30\%$ of the observed ridership levels. The total average error for the six sites was -.2%.

This report describes the forecasting model, the calibration and validation results, the sketch planning model and in appendices documents the technical details of the models. These appendices also include documentation of the computer program and a description of the format of the magnetic tape on which the program is contained.

SECTION 1

INTRODUCTION TO DEMAND RESPONSIVE TRANSPORTATION

1.1 Objective and Outline of Report

In the past, public transportation officials tended to concentrate their planning and design efforts on rail and fixed route bus systems. However, the combination of shifting residential densities and the desire for public transportation to serve a wider spectrum of travel needs has focused increasing attention on demand responsive transportation (DRT). Such transportation systems are in reality a wide range of possible service options that have one common element: they respond to the individual travel desires of passengers. For the purposes of this study, DRT systems were defined as transportation services which respond directly to calls for service from the public, do not use fixed schedules, and provide door-to-door service to customers.

This report describes a patronage forecasting model designed for use by local agencies seeking to determine the effect of different service areas, vehicle fleet sizes, fare structures and dispatching methods on total DRT patronage. Local agencies could use this model to help predict the economic viability of a specific DRT system or a range of alternative DRT systems.

The model consists of a series of relationships which collectively describe the major determinants of DRT patronage. The model has been implemented in a self-contained computer program designed for local use.

Recognizing that many agencies will not have the staff and resources to implement and use the detailed model, a simplified sketch planning model has also been developed. This model is a set of curves, or nomographs, derived from exercising the computer model, but its use requires only simple descriptions of the service area and DRT system.

The remainder of this section is a brief overview of the spectrum of possible DRT services.* Section 2 is a non-technical overview of the model system. All technical documentation of the model system, including calibration results and a description of some of the models which were tried but rejected in the course of the study, is contained in Appendices A and B.

Section 3 explains how to use the model by listing the required data and presenting an example based on Irondequoit, New York, a DRT system which offers a sophisticated combination of services. This section is supplemented by Appendix C, a user's manual for the computer program, and Appendix D, documentation of the available computer tape describing the program.

Section 4 describes tests of the detailed model on DRT systems in Davenport, Iowa and LaHabra, California. This chapter also serves to illustrate some of the issues users of the model should be aware of to interpret the model's output.

Section 5 describes the sketch planning model including the method used to derive it and its use and limitations.

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*More complete summaries are available in other sources, such as U.S. D.O.T., 1974).

The final section is a brief summary and conclusion which describes the role of planning tools in DRT design and identifies unresolved issues in DRT patronage forecasting.

1.2 Background

Demand responsive transportation (DRT) is a form of transport that, in a period of approximately ten years, has developed from a new service concept to well over one hundred operating systems in North America. DRT refers to a wide range of urban transportation options that have one common element; they respond to the individual needs of passengers, both when and where they want to travel. Unlike conventional public transit services which are constrained by fixed routes and schedules, DRT services are based on completely flexible routes and schedules.

Interest in demand responsive transportation arose in response to decreases in residential density and to increased diffusion of urban trips. These shifts, fostered by the emergence of the automobile as the dominant transportation mode, have reinforced the role of the automobile, and contributed to the deterioration of many public transportation systems. Because DRT vehicles are not constrained to fixed routes, they can more effectively serve low density areas. By providing door-to-door service, DRT offers a high quality alternative to the automobile, while at the same time providing a service well suited to groups such as the elderly and handicapped.

DRT systems are distinguished from the traditional taxi by their use of ride sharing - several groups may be served by a vehicle simultaneously. Thus, DRT systems seek to combine higher vehicle productivities (passengers per vehicle hour or vehicle mile), and high quality door-to-door service. When DRT research began in the mid-1960's, the only existing services that could be classified as DRT were a handful of shared-ride taxi services. The research at that time focused on ways of providing more efficient DRT services.

Early experiments with this "new generation" of DRT services were somewhat limited in their demand responsiveness. In some cases only a single major destination was served and service was restricted to people desiring daily travel (e.g., the subscription bus services implemented in Peoria, Illinois, and Flint, Michigan). In other cases, vehicles would operate on a basic fixed route but make detours to serve doorstep requests on demand (e.g., the route deviation systems in Mansfield, Ohio, and Emmen, The Netherlands). By the early 1970's, "many to many"* DRT systems were being introduced. Interest in the concept grew rapidly, and in August, 1974, a report by the U.S. Department of Transportation indicated that more than forty DRT systems had been implemented in North America.

Since that time, the number of DRT systems in operation has increased dramatically, despite the well publicized problems encountered in some of the larger scale systems such as Santa Clara, California and Haddonfield, New Jersey. The increased interest in DRT service can be traced to a number of factors. One is the suitability of DRT service for the elderly and handicapped. This is coupled with the availability of funding for non-profit agencies to provide transportation services through Health, Education and Welfare (HEW) and the Urban Mass Trans-

*Many origins to many destinations as opposed to the simpler "many to one"type of systems.

portation Administration (UMTA) 16b(2) Program. In addition, anticipation of the new Federal guidelines for serving the elderly and handicapped led many localities to develop special transportation services.

Another important factor in the spread of DRT service has been the growing emphasis placed by both FHWA and UMTA on low cost transportation alternatives. This emphasis culminated in the Transportation Systems Management (TSM) requirements. Demand responsive transportation is being recognized as a low capital cost alternative for providing a given level of service to low density markets with higher vehicle productivities(and lower cost) than could be achieved with fixed route operations. DRT can perform a number of major functions. For example, in low density areas, it can replace uneconomic fixed route services. It can also be used to provide collector/distribution service in an integrated feeder/line haul system.

1.3 Types of Demand Responsive Transportation Systems

The increased interest in DRT has been accompanied by a recognition of a broad range of service possibilities. A useful way to distinguish demand responsive transportation systems is to characterize them by their degree of demand responsiveness in space and time. At one end of this spectrum is the fully demand responsive system in both time and space, often known as dial-a-ride. In such a system, point-to-point service is provided on demand anywhere within a service area. This type of system is one of the most popular forms of DRT service and has been implemented in such places as Rochester, New York, and La Habra, California.

In a zonal dial-a-ride system, space responsiveness is constrained by limiting direct trips to locations within a given zone and requiring transfers for trips across zone boundaries. This approach is effective in large areas, particularly those which have a major activity center such as a shopping center which can serve as a transfer point. Many Canadian DRT systems, such as the one in Regina, Saskatchewan, and the Ann Arbor, Michigan system, are zonal systems.

Another type of DRT system which restricts the degree of space responsiveness is the many-to-one or many-to-few dial-a-ride. In such a system, passengers are picked up at any location, but taken only to one or a few major activity centers (and vice versa). This type of system is sometimes used to serve major employment or shopping centers. It may also be used to provide feeder service to a line haul facility.

The latter type of service is provided in Bay Ridges, Ontario, and a number of other communities. The ability of dial-a-ride to serve as a feeder system is receiving increased scrutiny by the U.S. Department of Transportation, and demonstration of this ability is one of the objectives of a major UMTA Service and Methods demonstration in Rochester, New York.

Route deviation service is less responsive, both in time and space. In this type of system, vehicles follow a regular route and adhere to a schedule but are free to deviate from the route to pick-up and drop-off passengers upon request. Following a deviation, the vehicle will return to the point at which it left the route. The origins of the route deviation concept can probably be traced back to the jitney; a more recent route deviation experiment was the Mansfield, Ohio system.

A variation of route deviation, known at times as point deviation, has fewer spatial restrictions. In a point deviation system vehicles are scheduled to depart from a series of checkpoints at regularly scheduled times. Vehicles are constrained only at the check points and can follow any path between checkpoints necessary to serve requested doorstep pick-ups and drop-offs. Point deviation service is presently being provided in Merrill, Wisconsin.

Another system that is restrictive in time but less restrictive in space might be called a discrete run time system. In such systems, vehicles are scheduled to leave a particular point at certain times, make loops through the service area to pick-up and drop-off passengers, and finally return to the starting point for the next scheduled run. This type of service is most often employed in feeder/distributer and zonal systems, as in Ann Arbor and Regina.

Another factor that impacts the time-responsiveness of a DRT system is the restriction on when a passenger can request service. In each of the services described thus far, passengers wanting to be picked up at their door could request service essentially just before they want to travel. Alternatively, passengers may be required to request service in advance. This type of "by reservation only" system would typically be introduced to allow time for efficient scheduling, which could increase the productivity of the service. In some systems, passengers have to request service at least one hour in advance, in other systems, 24 hours or more. In systems operating like this, including many specialized services for the elderly and handicapped, vehicles may not even have communication equipment.

The final type of service considered here, subscription service, is the least time responsive service. In this variation, passengers make regular trips to an acceptable destination (often only one or a few locations are acceptable) and must book service in advance. Regular routes are established so that each subscriber is picked up either at his/her door or at one of a series of checkpoints. Routes are changed periodically to incorporate new service requests if capacity exists. Subscription service, which offers fairly high vehicle productivity, is most frequently used for work trips as in the Rochester/ Greece, New York - Kodak Park subscription service.

Table 1.1 presents a simple classification of the various DRT and other transportation services in terms of time and space responsiveness. Table 1.2 summarizes the operating characteristics of some of the better-known demand responsive transportation systems.

Table 1.1

Time and Space Responsiveness of Transportation Systems

Space / Time	Fixed	Flexible
Fixed	Conventional Transit	Carpool, Vanpool, Subscription Bus, Point Deviation
Flexible	Jitney, Personal Rapid Transit	Premium Taxi, Private Auto, Many-to-Many Dial-a-Ride

Table 1.2

Characteristics of Selected DRT Systems

Location	Type of Service	Population Served	Population Density	Number of Vehicles in Service	Fares	Daily Patronage
Batavia, NY	many-to-many dial-a-ride subscription	18,000	4,200	5	\$.30-\$.40	400-500
Bay Ridges, Ontario	many-to-many dial-a-ride many-to-one feeder	14,000	3,500	6	\$.25	500-550
Greece/Rochester, NY	many-to-many dial-a-ride many-to-one subscription many-to-one feeder	70,000	4,600	15	\$.70-\$1.00	700-800
LaHabra, CA	many-to-many dial-a-ride	40,000	6,000	5	\$.40-\$.50	350-450
Davenport, IA	many-to-many dial-a-ride shared-ride taxi (privately operated)	100,000	5,000	10	zonal \$1.00-\$4.00	600-800
Regina, Sask.	zonal many-to-many feeder	18,000	7,000	4	\$.25	1000-1400
Merrill, WI	point deviation	10,000	2,000	2	\$.25-\$.50	300-400
Cranston, RI	many-to-many subscription for elderly and handicapped	10,000	500	3	\$2/month	200-250
Merced, CA	many-to-many subscription	30,000	3,000	4	\$.25	300-375
El Cajon, CA	many-to-many shared-ride taxi (publically sponsored, privately operated)	60,000	5,000	14	\$.50	550-650
Peterborough, Ont.	many-to-one shared-ride taxi feeder	10,000	1,000	10-15	\$.10	200-250

1.4 The Need for DRT Planning Models

When new DRT systems were implemented in the past, little information was available to help predict the demand for service. Most early models, such as the M.I.T. simulation model (Wilson, Sussman, Wong, Higonnet (1971)), predicted how a system would perform at assumed demand levels. Demand levels themselves have usually been estimated based on judgment and comparison with other DRT systems already operating.

DRT has often failed to meet expectations in many localities because of inaccurate forecasts of patronage. The overprediction of demand has led to the demise of some systems, when local officials viewed the system as a failure because it had not attracted the expected number of passengers. On the other hand, the underprediction of demand can have even more significant consequences. For example, the failure of the Santa Clara, California, system has been blamed, in part, on "too much success," i.e., there were more passengers than the system could handle. These failures were due to the lack of effective analysis tools for planning and, in particular, the inability to forecast demand.

Demand prediction for a demand responsive transportation system is more complicated than demand prediction for traditional fixed route service, not only because little experience has been acquired with DRT systems to date, but also for a number of other reasons inherent in the service concept. First of all, fixed route systems serve only specific corridors; so demand prediction requires consideration of only a limited number of origin/destination pairs. Prediction of DRT patronage, on the other hand, must be based on all potential origins and destinations in the service area and may also require consideration of other destinations which can be reached by the combination of DRT and rapid transit or bus service. Perhaps even more important, however, is the interaction of supply and demand. In a conventional fixed route transit system, level of service is not very sensitive to demand. For example, a passenger's ride time is dependent only on trip length, bus route, vehicle speed, and dwell time. Although level of service influences demand, routes and schedules can be considered the sole determinants of level of service. In DRT, however, level of service is highly dependent upon demand levels, and vice versa. A passenger's ride time depends not only on the length of his/her desired trip, but also on the number of other passengers served by the vehicle en route and the location of their origins and destinations.

Thus, the demand for DRT service is a function of service quality (i.e., level of service), which in turn is a function of demand. In other words, demand and service relationships must be satisfied simultaneously.

If demand responsive transportation is to play its most effective role in expanding public transportation services, it is important that new DRT systems be planned carefully. There is a need to be able to identify where DRT systems make sense, determine vehicle requirements, estimate the quality of service, and determine how many will use the service. This need led to the development of the demand/supply equilibrium modelling system for planning DRT systems described in this report.

1.5 Modelling Framework

Given the number of DRT service options that exist, it is not possible to develop a single model that can be used for planning all DRT services. The problem is to identify the most significant DRT service and to allow sufficient flexibility in the model to permit users to approximate other DRT services. Many-to-many dial-a-ride service was selected as the most common form of demand responsive service in operation and also because it is the most difficult to analyze with existing planning tools. For this system, demand prediction involves the determination of trip generation, destination choice, and market share (as opposed to demand prediction for a home to work subscription service which involves only market share estimation). The quality of service depends on a complex queuing process involving a wide range of factors including demand. Thus, many-to-many service appears to be a form of DRT service for which a comprehensive equilibrium model is particularly desirable.

Feeder service can be provided as one element of many-to-many service, as in Rochester, New York. Since feeder service is regarded as an important future role for DRT, this option has been considered in the model. In addition, shared-ride taxi service is generally provided in the form of many-to-many service. Since there has been growing interest in utilizing the private sector in the provision of public transportation, an increase in the number of shared-ride services is likely. Thus, it is also important to consider this option. The way in which these options are represented in the model and the overall model structure are described in the following section.

SECTION 2

OVERVIEW OF THE DETAILED MODEL SYSTEM

2.1 Introduction

DRT systems are difficult to model, characterized as they are by sophisticated services, a range of fares and fleet sizes which vary widely both among systems and within any individual system over the day. Any model for predicting the daily patronage on such transportation systems must of necessity simplify much of this complexity. The aim of the model development is to simplify without distorting the true causal mechanisms which determine why travellers do or do not use demand responsive service.

The model described here (and in more detail in the appendices to this report) was developed with two conflicting considerations in mind. First, it is clear that existing models for predicting demand responsive service patronage have sacrificed a great deal of behavioral content in order to achieve simplicity. They have used very limited data (Arrillaga, 1973), relied on rules of thumb to adjust survey results (Hartgen and Keck, 1976), have adopted functional forms without sufficient behavioral justification (Lerman and Wilson, 1973 and 1974), or utilized models estimated on data from conventional transit systems and used ad hoc parameter adjustments to reflect the differences (Pfefer and Stopher, 1976). (These methods are reviewed in Lerman, 1973, and Transport Development Agency, 1975.) The model developed in this study is significantly more detailed than previous attempts and incorporates a valid set of behavioral relationships.

A second consideration is that,because of the practical problems of poor data and very limited time and resources, the problem of forecasting DRT patronage must be simplified considerably. In addition, the data potential users of the model are likely to have imposes a constraint on the level of detail possible. Despite these limitations the model draws on recent advances in travel demand prediction methodology to achieve a model structure significantly different from previous models. This section provides the reader with a general overview of the structure of the model and a relatively non-technical description of each of its major components.

The models were based on two urban areas, Haddonfield, New Jersey, and Rochester, New York, both of which had DRT systems on which data were collected. Due to a small data sample and coding problems associated with the Haddonfield home interview survey, only the Rochester data were used to calibrate the final set of models.* The Haddonfield data did, however, provide an important starting point for the demand model development. Model specifications tested on the Haddonfield data permitted later efforts with the more complete Rochester data to be better focused. Appendix A describes calibration results from both data sets and their use in greater detail.

The next subsection of this section reviews basic equilibrium theory upon which the model is based. This theory suggests that valid

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*The Haddonfield data did not include trip destinations outside the DRT service area except to note that they existed. Furthermore, Haddonfield no longer had DRT service when this study was begun, so collection of on-board survey data to supplement the home interview survey was impossible.

patronage predictions for DRT services will require not only a set of models for predicting demand, but also a capability to predict how well a DRT system will perform under a given demand. Following this, Subsection 2.3 describes the overall structure of the model system, briefly summarizing the functional submodels and their interaction. Subsection 2.4 is a non-technical description of disaggregate choice models, the general demand modelling approach used in the study.

The following three subsections (2.5, 2.6, 2.7) focus on the separate components of the model system: the demand models (for both work and non-work trips), and the supply model. In these subsections, only a general description of the models is given, with more detailed, technical descriptions contained in Appendices A and B respectively. The final subsection of Section 2 (2.8) describes how these components are organized into a single model to predict DRT patronage and discusses the types of forecasts which can be obtained from the model.

2.2 Equilibrium in DRT Service

Demand responsive systems differ substantially from conventional transit in a number of ways. For conventional transit, the estimation of the level of service varaibles which may be present in a demand model is usually quite straightforward given the specification of transit routes, headways, etc. For example, in a fixed route bus system, level of service measures such as wait time and ride time are dependent principally on the headway, the route structure, the trip length and the vehicle speed. Significantly, for a broad range of demand these level of service parameters may be considered to be independent of the actual level of ridership.* This makes it possible to estimate patronage using only a demand model since there is little feedback between the demand side and the performance of the system.

Unfortunately, in demand responsive transportation systems the most important level of service variables are heavily dependent on ridership. Specifically, all service times, including wait and ride times, depend to a great degree on the level of demand over typical design ranges. This implies that to forecast demand (and also service characteristics), both the supply and demand relationships must be solved iteratively or simultaneously.

This situation can best be demonstrated by an example. For simplicity, assume that only one level of service characteristic (called "time")

*Clearly in heavily congested systems this independence breaks down, and wait time in particular may become highly dependent on the actual level of ridership. Similarly, when bus platooning becomes a problem, average wait times depend on the extent of the unrealiability in headways.

affects DRT demand. (In the actual forecasting model, wait time, ride time, and cost are used.) In most bus systems the service, or congestion, function is quite flat, as indicated in curve S_{BUS} in Figure 2.1. Demand responsive transportation, however, has performance characteristics similar to curve S_{DRT}, i.e., time varies significantly with demand over the entire range of usage. In this simplified example, the same demand curve (labelled D in Figure 2.1) is assumed for both systems.

The true equilibrium point for DRT is indicated as E_{TRUE} with associated demand D_{TRUE}; however, if service considerations are ignored (i.e., a flat supply function were used for DRT similar to S_{BUS}), the forecast equilibrium point would be E_F, and the associated demand would be D_F. Thus, in ignoring equilibrium effects, an error of $D_{TRUE}-D_F$ is introduced. This error can be compounded in actual practice when we introduce the full set of level of service variables. The essential problem is that for DRT systems, this error can be quite large.* Without a supply model, there is a real danger of even a well-formulated DRT demand model leading to poor forecasts. This danger is accentuated in the case of demand responsive transportation systems because the performance relationships tend to be fairly complex.

The model developed in this study eliminates this problem by simultaneously solving both the service and demand relationships to yield forecasts of service quality and demand level at equilibrium. The model also accounts for the fact that the number of vehicles operating may

*This problem is of course not limited to DRT analyses. It applies to any system in which there is congestion, i.e., in which level of service (supply) is sensitive to demand levels over the range of relevant designs (Manheim, 1976).

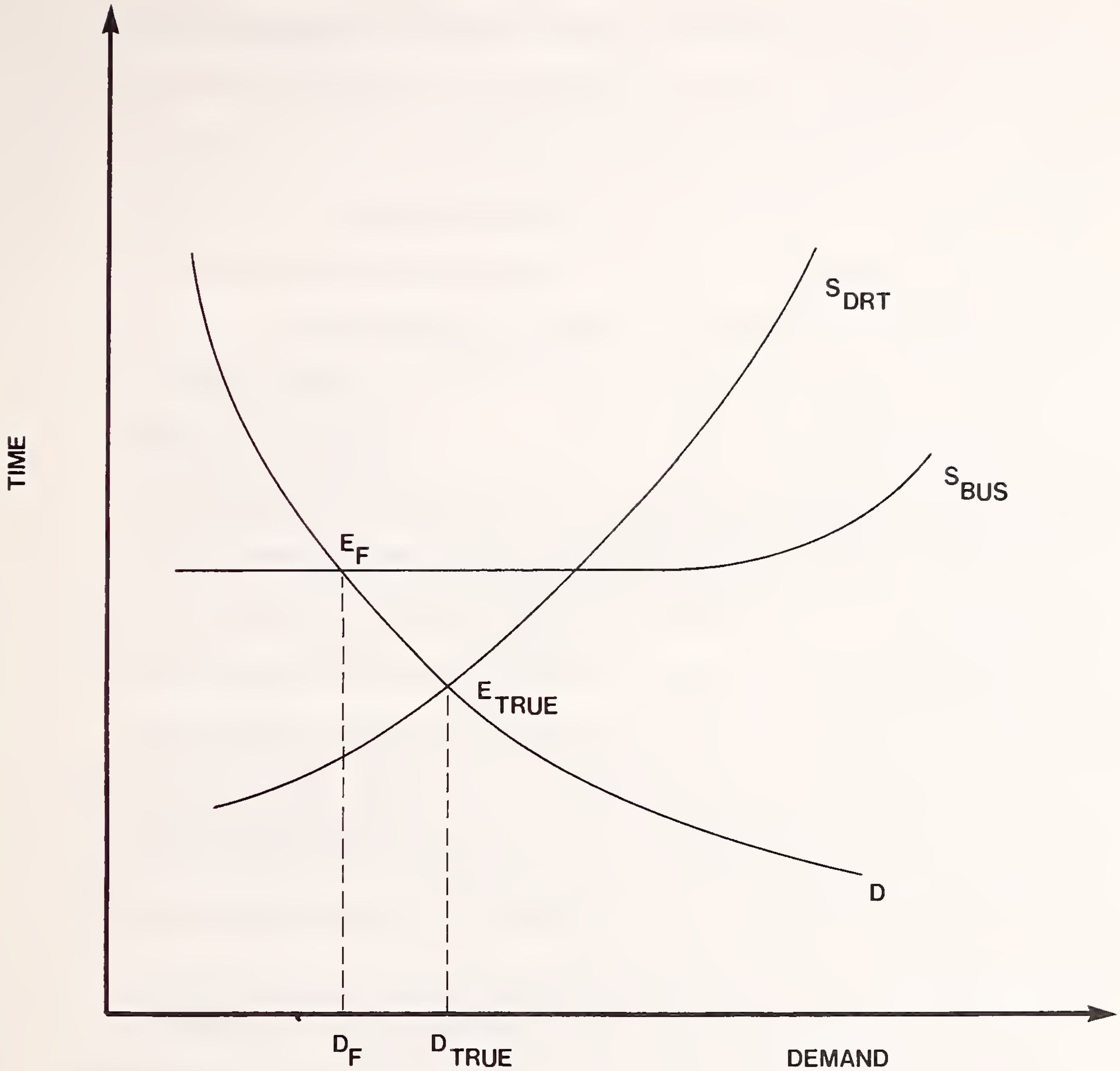

FIGURE 2.1

EQUILIBRIUM FORMULATION

vary over the day, that different service and demand curves pertain in different time periods. This is represented by permitting the user to define distinct periods of operation, during which the fleet and its average operating characteristics are assumed constant. The user can define an arbitrary number of such periods, over the day, each of arbitrary duration; an equilibrium is found for each period.

The model divides all travel in the area being analyzed into two types of trips, work and non-work. DRT patronage by each trip type is forecast with a separate demand model. The reason for this division of trips lies in the fundamental behavioral differences between work and non-work travel. Work trips are typically made on a regular basis to known destinations and can be assumed to be fixed in total number. DRT service can only divert work travellers from their current mode. On the other hand, non-work trips are more flexible; they are not made every day and in general there is substitutability among destinations. DRT service may not only cause modal shifts but may also induce travellers to change destinations and frequencies.

Equilibrium between service quality and demand in any period is established by summing the work and non-work trips and solving the DRT service relationship simultaneously with this total demand. In actual practice, these equations are too complex to solve analytically so an iterative approximation procedure is used.

2.3 Structure of the Model

In order to illustrate the overall structure, consider first a single period of operation. The model user specifies the values of the variables which describe the service area characteristics, as well as the start and end times for the operating period. These variables can be grouped into the following categories:*

1) Study area characteristics

   zonal system (coordinates of zone centroids)
   list of zones not served by DRT
   zonal areas
   zonal populations
   zonal employments
   work trip matrix
   socioceonomic characteristics distributions (auto availability, household size, number of residents over 16 years old, number of residents over 64 years old)**
   work trip departure time distribution**

2) DRT system characteristics**

   fleet size during period
   vehicle type (passenger car or bus)
   free vehicle speed
   dispatching system (computer or manual)
   fare per passenger
   time required for passengers to get on/off vehicle

3) Alternative mode characteristics

   times and costs for driving
   shared ride auto occupancy**

Note that the study area characteristics can include a list of zones not served by the demand responsive system. These <u>external zones</u>

*Some of these variables are constant over the entire day and need not be respecified in each period; some variables have preset default values. For example, data about the socioeconomic distributions at the zonal level can be developed by the model from much simpler data about the entire service area. More detail about the input requirements is given in Subsection 3.2 and in Appendix C, the Program Documentation.
**These variables have preset default values.

serve two functions. First, they may be reached by travellers who use DRT and line haul transit; such trips are part of the DRT demand. Second, they can be alternative destinations for non-work trips. A DRT system may divert some people from these destinations, thereby increasing daily DRT patronage from what would be predicted if such zones were ignored.

Given a DRT service area, the model executes a series of submodels as depicted in Figure 2.2. As illustrated, the demand for DRT service is comprised of work trips and non-work trips. The total demand from these two demand submodels is used as an input to the service submodel, while the level of service from the service sector is, in turn, an input to both demand submodels.

In practice, the service and demand sectors are executed iteratively, each using the output from the other. The resulting solution includes information about DRT vehicle productivities, total DRT patronage, average DRT wait time and average DRT ride times. Additional information about trips on other modes, DRT market share, and trip distribution is also available.

Both the number of zones and operating periods is user specified, but the computational requirements of the model increase in proportion to the number of periods, the number of iterations used in the equilibration procedure, and the square of the number of zones. The use of a large number of zones also requires a great deal of core storage, thereby increasing computer costs. Finally, the data required increase with

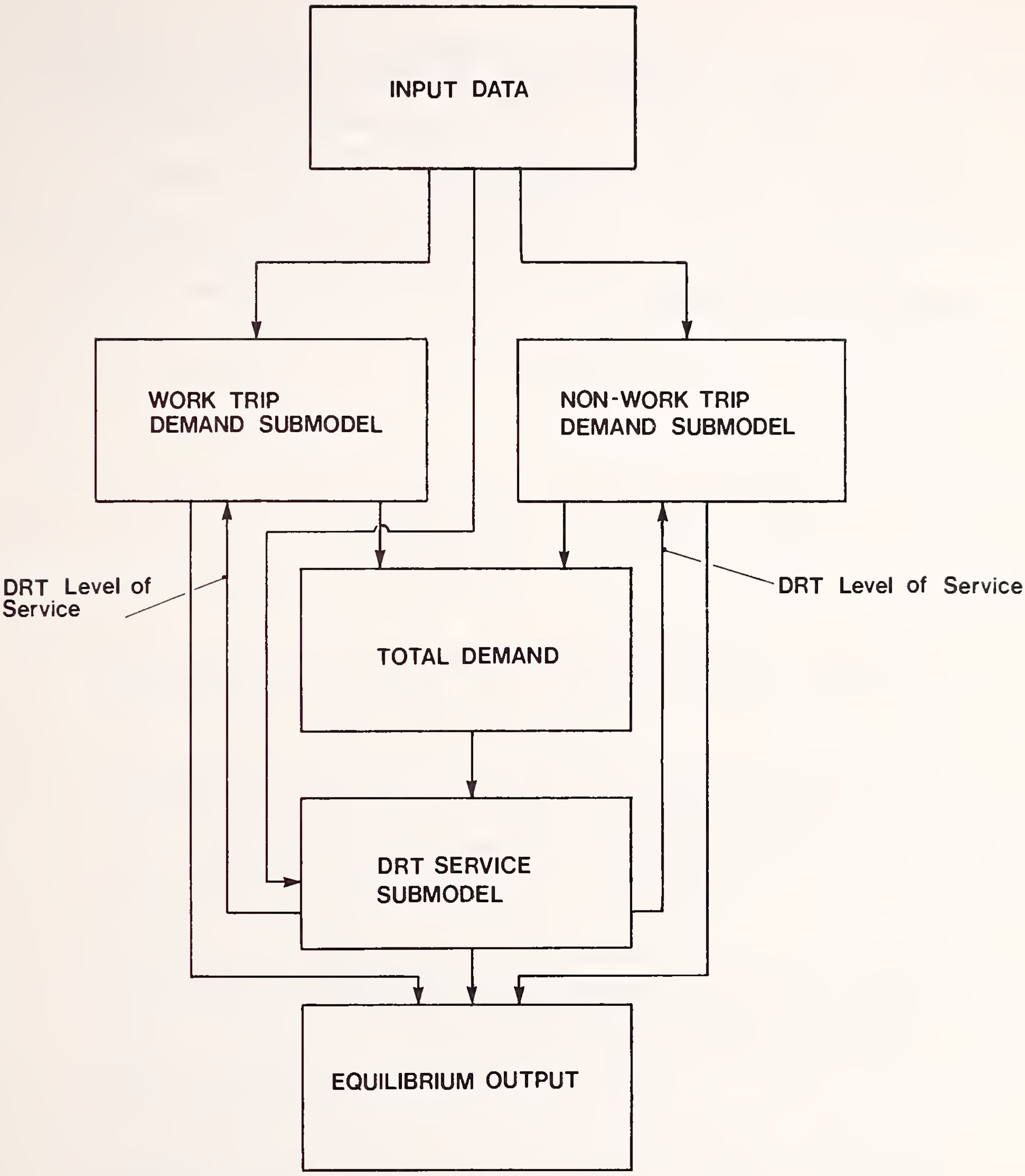

FIGURE 2.2

GENERAL FLOW OF THE MODEL SYSTEM

the number of zones. For these reasons, the model system was designed for zones of roughly census tract size,* though analyses on large service areas will require some grouping of tracts. The total number of zones should ideally be less than twenty** and those users contemplating considerably larger problems should carefully consult the user's manual in Appendix C.

*Census tracts contain, on the average, about 4,000 inhabitants.

**In Davenport and LaHabra, 22 and 15 zones were used, respectively.

2.4 The Demand Methodology: Disaggregate Choice Models

In order to clearly present the separate demand components of the model system, the demand modelling methodology is first briefly reviewed. There are four major characteristics of the demand methodology. First, all the demand submodels in the model system are disaggregate choice models, which means that they focus on the trip-making behavior of individual travellers; in contrast, aggregate models represent the behavior of groups of individuals.

Disaggregate models offer a number of significant theoretical and practical advantages over their aggregate counterparts. The most critical of these advantages are as follows:

1) Disaggregate models, because they consider actual individual travel behavior, are much more likely to produce behaviorally valid models than are aggregate models.

2) Disaggregate models are not based on a single geographical coding system. Consequently, as recent studies by Atherton and Ben-Akiva (1976) and Pecknold and Suhrbier (1977) have indicated, models estimated on disaggregate data are more likely to be geographically transferable than their aggregate counterparts.

3) Disaggregate models require considerably less data for estimation than do aggregate models. This was particularly significant in this study because available data samples were quite small. Furthermore, DRT ridership in these samples was low, and it was essential to maximize the efficiency with which this information was used.

4) Disaggregate models are much more statistically reliable than aggregate models because they contain no within-group variability; it has been shown that within-zone variability is often greater than between-zone variability. In aggregate models, this within-zone variability is lost by using zonal averages.

The second aspect of the demand forecasting methodology used here is that it is choice-oriented. By this it is meant that each traveller is making a selection of one of a set of possible options. For example, in the work trip model each worker was represented as having a choice among driving alone, sharing a ride with someone, and taking DRT, either as an access mode where relevant or as a direct mode of travel.* For any trip, only one mode of travel can be selected. In addition, in the more complex non-work models, travellers select not only their mode of travel, but also their destination.

Obviously, it is impossible to predict precisely what any single traveller will choose to do. Disaggregate choice models explicitly recognize this by focusing on the probability of each decision being made. In the models most generally used, every alternative available to a person typically has a non-zero probability of selection,but some alternatives may be infeasible for some individuals. For example, travellers who lack a driver's license cannot drive alone; they are restricted to making some ride sharing arrangement if they want to travel by private automobile.

While there are a number of different disaggregate choice models, the one used in this study (and the one most widely used in transportation planning) is the multinomial logit model. The theory behind the development and calibration of this model is quite complex; however, its basic logic is straightforward. Every alternative available to an individual has associated with it some measure of desirability, termed

*Use of fixed route bus in the available data was too low to include it as a feasible option. The methodology used (the multinomial logit model) has the fortunate property that such an omission does not affect the calibration results.

a utility, computed as a function of both the attributes of the alternative and a set of model coefficients.*

As a simple example of the logit model, suppose the utility functions for three modes of travel are as follows:

$$V_{DA} = 1.0 - .2(\text{drive alone travel time})$$

$$V_{SR} = .5 - .2\ (\text{shared ride travel time})$$

$$V_{DRT} = -.2\ (\text{demand responsive travel time})$$

where V_{DA}, V_{SR}, and V_{DRT} are the drive alone, shared ride and demand responsive transportation utilities respectively.** The constants in each equation represent a "pure alternative effect," or bias either towards or away from the mode depending on whether the term is positive or negative. The level of service coefficients represent the effect of differences in measured service quality.

In the multinomial logit model, the probabilities of someone selecting each of the three alternatives are then:

$$\text{Prob (drive alone)} = \frac{e^{V_{DA}}}{e^{V_{DA}} + e^{V_{SR}} + e^{V_{DRT}}}$$

*The coefficients are calibrated using data from observed choices and are built into the model system. The actual values of the coefficients and the procedures used to obtain them are described in Appendix A. For the purposes of this exposition, assume that a statistically valid set of coefficients exists.

**These utility functions are hypothetical examples. More realistic forms include out-of-vehicle time, cost, auto ownership, household size and a range of other factors. In addition, many of these variables, such as autos per household member or cost divided by income, are combinations of separate factors.

$$\text{Prob (shared ride)} = \frac{e^{V_{SR}}}{e^{V_{DA}} + e^{V_{SR}} + e^{V_{DRT}}}$$

$$\text{Prob (DRT)} = \frac{e^{V_{DRT}}}{e^{V_{DA}} + e^{V_{SR}} + e^{V_{DRT}}}$$

In the following two subsections, the description of the demand models will focus only on the factors which enter into the various utility functions; the functions themselves and their coefficients are described in Appendix A.

2.5 The Work Trip Demand Model

The work trip demand model begins operation in any time period by using two of the inputs, the daily work trip origin-destination matrix and the work trip departure time distribution, to compute the total number of work trips being made within the area under consideration during the operating period.

Suppose, for example, that the specified operating period was from 10:00 AM to 2:00 PM, and that 10% of all work trips were made in that interval. Each entry in the daily work trip matrix would be multiplied by .10* to represent the pool of potential DRT work trips in that period. Note that those trips which begin in the operating period but might not terminate within it are included in the pool.

The work trip demand model then divides this pool of travellers between the various available modes by applying a logit mode choice model on an origin-destination basis for every socioeconomic group. During each iteration of the equilibration process,the model system takes each origin-destination pair and for each socioeconomic group computes the utility of each mode. These utilities are then used in the logit model to estimate the number in each socioeconomic group using each mode. The total number of DRT work trips from an origin i to destination j is determined by

*Note that this distribution is preset in the model with default values derived from a study of travel time of day (Peat, Marwick & Mitchell, 1972). The user can override these default values if desired.

$$\sum_{\substack{\text{all socioeconomic} \\ \text{groups}}} [\text{Prob(member of group uses DRT)}] \times [\text{Number of group members making work trips from } i \text{ to } j]$$

At each iteration the output of the submodel is a DRT work trip origin-destination matrix for the operating period.

While the original model was calibrated using four modes (drive alone, shared ride,and DRT, either as a direct mode or as access to linehaul transit), it is possible to extend the model to include fixed-route bus by adding an appropriate utility function to the demand model. (The software is equipped to accept such inputs, and users interested in this type of application are referred to Appendix C).

Table 2.1 presents the variables used in the utility functions to determine the choice probabilities. The actual structure of the utilities and the calibrated coeficients are presented in Appendix A.

Note that Table 2.1 does not include time reliability. All attempts to include variables representing this factor produced coefficient estimates which were statistically insignificant, and/or had a counter-intuitive sign. Appendix A discusses the reasons for this in somewhat greater detail. However, some of the major problems were:

1) lack of adequate data - Measurement of DRT reliability on an origin destination basis requires a fair number of repeated observations of each trip. Even after using many days of DRT data, very few origin-destination pairs had enough trips to estimate reliability.

2) high collinearity - In any DRT system, time reliability measures tend to be highly correlated with trip time; time variance on long trips is higher than on short trips. With such high collinearity, statistically significant coefficients for both travel time and variance of time are difficult to obtain.

MODE	VARIABLES
Drive Alone	direct driving time walk time to and from parking out-of-pocket cost (including parking) autos per household member over 16
Shared Ride	direct driving time + ride sharing penalty time to park and walk both at origin and destination out-of-pocket cost per shared ride group member autos per household member over 16
DRT	DRT in-vehicle travel time DRT wait time DRT fare

Table 2.1 - Variables in the Work Trip Model

3) <u>lack of variation</u> - For any DRT system, the amount of variation in any reliability measure (aside from collinearity with travel time) is likely to be small. Thus, without taking home interviews or other surveys from many different DRT systems, each with different levels of reliability, it is difficult, if not impossible, to measure the effect of reliability on demand. Furthermore, even if survey data from many sites were available, problem (1) above would make the augmentation of such data with adequate level of service information prohibitively expensive.

For these reasons, measures of time reliability on DRT were dropped from the final model specifications. In addition, a number of modifications to the final work trip model were made in order to reduce the amount of data needed to forecast with the model and to resolve some statistical problems encountered in the work trip model calibration. In particular, because of either collinearity problems or a lack of variation in the data, the cost coefficient never became significant. In order to introduce cost in the model and have a satisfactory model for forecasting purposes, the work trip model was constrained by using empirical results on cost coefficients from other modelling efforts.

2.6 The Non-Work Trip Demand Model

Prior models of non-work travel demand have generally overlooked two important conceptual difficulties. The first of these is the occurrence of complex tours; a series of trips with more than two legs, beginning and ending at home (i.e., tours other than home-destination-home). Trip tours with multiple destinations can be more than 50% of the total number of trips taken during a day (Adler, 1976). The second difficulty is the phenomenon of mode changes in either a simple or complex tour. For example, a passenger might take DRT from home to his/her first stop, fixed-route bus to a second stop, and share a ride with a friend to go home.

These phenomena are particularly important for non-work trips, and since this is a primary market for DRT systems, it was felt necessary to develop a model which acknowledged their existence.

The model developed is a stochastic simulation. The service area population is represented by a list of so-called "entities," or pseudo-individuals, each associated with some fraction of the non-work trip-making population. Within any period, the trips made by each entity are determined by a random process defined below, and the resulting trip totals are appropriately expanded to the entire population. The precision of the simulation can be controlled by the user by selecting the desired number of entities; the more entities simulated, the greater the precision of the forecasts.

The conceptual basis of the model can be captured by considering a potential trip-maker who begins the day at home. When (and whether) to make a trip can be represented by a distribution of dwell times at home. This distribution is defined as starting in the morning when all potential travellers are at home, and describes the time of the first departure from home for members of a socioeconomic group. The distribution also includes some probability of the individual staying at home for the entire day and thereby not making any trip. If, however, the individual chooses to make a trip, he/she must then select among all possible destinations and modes. This decision can be represented with a joint disaggregate choice model in which all possible mode and destination combinations are available alternatives, one of which is selected. Having arrived at some destination, the decision on when to leave can be represented by another distribution of time, this one describing how long people stay at locations other than home. After selecting a departure time, the individual again makes a mode-destination decision, where the destination decision may or may not be to return home. If the traveller returns home, the entire process begins again with only one exception; the distribution of time at home is different if the traveller has already left home at least once than if he/she has not left home. Thus, time at home is described by <u>two</u> distributions in the model.

Obviously, this modelling approach is a simplification of the true behavioral process. Travellers do not necessarily decide on each leg of a complex tour step by step; rather, they may plan an entire trip as a single entity. Models which account for more complex tour choice mechanisms are not computationally feasible. The approach developed in this study represents a major improvement over previous practice, and is a feasible modelling strategy for a reasonably small number of zones.

The model logically involves the five following separate submodels:

1) the distribution of time of the first departure from home;

2) the distribution of dwell time at non-home locations;

3) the distribution of dwell time at home after returning from a trip tour;

4) the joint mode and destination choice model for trips starting at home; and

5) the joint mode and destination choice model for trips starting away from home.

Clearly, the three time distributions are unlikely to be the same; for example, the average time at home will be greater than the average time away from home. In addition, the shapes of the distributions are very different. The mode-destination decision will depend on the individual's present location. An individual away from home clearly has a high probability of choosing home as a destination. On the other hand, returning home is obviously an irrelevant alternative when one is home to begin with.

Within the analysis period, time is, for convenience, considered in discrete intervals, as the individual moves from time interval to to time interval, he/she makes various travel decisions. This process for a particular individual is represented diagrammatically in Figure 2.3 for an analysis period of 20 intervals and a service area of 10 zones. The individual lives in zone 5 and begins the analysis period at home.* When to make a trip is stochastically determined by drawing from the distribution of times at home. In the figure, the outcome of this random draw is depicted by having the individual leave zone 5 (home) in interval 2. The trip destination is also a stochastic process which is an output of the at-home mode-destination model. (Note that for the sake of clarity the modal decision is not represented in the diagram.) The figure shows that the individual selects zone 8 as his/her destination and arrives there after travelling for three time intervals. (The journey requires a travel time which varies with choice of mode and destination.) Having reached zone 8, the individual remains a length of time stochastically determined by the distribution of times away from home. After deciding to depart in time interval 7, the away-from-home destination model probabilistically determines the next destination. The individual in the diagram continues the tour by proceeding to zone 2 and then goes home in accordance with the appropriate choice models. The simulation process continues until the elapsed time is beyond the duration of the specified operating period. When this occurs, the current location of the individual and the time of the next trip are

*The period described here is the first of the day, so all travellers are initially assumed to be at home. In later time periods, people will be at various non-home points, depending on the simulated outcome of their prior travel choices.

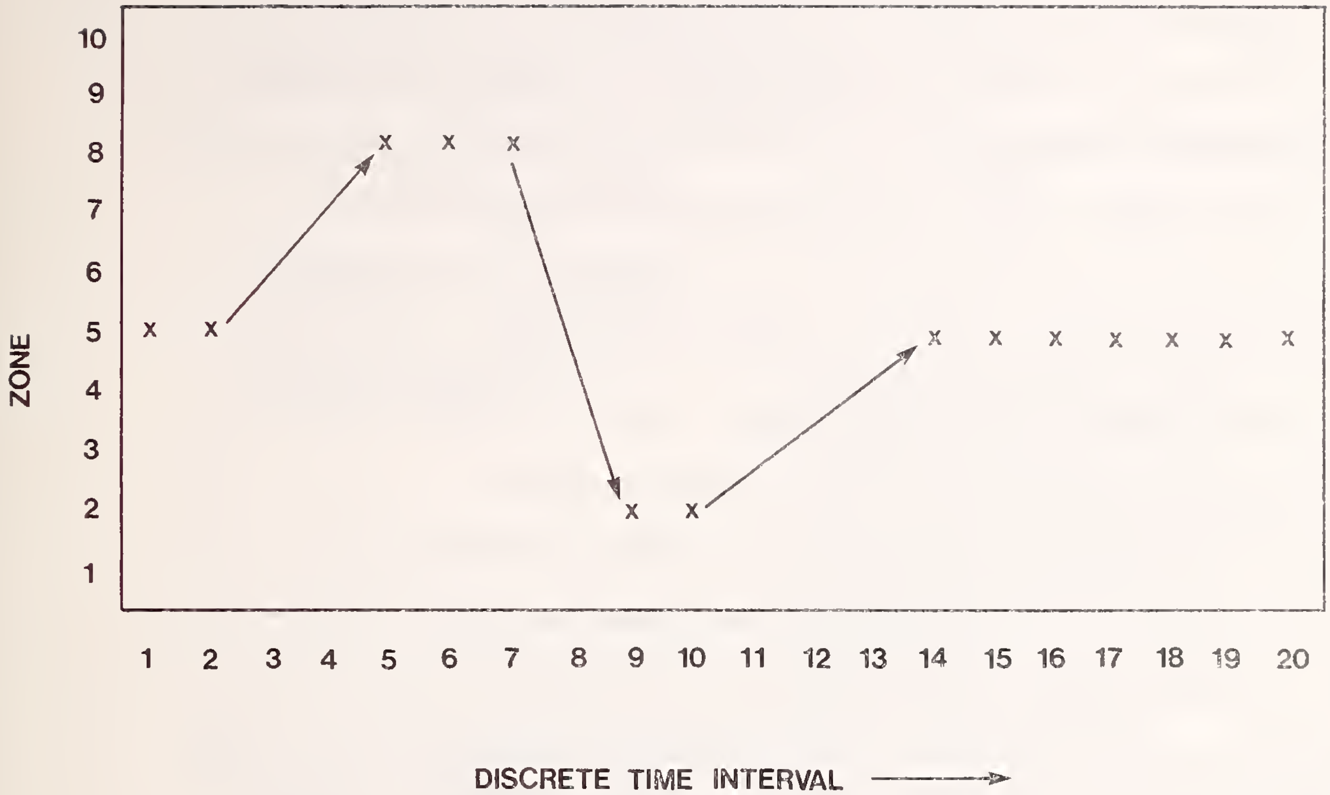

FIGURE 2.3

AN INDIVIDUALS TRAVEL PATTERN WITHIN A SINGLE ANALYSIS PERIOD stored and used for later periods.*

For computational reasons, every trip to a destination is counted as partial trips on all the available modes by computing the probability the simulated individual will choose each mode. To do this, the model uses the joint mode and destination choice probabilities to derive the various modal choice probabilities conditional on the destination choice (as determined by drawing from the joint mode and destination choice probability distribution). These probabilities then become fractions of simulated trips.** Since the amount of time needed for the individual to make the trip depends on which mode he/she would take, a random draw of the times on the available modes is made, where each mode's probability of being used is based on the choice model prediction.

Table 2.2 presents the variables in the model which affect each of the five components of the non-work trip demand submodel. Distributions of time at home and away from home were developed by using observed data from one of the calibration cities, Rochester, New York, and fitting plausible functional forms for various socioeconomic groups. A series of statistical tests were performed to determine whether various socioeconomic groups have distributions with significantly different means, and where appropriate, some groups were combined into single distributions. Except for the dwell time away from home, these distributions vary by auto ownership level and age of the traveller.

*There is no guarantee that travellers will reach home by the end of the day. However, this may be realistic and is of little practical significance in any case.

**This was necessary because the choice probability for DRT is generally small, and the number of DRT trips in a simulation without this modification would be very small unless a large number of simulations were made. In the validation tests, for example, the number of required simulations would have to have been increased by an order of magnitude to obtain the same level of precision.

MODEL COMPONENT/CHOICE	VARIABLE(S) AFFECTING CHOICE
Distribution of time of first departure from home	auto ownership age of resident
Distribution of time of sub-sequent departures from home	auto ownership of household age of resident
Distribution of times away from home	auto ownership
Mode and destination choice starting at home	auto ownership of household number of household members greater than 16 years old in-vehicle time for mode/destination combination out-of-vehicle time for mode/destination combination cost of mode/destination combination population of destinations employment of destinations area of destinations
Mode and destination choice starting away from home	same as above, but with separate term representing the alternative of going home

Table 2.2 - Variables in the Non-Work Trip Model

Two joint choice models (one for trips starting at home, and the other for trips starting anywhere else) were also calibrated using the Rochester data base. Due to the very small sample in Haddonfield and the lack of trips to places outside the DRT service area, the Haddonfield models, while generally consistent with those from Rochester, were not used for the final version.

Unlike Table 2.1, the modal utility functions are not listed in Table 2.2. This is because, while the work trip model only has three alternatives available for any traveller, the non-work model evaluates the utility of every available mode/destination combination. References in Table 2.2 to variables such as "out-of-vehicle time for mode/destination combination" imply that every alternative is identified as a destination reached by a mode, and the corresponding variable in the model is the out-of-vehicle time for that trip. All times and costs in the non-work model are defined the same way as in the work trip model, and driving alone is assumed to be available only to licensed drivers residing in households owning automobiles.

2.7 The Service Model

The service model is a set of equations which relate wait and ride time on DRT to various system parameters. In developing the model, care was taken to ensure that all relevant variables describing the DRT system were included, and it was calibrated over a wide enough range for it to be reliably used for any reasonable system.

The model predicts wait time, defined as the time between the call for service and the arrival of the vehicle, and ride time, the actual time spent on board a DRT vehicle. Experiments with the M.I.T. simulation model indicated that mean system wait time could serve as a surrogate for individual passenger wait time (see Appendix B). Individual passenger ride time was found to be a linear function of trip distance.

Inputs to the service model, discussed in detail in Section 3, include the following:

1) demand rate (passenger demand per hour)
2) service area size (square miles)
3) load and unload times (minutes)
4) trip length* (miles)
5) mean trip length*
6) street network adjustment factor (ratio of street distance to airline distance)
7) vehicle speed (miles per minute)
8) vehicle fleet size
9) weights on in-vehicle and out-of-vehicle times reflecting dispatching system parameters
10) vehicle fleet size adjustment factor
11) group size adjustment factor.

*Used for ride time prediction only.

Demand density for a given operating period is the output of the two demand submodels. Service area size is developed within the software by summing the areas of analysis zones, a user supplied input. Load, unload times are the average time it takes for a passenger to enter and leave a vehicle respectively and are supplied by the user. Trip length is supplied by the software for a given trip; a built-in program develops trip length based on user supplied zone centroid coordinates. Mean trip length, the average length of DRT trips that are taken, is an output of the demand model and an element of the equilibration process. The street network adjustment factor is a user supplied input, used by both the supply and demand models. Vehicle speed is a user supplied input that can be set either at the same level as automobile speed, or at any desired level. Vehicle fleet size is a user supplied input that can be varied from period to period. The dispatching system parameters are user supplied inputs, described more fully in Section 3, which reflect different types of dispatching systems. The vehicle fleet size adjustment factor, considered only for wait time calculation and explained in Appendix B, is supplied by the user. The group size adjustment factor is a representation of the average number of persons who comprise a single trip.* This factor is supplied by the user; different values can be supplied for work and non-work trips.

Vehicle capacity is not an input parameter, as discussed in Appendix B. However, in order to be able to model shared ride taxi service

*In many cases two or more persons will travel together. However, as far as a DRT vehicle is concerned, a group of persons travelling together is equivalent to a single trip since capacity is virtually never exceeded.

as well as dial-a-ride service using larger vehicles, two sets of model coefficients are provided, as described in Appendix B. One set applies to systems using standard auto-like vehicle, and the other applies to larger vans or buses.

2.8 Equilibrium

The process by which the service submodel and the two demand submodels are brought into equilibrium is conceptually straightforward. In any period of DRT operation, the model system is initialized with some value of DRT demand, expressed as a modal split for work trips and a total non-work ridership. This initial DRT ridership is used as an input to the service model. The predicted DRT level of service is then input to both the work and non-work demand procedures, which then produce a new total DRT patronage forecast. This iteration between the service and demand submodels continues until the change in demand from one iteration to the next is below a pre-specified tolerance level. The model finds the equilibrium for each period using the prior period's result as an initial state.*

A modification to this procedure was made to improve the speed of convergence and reduce problems of oscillation in the equilibration. A damping procedure was developed which placed both upper and lower bounds on the possible vehicle productivity (passengers served per vehicle hour). These initial upper and lower constraints are quite loose. (Default values are 12 and 2 passengers per vehicle hour respectively.) However, as the forecasting process proceeds, the constraints become tighter so that they reduce the range of movement of the productivity.

The demand level to be used in the service model at any iteration is determined by a two step procedure. First, if the unadjusted forecasts violate either of the current bounds, it is set equal to the vio-

*As discussed above, the non-work trip demand submodel requires the location of each simulated entity from the prior period.

lated bound. Then, in order to reduce oscillations in the forecast, the bounded forecast is averaged with the adjusted forecast from the last iteration.

For example, suppose the initial demand for a two hour period in which five vehicles are operating was assumed to be eighty passengers. This implies a productivity of eight passengers per vehicle hour. Since this violates neither the upper or lower constraint on productivity, it is left unaltered. The service model is then invoked to forecast the level of service (wait times and ride times) assuming eighty DRT passengers in the period. The resulting level of service is then input to the work and non-work demand submodels.

Suppose the resulting demand forecast was only eight travellers, implying a new, unadjusted productivity of one passenger per vehicle hour. If the default bounds on productivity are being used, this unadjusted productivity violates the lower bound, so it is reset to the lower bound value of two.

It is at this point that the averaging procedure is applied. Rather than using the productivity of two passengers per vehicle hour as an input to the next iteration of the service submodel, the current value is averaged with the previous productivity of eight, resulting in an adjusted productivity of five. Furthermore, since the previously estimated demand level of eighty was clearly too high, the upper bound on productivity is lowered to eight.*

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*The fact that a demand of eighty passengers was too high can be inferred from the results of the following iteration. A demand of eighty produced service level forecasts which were so low that the next demand forecast fell to only eight. Had the demand forecast gone up it would have indicated that the forecast of the eighty passengers was too low. Equilibrium is defined as the demand and service levels at which there is no change from one iteration to the next.

The procedure continues until either the change in productivity between iterations is very small or a pre-specified maximum number of iterations is performed. In general, the procedure terminates with the adjusted lower and upper bounds fairly close to one another so that the user can infer the reasonable range of forecasts. It is recommended that users do not attempt to achieve a very close approximation to equilibrium, since doing so will require a large number of simulated entities and iterations. Rather, users should run the equilibration procedure for about four to six iterations and estimate the final productivity based on the series of constrained and unconstrained productivities. An example of this method is given in Section 4, Validation.

SECTION 3

USING THE DETAILED MODEL SYSTEM

3.1 Introduction to Model Data Needs

The detailed model system described in the previous section provides a flexible and general tool for aiding in the design of DRT systems. However, in order to utilize it effectively the user must provide a reasonably accurate description of the problem at hand in a form consistent with the model's data requirements.

A discussion of the particular format and input requirements of the model system is reserved for Appendix C, the Program Users' Manual. The objective of this chapter is to outline the specific data items required to run the model system and to present some of the options open to the model user. In addition, an extended example of how a problem can be organized into a form which can be analyzed with the model is presented.

In general, the user can supply all inputs to the submodels; however, default values have been included in the model wherever possible. This allows the user to concentrate on those variables which are most important in the design of DRT systems. Also, the user who is unfamiliar with the model system does not have to be concerned with understanding and providing the full array of possible inputs.

At the simplest level of detail, the user must supply service area characteristics and model parameters including:

1) zonal data including:

    coordinates of centroid
    area size
    employment
    population

2) a daily origin-destination (O-D) work table

3) the number of non-workers over the age of 16 in the service area

4) level of service for non-DRT modes which are available including

in-vehicle times on an O-D basis
out-of-vehicle times on an O-D basis
fares on an O-D basis or as an average system fare

5) the DRT fare structure, either in O-D form or as a single system average

6) number of vehicles in service during each operating period and their capacity

7) number of analysis zones served directly by DRT and the number of zones available through a feeder connection

8) beginning and end of each analysis period

9) initial estimate of DRT patronage

10) desired precision of the model results.

Users who are familiar with the model or who have special problems for which the default values are inapplicable might consider overriding the default values used for other variables including:

1) percent of total population over the age of 64

2) auto occupancy of shared ride trips

3) work trip distributions by time of day

4) average number of people riding together in groups on the DRT systems

5) effective vehicle fleet size adjustment factor

6) vehicle speed for DRT

7) load and unload delays for DRT

8) dispatching system parameters.

Finally, there is a third level at which the user can make adjustments to the model system. The data at this level are generally very difficult to generate, so it is expected that most users, although they have the option, will never have occasion to override the default values for the following:

1) household size and auto availability distribution of population

2) distribution of dwell times at home and away from home for persons making non-work trips

3) percentage of residents who make non-work trips in a given day.

The following four sections discuss these inputs in much more detail. These sections are organized according to the functional relationships between the data items.

3.2 Data Needs: Run and Period Control Parameters

As discussed in Section 2, the user exercises control over the program at the level of the entire run as well as for each period being analyzed. The parameters at the user's disposal for this purpose are described below.

1) Modal Availability

The user can specify which modes are to be included from among the four basic modes available (drive alone, shared ride, DRT, and regular transit bus). Of course, the availability of a mode implies the need for level of service data associated with that mode. (See Subsection 3.4, Demand Model Inputs, for a discussion of level of service.) Additionally, the user can indicate the existence of a linehaul service running out of the service area by specifying external zones. When linehaul service exists it implies access by driving alone, sharing rides, and DRT, and whatever subset of those three the user specifies. Even though a mode is generally available, it can be unavailable for certain periods of the day or for certain O-D pairs. (See Subsection 3.4 for further discussion of this feature.)

2) Precision of Simulation Model Results

The precision of the non-work trip simulation can be improved by increasing the number of individuals, or entities, simulated. Using more entities means that the core and CPU time required will also increase. A satisfactory range for this value is from 500 to 1,000 entities with larger numbers of zones requiring higher values. Users should recognize that higher precision is achieved at the expense of increased computation cost.

3) Definition of Analysis Period

The user defines his/her analysis periods by specifying a series of inputs for each such period. Periods must not overlap and they must be contiguous in order for the non-work model to make sense. The user decides how operating periods should be structured, based on the following considerations:

a) Separate periods are required when a system characteristic changes (such as vehicle fleet size), when the level of service for a competing mode changes (such as bus level of service changing from peak to off-peak), or when the demand pattern changes (end or beginning of the work trip peaks).

b) Separate periods are warranted if the user wants detailed results by time of day.

c) Some periods may be superfluous if they have identical characteristics to others previously run.

d) The greater the number of periods used, the greater the cost of running the system.

4) Convergence Criterion

Equilibrium is reached each period by iterating between supply and demand, and as the number of iterations increases so does the precision of the results. The user controls this process by setting the maximum number of iterations to be performed as well as an error limit. When the built in error measure reaches the limit specified by the user, the process is terminated. The error measure used in an "average squared differences" measure defined as:

$$E = \frac{\sum_{\substack{\text{O-D}\\\text{pairs}}} (T_i - T_j)^2}{\sum_{\substack{\text{O-D}\\\text{pairs}}} T_i}$$

where

T_i is an O-D pair's DRT trip volume as forecast by the demand models on the i^{th} iteration

T_j is T_{i-1} except when i=1. In that case T_j is based on the initialization parameter.

3.3 Data Needs: Service Area Description

At the simplest level of detail, the user must describe the DRT service area and any external zones by supplying the following:

1) Selection of Internal and External Zones

The user should select a set of zones based on census tracts or about the size of census tracts. The zones should be grouped according to whether DRT service is available in them or not, and those with service should be assigned the lowest zone numbers. All zones not served directly by DRT should be assigned zone numbers starting with the first unused zone number. As discussed in Section 2, the total number of zones to be considered should be kept to a minimum because of the large cost of analyzing more than about twenty zones. In addition, the cost or preparing data increases dramatically as the number of zones increases.

2) Definition of Work Trips and Non-Work Population

The user must specify a home-to-work origin-destination trip table as a basic input to the work model. A person who lives in Zone A and works in Zone B is represented as a single O-D movement from A to B. This matrix is internally reversed after 12 noon to account for work to home trips. Another basic input (to the non-work model) is the number of people who are candidates for making non-work trips. The number who actually do make non-work trips is predicted by the model. Candidates are defined as the number of non-workers living in the area served by DRT who are older than 16 years.

3) Distribution of Work Trips by Time of Day

The work model uses a distribution of work trips by time of day to determine what fraction of work trips in each O-D cell are made during each analysis period. The user can override the defaults by supplying different values for this distribution. This input can also be used to "turn off" the work model during particular periods of the day by setting the fraction of trips to zero. This may be appropriate when DRT service is not directed towards workers or when work trips are so insignificant that the user simply wishes to ignore them.

4) Definition of Zonal Characteristics

For each zone the user must specify the following data:

a) Zonal area in units of square miles
b) X and Y coordinates of the centroid of the zone in miles*
c) Zonal employment
d) Zonal population

The user may also override any of the service area default values previously defined.

5) Socioeconomic Characteristics of the Residents of the DRT Service Area

The model system requires information about three socioeconomic variables: autos per household, persons over the age of 16 per household, and the percent of the population over the age of 64. The user can input areawide distributions for each of the first two. These distributions are used to create market segments that have different auto availability because auto availability is an important factor in both the work and non-work models. The information about the percent aged is used in the dwell time distribution component of the non-work model.

*The setting of the point (0,0) in the coordinate system is arbitrary and does not affect the forecasts.

6) Dwell Time and Departure Time Distributions

The departure and dwell time distributions such as those which are provided as defaults in the model system are not likely to be available to the user except when a very detailed data base such as a home interview survey is available. Even then, a substantial amount of processing may be involved. However, if a user has this information it can be input or compared to the distributions presently in the system. The functional characteristics of the distributions are discussed in Section 2. A detailed description of the structure of these distributions is presented in Appendix A.*

*The distributions used were obtained from an analysis of Rochester data and are representative of residents in medium density suburbs with a fairly heterogeneous population mix.

3.4 Data Needs: Supply Model Inputs

As discussed in Section 2, certain outputs of the demand model serve as inputs to the supply model, while other supply model inputs are user specified. These inputs describe service area characteristics and DRT system characteristics.

The only service area characteristic that can be input by the user is the street network adjustment factor, since area size is computed by the program from other inputs. As noted in Section 2, the street network adjustment factor is the ratio of street distance to direct distance for an average trip. A rectangular grid system has an adjustment factor of 1.273; i.e., in a perfect grid, the average street distance between two points is 1.273 times the direct airline distance. In more realistic situations, the street adjustment factor can be calculated by selecting random trips and using a map to plot actual routes. For most communities this ratio will be in the region of 1.2 to 1.4, depending on the extent of cul-de-sacs, one way streets, through streets, etc.; for areas which have natural barriers (like rivers), the value may be slightly higher. A default value of 1.3 has been incorporated in the model.

The following characteristics of the DRT system are the design parameters over which the user of the model system has some control:

1) Vehicle Fleet Size

Vehicle fleet size can be set at any value by the user, and can be set to different values for different time periods.

2) Effective Vehicle Fleet Size Adjustment Factor

System wait time is impacted by the extent to which vehicles enter and leave service throughout the day for driver breaks and reliefs or ends of vehicle operation. As far as wait time is concerned, there is an effective vehicle fleet size which is smaller than the actual vehicle fleet size. This concept is discussed in detail in Appendix B. The effective vehicle fleet size adjustment factor would be set to 1.0 for an idealized system in which vehicles are in continuous service.

There has been no concrete methodology developed to compute the adjustment factor for an average system. However, simulation experiments comparing predicted and actual DRT system performance suggest that the factor would generally be in the range of 0.7 to 1.0, where the low end represents a system where vehicles enter and leave service frequently. A default value of .85 has been built into the model. This value is probably suitable for most real world situations.*

Since the effective vehicle fleet size adjustment factor can be varied for different time periods, it is possible to set it to one for short periods where vehicles do not leave service, and to less than one for longer time periods.

3) Vehicle Speed

Vehicle speed, the average speed while in motion, is a function of the type of vehicle being used, local topography and local traffic con-

*The distance that the vehicles have to travel to the garage or other relief points is also a factor. Furthermore, different relief policies affect this in different ways. For example, dynamic relief, in which drivers are brought to the vehicle while it is in service will have less of an impact. For a more complete discussion of this see Wilson (1975), "The Effect of Driver Reliefs on Dial-a-Ride Performance."

ditions. In many cases it will be identical to average auto speed, although if large vehicles are being used the DRT vehicle speed would probably be somewhat lower. Most existing systems have vehicle speeds in the range of .18 to .32 miles per minute. A default value of .25 miles per minute (15 miles per hour) has been built into the model which can be overridden by the user.

Note that this parameter does not include delays for picking up and dropping off passengers, but does include time spent at red lights or stop signs, as well as acceleration and deceleration.

4) Load and Unload Delays Per Passenger

Stopping to pick up and drop off passengers and waiting for new pickup instructions results in vehicle delays, the extent of which will impact overall system performance. There is no standard way of estimating loading and unloading delays. Measurements of the pickup delay in actual systems ranged from .375 minutes in Batavia, to 3.5 minutes in Rochester, although in the latter case there was a major communication problem that was causing part of the delay. A reasonable range of values would be .35 to .80 for both load and unload delays. In some cases pickup delays may be greater because passengers require time to get from home to the waiting vehicle. A default value of .5 minutes has been built into the model for each of these values. A higher value might be used for loading delays in a shared ride taxi system, where passengers might be accustomed to waiting in their homes. A higher value for both these delays should be used in a system where a large number of passengers are expected to be elderly.

5) Dispatching System Parameter

The type of dispatching system used can have a significant impact on the quality of service. There are many types of dispatching systems, algorithms and policies that can be used for DRT systems; however, this is not the appropriate place for a full discussion of those options. For the purpose of the model, dispatching options have been collapsed into two parameters, defined as α and β. α is a measure of whether the system is computer or manually dispatched. Its presence in the model is based on the assumption that computer dispatching results in a better level of service (represented by reduced wait time) than manual dispatching.* This assumption is supported by the results of the Haddonfield, New Jersey DRT demonstration project, the only system to have successfully implemented computer dispatching prior to the development of this model system. α should be set to 0 for forecasting the performance of a computer dispatched DRT system. For manual systems, a suggested range for α, based on the Haddonfield results, would be .1 to .3. Users should consider a value of α from the lower end of this range for systems when anticipated demand is low (vehicle productivity of 3 to 4 passengers per hour) and a higher value of α for systems with higher anticipated demand levels. A default value of 0 has been built into the model so if the model is to be used to forecast for manually dispatched systems, α should be reset.

*This is still an area of dispute among DRT system designers. Certainly an inefficient computer dispatch system is likely to perform more poorly than a well-organized manual system.

β reflects the relative importance the dispatching system places on wait and ride time and is discussed in more detail in Appendix B. It has been found that an equal weighting of wait and ride time in a computer dispatch system will result in the lowest total travel time. Thus, the Haddonfield system and the computer system being implemented in the Rochester, New York, DRT system have utilized an equal weighting on wait and ride time in the scheduling algorithm. This corresponds to $\beta=0$. It is suggested that β be set to 0 if α is set to 0, i.e., for a computer dispatched system, although it is certainly plausible for a computer system that does not weigh wait and ride time equally to be implemented.

Observations of manually dispatched systems have indicated that both dispatchers and drivers place a greater weight on ride time than on wait time because of their concern for passengers "already on the system" (i.e., on board the vehicle). They therefore attempt to minimize ride time at the expense of wait time. To model this situation β should be set greater than 0; a value of .3 is suggested. A default value of $\beta=0$ has been used with a suggested range of -.6 to +.6, with negative values corresponding to a greater weight on wait than ride time.*

6) Group Size Adjustment Factor

This factor is one characteristic of demand rather than of the system. It is necessary because the performance of a DRT system is a func-

*When $\beta > 0$, because of the structure of the model, it is theoretically possible for calculated ride time to be less than the minimum direct ride time. The software will test for this, and set ride time equal to the maximum of these two values. Thus, a very high value of β will simply result in service times corresponding to premium ride taxi.

tion of trips by passenger groups (or fares) and not of passenger trips. That is, it does not take a significantly longer time for a DRT vehicle to serve two passengers travelling together than to serve a single passenger. Since the demand model predicts passenger trips, it is necessary to factor down the total before entering the supply model.

The factor is simply the average number of passengers in a group. Experience with actual DRT systems suggests that for the work trip this value is approximately 1.0 (since family members or neighbors typically do not work at the same location), while for the non-work trip it is about 1.2. These values have been used as defaults. As pointed out earlier in this section, this factor is also considered in developing the fare matrix, and is likely to be a function of the DRT fare structure. If each person is required to pay full fare regardless of whether he/she is travelling in a group, the average group size will probably be smaller than if each group has a single charge, regardless of the number in the group.

3.5 Data Needs: Demand Model Inputs

All of the demand model inputs discussed in this subsection are input by period and as such can be changed from period to period. This is especially useful in the event that the user wishes to model a policy which limits access to certain zones by one or more modes during certain periods of the day. Any variables which are not explicitly changed from period to period remain the same. All times discussed are in units of minutes and all costs are in units of cents. Each of the demand model inputs and related functions are described below:

1) Availability of Alternatives

Each of the four basic modes has an associated in-vehicle travel time matrix. A mode is considered to be unavailable for an O-D pair if the value of the in-vehicle travel time is less than or equal to 0 minutes. In the case of DRT, this time is computed by the supply model for all internal trips and is never zero. However, drive alone, shared ride, and bus times are input in UTPS format matrices. Thus, matrices with zero values in some cells exclude certain modes from consideration for selected O-D pairs. The case of feeder to line haul service is handled in an analogous manner. The feeder in-vehicle time matrix defines (with positive values) those line haul access points in the DRT service area. The model has a route finding algorithm which is invoked to determine the best access point for each DRT service area zone, and the resulting level of service for drive alone, shared ride, and DRT if they are available.

2) Required Matrix Inputs - Travel Times for Drive Alone, Shared Ride, Bus, Transit Linehaul; Transit Linehaul Fares

Matrix inputs are the most general method of representing level of service data. Unfortunately, they are also the most difficult and time consuming for the user to prepare. In an effort to save the user some effort, some of the demand inputs can optionally be input as single areawide constants; these are discussed in the next subsections. It was felt that such a simplification would be unacceptable in the case of travel times as well as the fare for the linehaul service, so the following are always input in tables:

a) <u>Drive alone and shared ride in-vehicle times</u> - These times should be based on the user's knowledge of congestion conditions, street system layout, etc. They represent average values for zone to zone movements and do not include parking times. As a first approximation the user could consider using a systemwide average speed, the street adjustment factor, and the zonal coordinates to externally compute the origin-destination times.

b) <u>Fixed route bus in-vehicle and out-of-vehicle times</u> - These values can generally be derived from route schedules in a fairly straightforward manner. The out-of-vehicle times should consist of origin zone walk time plus about one half the headway (up to a maximum of 30 minutes) for initial wait time, plus any transfer times involved in the trip. If a transfer at B is involved in going from A to C, then the A to C level of service is simply the sum of A to B and B to C unless the schedules are designed such that the transfer at B can be made in less than half the headway of the B to C service. The difficulties with constructing this level of service arise in aggregating routes between O-D pairs and in determining the initial walk times. This may necessitate redrawing some of the zonal boundaries, and the user should refer to the discussion of the validation data preparation in Section 4 for additional information.

c) <u>Linehaul times and fares</u> - Linehaul service is derived in the same way as bus service except that if the nature of the service is radically different from bus (a rail commuter line, for example), other methods will have to be used for approximating wait times. The times and fares are added to those of the access mode so it is not possible to have special fares for people who transfer from DRT.

<u>3) Optional Matrix of Areawide Constants - DRT and Bus Fares</u>

The model system uses fare matrices internally, but the user has the option of inputing single areawide fares for bus and DRT. Both these fares are those experienced by the individual passenger. Thus, if either fare system allows discounts for groups, the elderly, etc., this must be accounted for in preparing the inputs.

4) Areawide Auto Speed and Shared Ride Penalties

Part of the cost of both drive alone and shared ride alternatives is the operating cost of the trip being considered. The cost submodel uses an average, user-specified auto speed as an input. The effects of trip deviations to pick up other riders can be accounted for by inputing penalties for shared ride for both in-vehicle and out-of-vehicle travel time. These numbers are average values which must account for sharing rides within the same family as well as among co-workers who might be quite far apart.

3.6 Example Problem

The example problem developed in this subsection serves to illustrate how the model can be used. While this problem is fairly complex and considers many unusual situations which might not be encountered by the user, it does indicate how a user should use the system and how he/she might handle more complex situations. These complications will be introduced in the following discussion after a review of the more basic elements of model set-up.

1) Site and Service Description

The example considers the town of Irondequoit, New York. A demand responsive transportation system was implemented in Irondequoit in April, 1976, as a second DRT service module in the UMTA sponsored Service and Methods Demonstration of integrated fixed route/DRT service in the Rochester metropolitan area. The first DRT service in that demonstration is the Greece-Rochester system on which the demand model was calibrated. The Town of Irondequoit and its relationship to the Rochester metropolitan area is shown in Figure 3.1.

The Irondequoit many-to-many DRT service area is shown as the shaded area in Figure 3.2. Although it is this element of the overall service that we are trying to model, the many-to-many service is not the only transit service in the area, nor is it the only form of DRT service. The services available in Irondequoit during different times of the day are discussed below.*

*The services described here were implemented in April 1976. The service configuration has since changed somewhat.

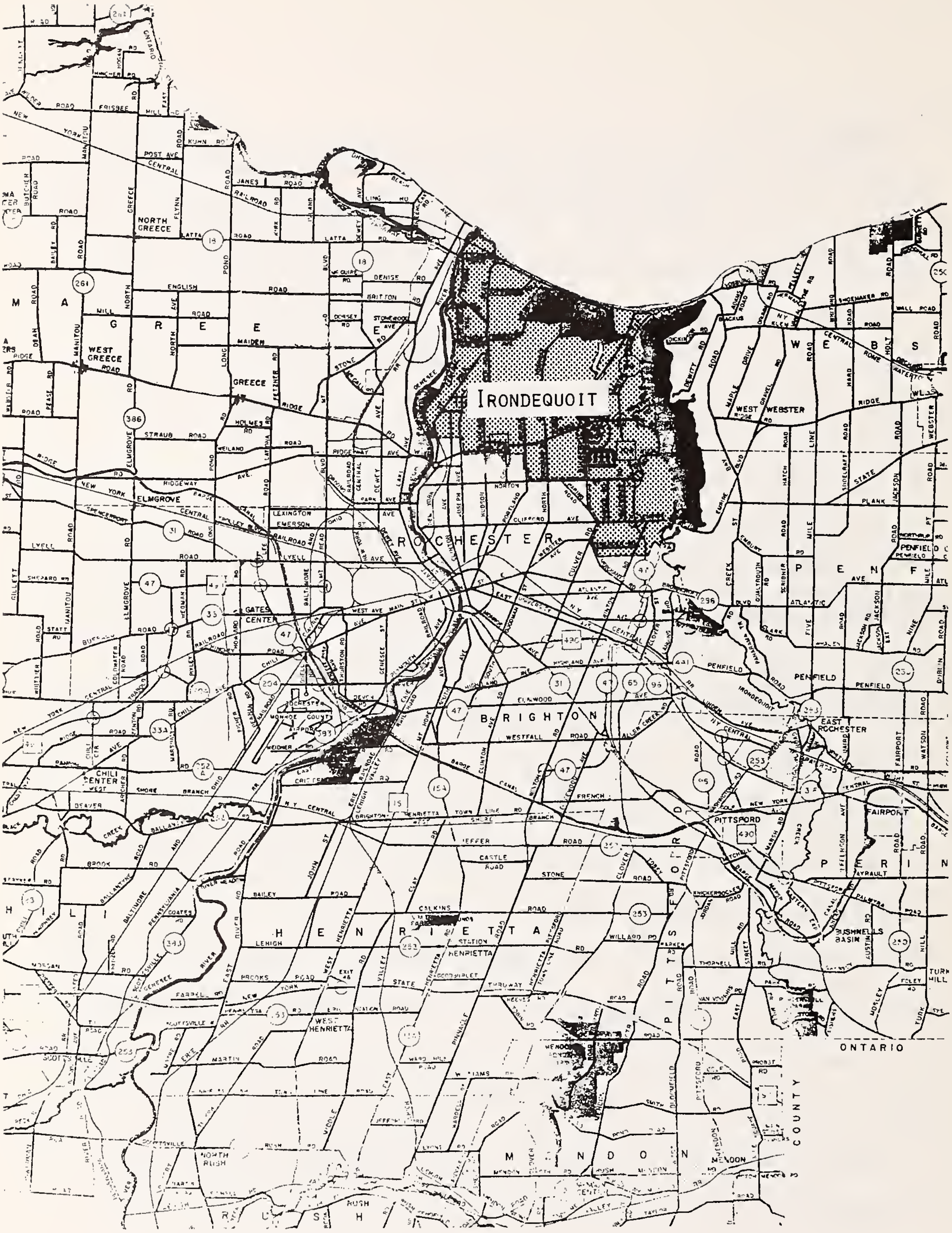


Figure 3.1 - Irondequoit and its Relationship to the Rochester Metropolitan Area

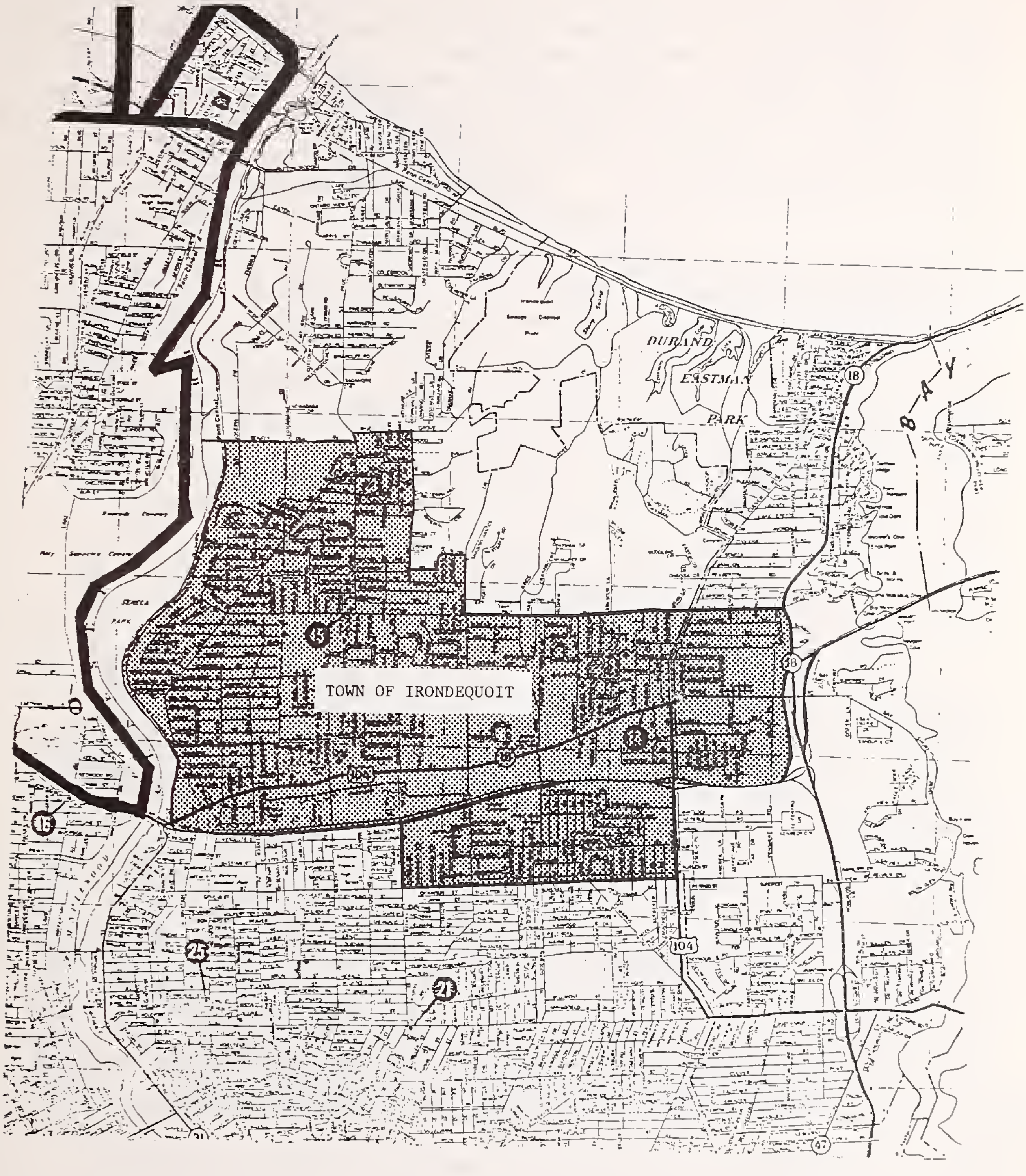


Figure 3.2 - Irondequoit Many to Many DRT Zones

a) Peak hour services (6:30-9:00 AM; 3:00-7:00 PM) - During peak periods a number of fixed routes (shown in Figure 3.3) serve the area, connecting the town with the Rochester central business district (CBD). Limited service is also provided to the Kodak Park employment complex in neighboring Greece. In addition, a subscription service is offered from the eastern part of town to Kodak Park (West), with one trip arriving at Kodak at 7:30 AM and leaving in the afternoon at 3:30. Many-to-many DRT service begins operation at 8:00 AM, and is also provided in the afternoon peak.

b) Midday service (9:00 AM - 3:00 PM) - Many-to-many DRT service is provided throughout the midday period. Bus routes 7, 9, 11 and 12 are terminated at Ridge Road during this period, as shown in Figure 3.4. DRT service acts as a feeder to these routes, as does a fixed route loop bus service, also shown in Figure 3.4. Route 5 within the service area is converted into a route deviation service. The small DRT vehicles on this service follow the basic route, but can deviate to specified areas (shown by the dotted lines in Figure 3-4) to pick-up and drop-off passengers upon request, then connect with the regular route 5 at Ridge Road to allow transfers.

c) Early evening service (7:00-9:00 PM) - Service during this period is identical to the midday service except that the loop bus service is not offered.

d) Late evening service (9:00 PM - 1:00 AM) - Many-to-many service ends at 9:00 PM, although the route deviation service continues until 10:00 PM. The major change during this period is the introduction of "urban PERT" service. Routes 5, 7, and 9, operating between Irondequoit and the Rochester CBD, are replaced by the three route deviation zones. Fixed route service is still provided at the regular off-peak fare of 25 cents but doorstep pick-up and drop-off within the route deviation zone is also offered at the regular DRT fare of $1.00.

2) Setting up the Model Inputs

a) Zone System

The first step in setting up the model is the establishment of an appropriate zone system. The easiest approach is to use census tracts as zones. The actual DRT service area is considered first. In the Irondequoit case, some census tracts are entirely within the service area; others are partially within the area, and partially outside the area.

Figure 3.3 - Irondequoit Peak Hour Bus Routes

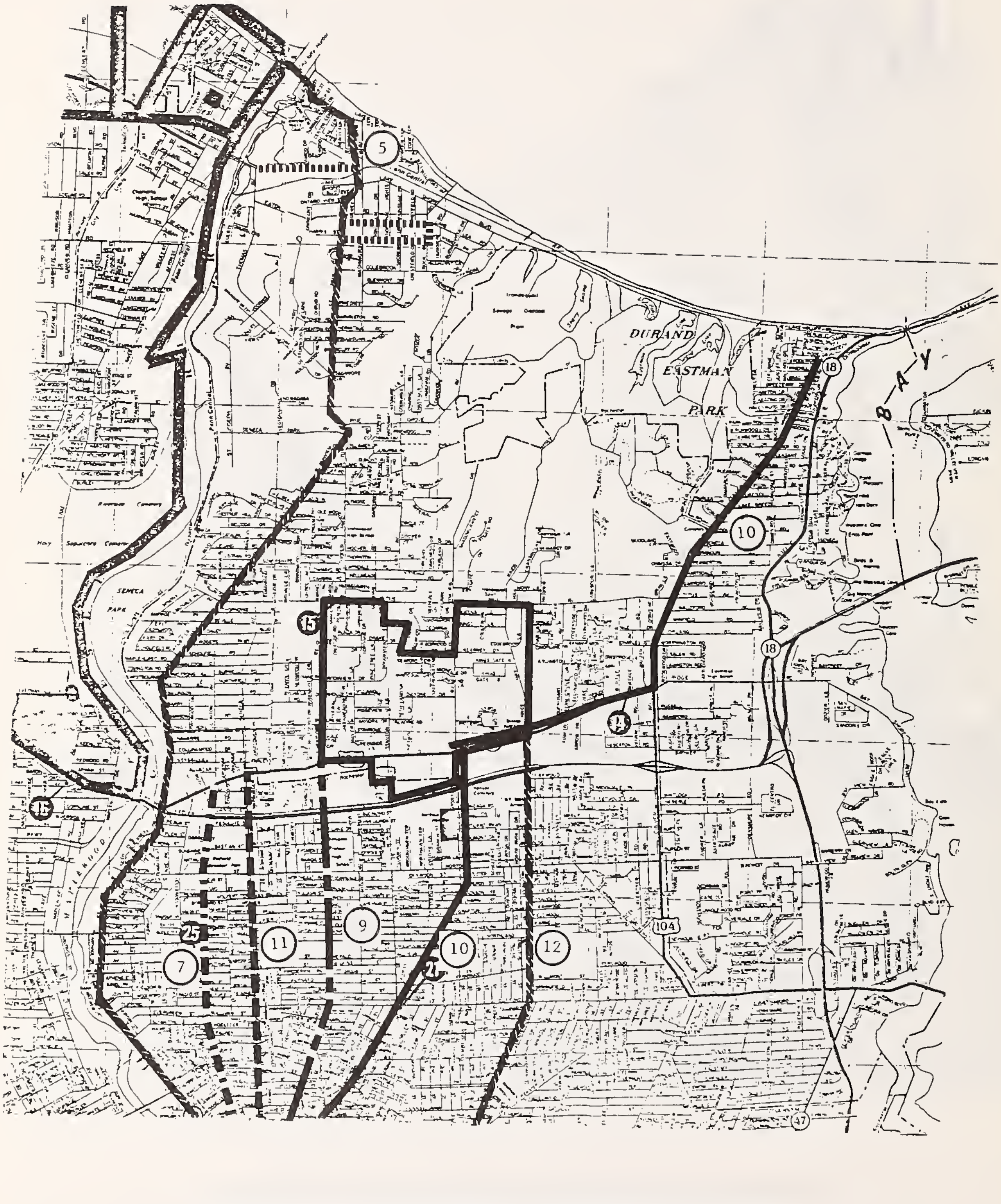


Figure 3.4 - Irondequoit Off-Peak Bus Routes

Thus, the service area will consist of some entire census tracts and some partial tracts.

While in some cases only the service area need be represented, in Irondequoit, which is part of a larger metropolitan area, there are undoubtedly trips made beyond the service area boundaries. Furthermore, DRT service in Irondequoit is used to provide access to line haul services which leave the area. Therefore, a set of external zones must also be specified. Recalling that the cost of running the model is highly sensitive to the number of zones, care must be taken in selecting external zones. A balance must be struck between the desirability of separating areas with different characteristics and minimizing the total number of zones. The following external zones are suggested for Irondequoit:

> the remainder of the Town of Irondequoit which does not have DRT service;
>
> the Greece/Rochester DRT service area, since fixed route bus service is available from Irondequoit to Greece, and since passengers are allowed to transfer between the DRT systems in Greece and Irondequoit;
>
> the Rochester CBD;
>
> the sector located between the Rochester CBD and Irondequoit (which has evening route deviation service);
>
> the remainder of the City of Rochester plus the suburbs east of Irondequoit. (This assumes that very few trips are made from Irondequoit to southern suburbs or western suburbs other than Greece.)

The entire suggested zone system is shown in Figure 3.5. Once the zone system is established, a coordinate system must be created to allow measurements of distance. The orientation of the coordinate spacing is

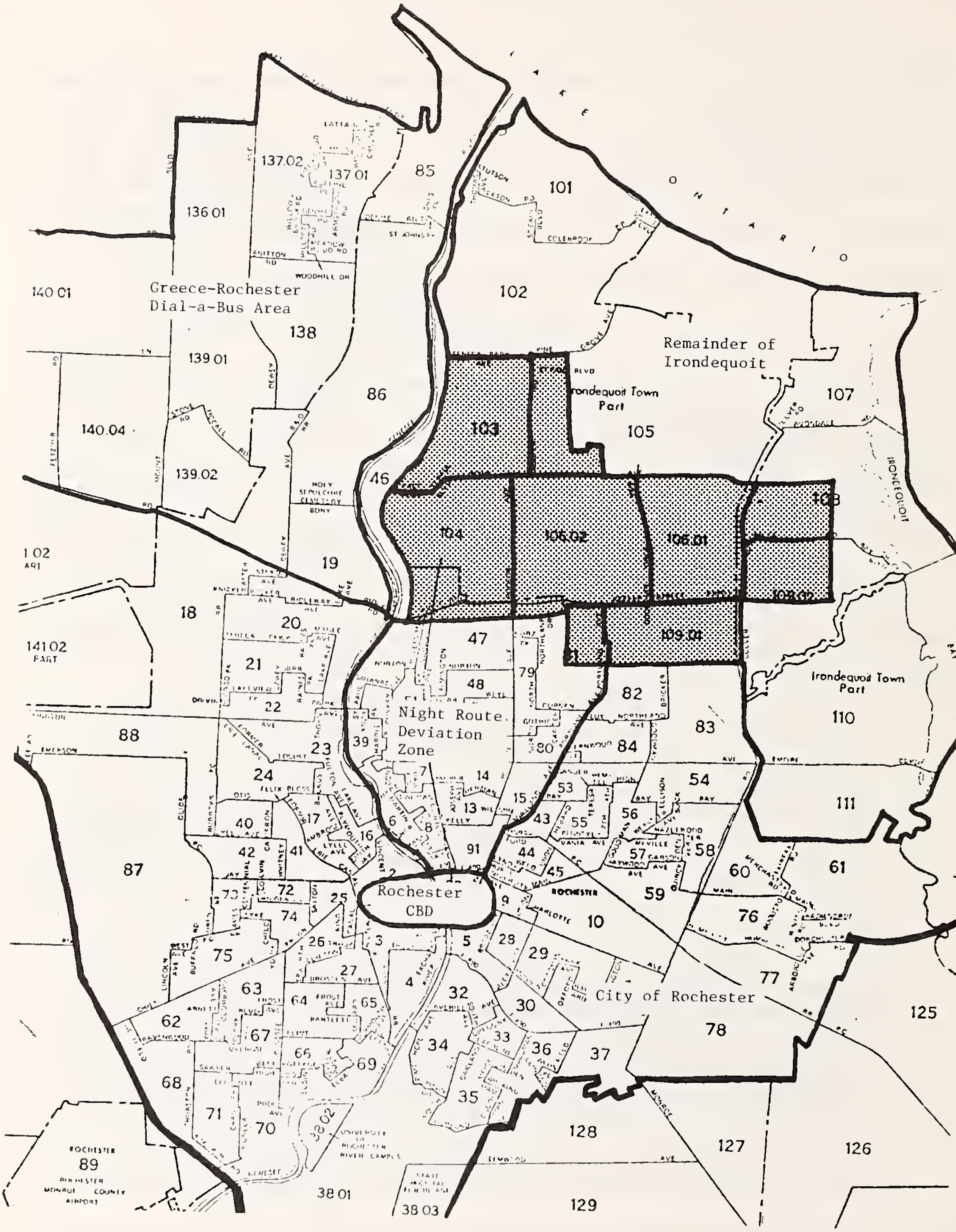


Figure 3.5 - Suggested Irondequoit Zone System

entirely arbitrary. A spacing of .5 miles between grid lines is suggested.

b) Zonal Data

Information that must be collected for each zone includes the following:

zone centroid coordinates from the coordinate system;

population - from census* (or local census update);

zonal area - from map with use of planimeter or other such device;

intra-zonal trip distance - for square zones, the expected average trip length, assuming origins and destinations are uniformly distributed, is approximately equal to a/2 , where a is the zone area in square miles. Estimates based on formulas such as these are sufficient for the purposes of the model.

zonal retail and wholesale employment**

c) Work Trip Data

Two work trip distributions are needed: 1) a zone-to-zone work trip matrix; and 2) a distribution of work trips by time of day. The former information is available for all urban areas through the U.S. Census (third count). In the case of Irondequoit, the local Municipal Planning Organization, the Genesee Transportation Survey, had this information on tape. For areas that do not have ready access to this data, there are services that have all census tapes, and will sell copies of the tape or printouts. If the user cannot obtain the data, he/she will be required to construct an artificial work trip matrix based on readily available

*For zones that include only part of a census tract, population estimates can be based on consideration of the area percentage of the entire tract, plus observation of maps and informed estimates about relative population density.

**The following Standard Industrial Classification (SIC) codes are suggested: Wholesale Trade (Division F), Retail Trade (Division G), Finance, Insurance and Real Estate (Division H), Service (Division I), Public Administration (Division J).

data such as the number of employees by industrial classification living in each census tract, and knowledge of the local community.*

The time of day distribution of work trips is typically not readily available, unless a detailed travel survey has been conducted recently. Users unable to obtain such a distribution can use results from similar studies conducted in other areas or rely on the default values. The user might modify existing distributions using knowledge of local conditions (e.g., a predominance of local jobs which begin at 9:00 AM), as described for the validation sites in Section 4.

d) Socioeconomic Characteristics

Areawide socioeconomic characteristics to be determined include:

automobile ownership distribution

number of non-workers over the age of 16

percent of total population over the age of 64

the distribution of household size over the age of 16.**

While the first three characteristics are readily available from the Census, the last category of data is generally not readily available. Overall household size distribution is a second count census data item. Household size versus age of household members may be available from fourth count census tapes or local travel surveys. For users who do not

*As discussed earlier in this chapter, the work trip matrix is entered into the model in one way format, e.g., home-to-work. The model automatically reverses the trip direction for the trip home.

**The actual distribution desired is automobile ownership versus household size over the age of 16. This information may be available on a sixth count tape, but would be very hard to obtain. It may also be available if a local travel study has been undertaken. The model system has the capability to approximate this distribution from the two marginal distributions.

have access to this data, the necessary distribution can be reasonably approximated by modifying the overall household size distribution. Table 3.1 lists a suggested method for converting household size to household size over the age of 16, based on information on the difference between the two distributions in Rochester and Haddonfield and simple common sense (e.g., all one person households consist of one person over the age of 16).

e) DRT Service Data

For an analyst planning a new DRT system, characteristics such as vehicle fleet size are design parameters. Since the Irondequoit system is already designed, the model is being used to predict the ridership based on the following known characteristics of the system:

vehicle fleet size - an average of three vehicles are used throughout the service day;

vehicle speed - average speed is approximately 13 miles per hour;

load, unload times - average 2.8 minutes and 1.8 minutes respectively as measured in Greece;

fare - base fare \$1.00 plus 25¢ for additional passengers. Assuming average group size for work trips of 1.0, the average fare is \$1.00. Assuming average group size for non-work trips equals 1.2, average fare = (1.00 + .2 x .25)/1.2 = \$.875. These are areawide fares.

α, β - set at default values.

3) Analysis Periods

Changes in the services during the day provide natural analysis periods in Irondequoit. Suggested periods are:

8:00 AM - 9:00 AM - morning peak during which many-to-many service is offered;
9:00 AM - 3:00 PM - midday service

Table 3.1 - Assumption About Household Size Distribution

Household Size all ages	Percent Household Size over age of 16
1 person	100% 1 person
2 person	80% 2 person 20% 1 person
3 person	40% 3 person 40% 2 person 20% 1 person
4 person	30% 4 person 30% 3 person 20% 2 person 20% 1 person
5 person	10% 5 person 30% 4 person 30% 3 person 20% 2 person 10% 1 person
6 or more persons	5% 6 or more persons 10% 5 person 30% 4 person 30% 3 person 20% 2 person 5% 1 person

3:00 PM - 7:00 PM - afternoon peak period
7:00 PM - 9:00 PM - evening service.

Since many-to-many DRT service is not offered after 9:00 PM, there is no need to model late evening service. Also, since service begins well past the actual start of work trips in the morning, the total number of work trips in the afternoon for which DRT is an option should be scaled down.

3.7 Special Issues in Complex Service Areas

Thus far the set up of the model has been fairly straightforward, but the existence of alternative public transit services in Irondequoit introduces an additional level of complexity. Many model users might wish to ignore this question unless faced with a situation as complex as that of Irondequoit. However, if alternative bus routes do exist, their consideration can prove quite time consuming.

The first issue to be considered is fare in terms of time of day variation and also variation for different origin-destionation pairs. Different fares are charged during peak and off-peak periods on Irondequoit bus routes. The peak period fare is 40¢ for all persons, but during the off-peak, the fare is 25¢ for the general public, and 20¢ for senior citizens. Ideally, the model would be able to distinguish between regular and senior citizen fares; however, this capability has not been included in the system. Therefore, an estimate of the average fare paid by the passenger should be made. Assuming that the percentage of all trips which are made by the elderly is approximately the same as the percentage of elderly in the total population (an assumption that is true in some areas but not in others), the average fare can be computed as:(.9x$.25)+(.1x$.20)= $.245. Thus, in this case, the impact of the senior citizen fare is virtually negligible.

There are two considerations that affect the decision whether or not to use a single areawide fare. First of all, any trips requiring a transfer cost an additional five cent transfer charge, so the fare is not the same for all zone pairs. Secondly, the fare differential between fixed route and doorstep service on the route deviation service must be considered. Determining the fare to use for this service requires resolution of the entire question of dealing with hybrid services.*

There are two basic ways to represent route deviation within the model system. On the simplest level, if route deviation is available in addition to many-to-many service, the fixed route and demand-responsive components of the route deviation system might be "merged" into a single "fixed route" service which displays combined characteristics. Thus, if the fare for the fixed route option is 25¢ and the fare for deviation service is 40¢, and it is expected that 30% of the users choose the deviation system, we might calculate an "effective" fare of (.7 x \$.25) + (.3 x \$.40) = \$.30.

The alternative approach is to consider the fixed route and deviation options as totally separate services. The former would be modelled as a fixed route service with an in-vehicle travel time penalty to reflect the impact of deviations. The latter would be modelled as a DRT system separate from the basic many-to-many system being analyzed, but with the same demand model being used. It would be desirable, in this case, to use a revised supply model which more closely represented route deviation service.

Since the present supply model is not designed to consider a route deviation service, and since in Irondequoit the route deviation service

*The checkpoint subscription service offered to Kodak Park is much easier to deal with. A checkpoint subscription service is essentially a fixed route service, since it makes only fixed stops once a route has been established. In fact, since in Irondequoit the service is offered before many-to-many service begins in the morning, it probably need not be considered at all.

is designed to serve primarily as a fixed route service with only a limited number of deviations permitted because of service area constraints, the former approach is more appropriate. The fare to be used in the model for this service should then be an average or effective fare. Since deviations are available to limited locations only, one might consider using a fare matrix with different average fares for different trips. However, closer examination of the system indicates that, at least as far as the impact of the route deviation service is concerned, a fare matrix is probably unnecessary. A maximum of 10% of the passengers use the deviation option in Irondequoit; many of these are senior citizens who do not pay a deviation charge. Thus, the average fare in areas where deviations are allowed is not significantly different than the base fare.

The five cent transfer fare will, in general, have an insignificant effect on ridership levels. Thus, unless one is interested in exploring the effect of significantly raising the transfer charge, single fare rather than a fare matrix would suffice.

The second major input related to the fixed-route bus mode is in-vehicle travel time. This input must be in matrix form. To develop this matrix, it would probably be best to overlay a route map on the zone system map. All interzone and intrazonal trips, that are connected either by a direct route or via transfers should be identified.* A value of 0 should be entered into the matrix for zone pairs that are not connected. The travel time between zone centroids should be fairly

*Transfers should be considered feasible only when routes cross or come within about 1/8 mile of each other.

easily computed from the bus schedules. (In Irondequoit the route deviation schedule is designed with sufficient slack to allow deviations, and thus should give an accurate picture of travel times.)

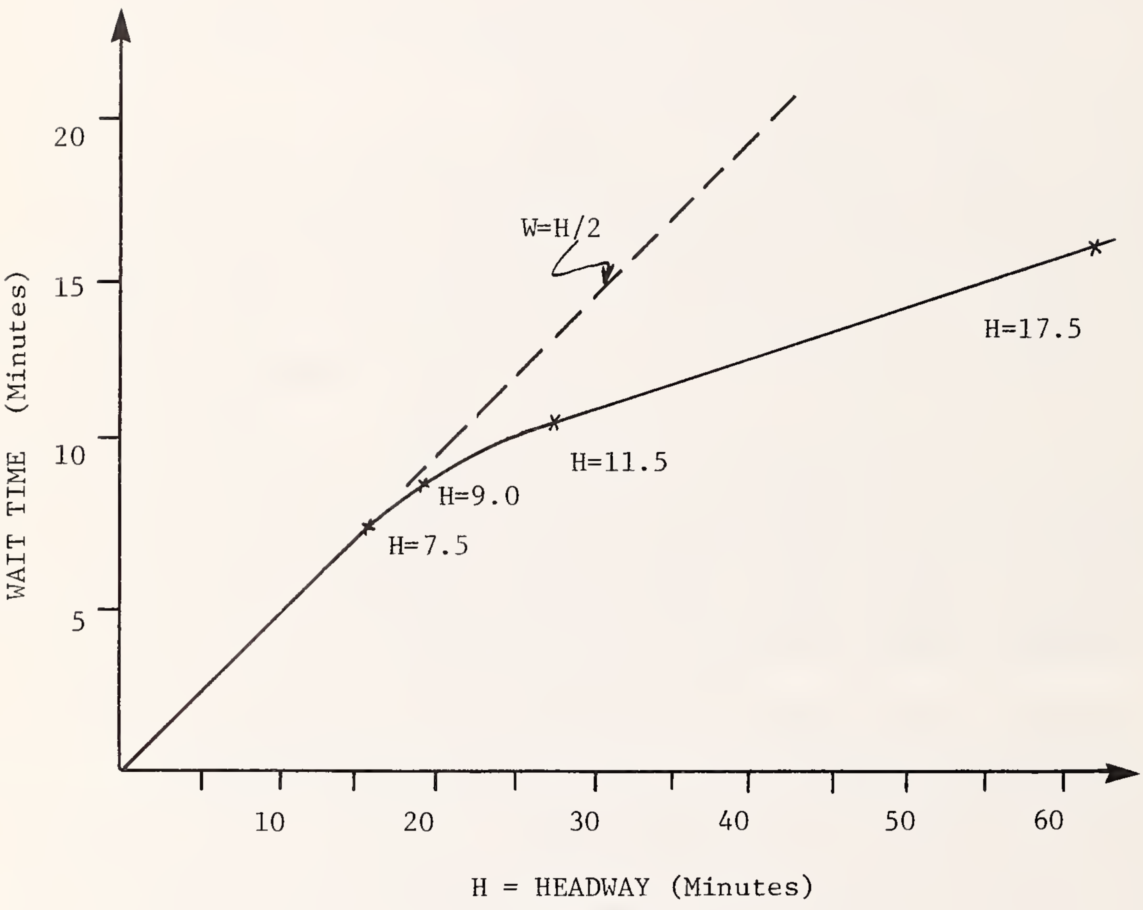
Note that in the case of Irondequoit loop bus (or any other similar service which operates in one direction only), the in-vehicle travel time matrix will not be symmetric. Note further than in the case of Irondequoit, some origin-destination pairs that may be linked during peak hours may not be linked during the off-peak.

The out-of-vehicle time matrix is probably the most difficult of all model inputs to develop. Out-of-vehicle time has three components: wait time, transfer time, and walk time. Consider wait time first. It has been demonstrated that for headways of up to about one-half hour, mean wait time equals approximately one-half the headway. In other words, passengers are not affected by the actual scheduled time, and arrive randomly at the bus stop. As the headway increases beyond 30 minutes, passengers become more aware of the schedule, and are more likely to schedule their arrival at a bus stop to be a few minutes before the scheduled bus arrival. One study (Wilson, Kullman and Pecknold, 1972) has suggested the relationship shown in Figure 3.6 as an approximate relationship between wait time and headway. This model deviates from the line representing half the headway in the region of 15 to 20 minute headways.

In Irondequoit, all bus routes operate on 30 minute headways or less, with the exception of the loop bus which operates on 45 minute

Figure 3.6

BUS WAIT TIME MODEL AS A FUNCTION OF HEADWAYS

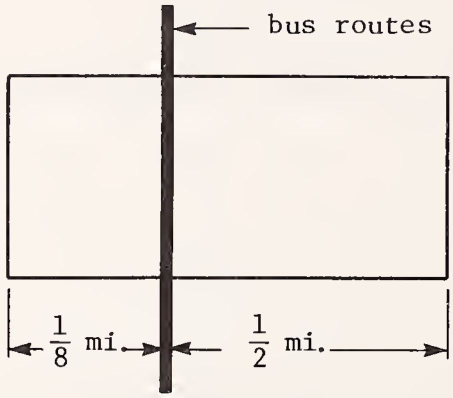


headways. Thus, the approximation of one-half of the headway can be used as the wait time estimate for all routes except the loop bus, which would have an estimated wait time of 18 minutes. Note that different wait times exist during different time periods of the day. However, in the case of the routes with variable headways during a given time period, an average wait time can be used. For example, route 5 during the peak operates on an 8-15 minute headway; the average headway during this period is approximately 10 minutes. Furthermore, the headway on route 5 is shorter at Ridge Road than in Summerville, the northwest portion of Irondequoit (e.g., some runs to Rochester CBD originate at Ridge Road). Thus, different wait times will prevail along different parts of the route.

Transfer time can be calculated by determining the mean scheduled gap between vehicles for trips requiring transfers. In this case, it is suggested that a transfer time penalty of perhaps 3-5 minutes be added to <u>all</u> transfer times to account for schedule unreliability.

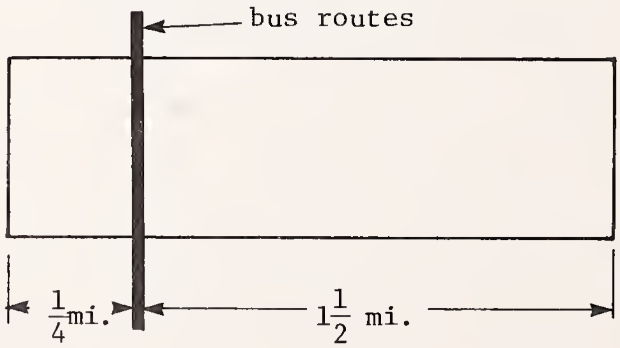
Estimation of walk time is a classic problem in transit analysis. The simplest approach used is to measure the distance from the zone centroid to a bus route and use this as the average distance a person will walk. This technique typically results in a significant underestimate of walk time. For example, in a zone in which the bus route crosses the centroid, a clearly erroneous walk distance of 0 would be predicted. Similarly, in large zones, even where the bus route does not cross the centroid, the distance between the centroid and the route may not represent the average distance a person would have to walk to reach a route.

A graphical representation is useful to illustrate a way in which walk distance might be estimated. Consider first the following situation:



In this case, the average walk distance in the left portion of the zone would be one-sixteenth of a mile, while the average walk distance in the right portion would be one-quarter mile. Assuming that people are uniformly distributed throughout the area, four times as many people would live in the right portion as in the left portion. The weighted average walk distance is therefore (4/5 x 1/4) + (1/5 x 1/16) = 17/80 or .21 mile.

But consider the same type of situation, with the following dimensions:



The average distance in the left portion might again be estimated as one-half the width, or one-eighth mile. However, to assume that the average walk distance in the right half would be three-fourths of a mile would probably lead to a very low prediction of ridership, since few persons are likely to walk three-fourths of a mile. The actual average walk distance is likely to be much shorter, since only persons living closer to the route are likely to use it. But to use a very low walk distance would likely yield overestimates of demand.

One way of dealing with this problem is to subdivide the zone into two zones, one which has bus access, and one which might be considered to have no access at all. However, as noted earlier, the cost of running the model is very sensitive to the number of zones. Therefore, the user may wish to avoid establishing additional zones and use an alternative approach for estimating wait time in these situations. A possible approach would proceed as follows. For area widths of up to about one-half mile (i.e., distance between zone border and bus route), one-half the width would be used as an estimated walk distance. For greater widths, walk distance would be set at one-fourth of a mile, plus a percentage (less than 50%) of the distance greater than one-half mile that decreases with increasing width. This "compromise" value is less than half the total width (which would be expected to result in an underestimate of demand) but greater than the actual average walk distance (which would be expected to result in an overestimate of demand). This "compromise" approach should result in more reasonable predictions.*

Once walk distance is obtained for each zone, the time it takes to walk that distance can be estimated by applying an average speed of about twenty minutes per mile.

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*Because the model system has been designed as a DRT model, and many assumptions have gone into the fixed-route bus portion of the model, the user is cautioned not to spend too much time worrying about developing accurate estimates of out-of-vehicle time.

The route deviation system in Irondequoit adds further complications to the estimation of out-of-vehicle time. As briefly noted earlier, a reasonable approach to estimating walk times for the route deviation system would be to estimate the average walk time in the zones in question.

SECTION 4

VALIDATION

4.1 Choice of Validation Sites

Validation of the model system was conducted with data from two sites which were selected to reflect differences in geographical location, type of development patterns, type of service offered, and size of service area. The existence of a stable DRT system was another important criterion so that actual patronage could be compared with model predictions. Based on these criteria, Davenport, Iowa, and LaHabra, California, were selected to test the model.

Davenport is an older, fairly dense midwestern city with a population of about 100,000. LaHabra is a new, suburban area and is part of the Los Angeles metropolitan area. Demand responsive service in Davenport is privately owned and operated, has fares in excess of $1.00, and uses standard five-passenger automobiles. In LaHabra, the service is publicly operated and subsidized, with a maximum fare of 50¢, and utilizes twenty-one passenger minibuses. While many DRT trips in Davenport are oriented to the downtown area, trips in LaHabra are more uniformly distributed throughout the area. Thus, the application of the model to those areas should provide important information on its ability to model sharply different systems, both of which differ substantially from the calibration sites. The two sites are discussed in more detail below.

4.2 Davenport, Iowa: Site Description

Davenport, Iowa, a city of just under 100,000 persons, is part of the "Quad Cities" area, which includes Davenport and Bettendorf, Iowa, and Rock Island and Moline, Illinois. The CBD's of all four cities lie along the Mississippi River, with downtown Bettendorf lying three miles to the east of downtown Davenport, and Rock Island and Moline mirroring these cities on the other side of the river. Total population of the Quad Cities area is 310,000. Davenport and the Quad Cities are shown in Figure 4.1.

Demand responsive transportation is provided in Davenport in the form of shared ride taxi service, operated by the Royal Cab Co. The service is operated on a profit-making basis and is one of the few DRT services in the country that is profitable. Since shared ride taxi service is virtually identical in concept to the many-to-many DRT service offered by the public sector in Haddonfield and Rochester (as well as other locations), the model system should be able to predict shared ride taxi ridership. Davenport was selected as a validation city specifically to test the model's ability to forecast patronage in a shared ride taxi system.

Service in Davenport is provided with a fleet of 12 taxicabs. Yearly ridership on the system reached a high of over 500,000 in 1974. It has since declined somewhat because of the destruction of almost one-half of the vehicle fleet in a garage fire. The Davenport area is also served by a fixed-route bus system.

The first step in setting up the validation runs was the establish-

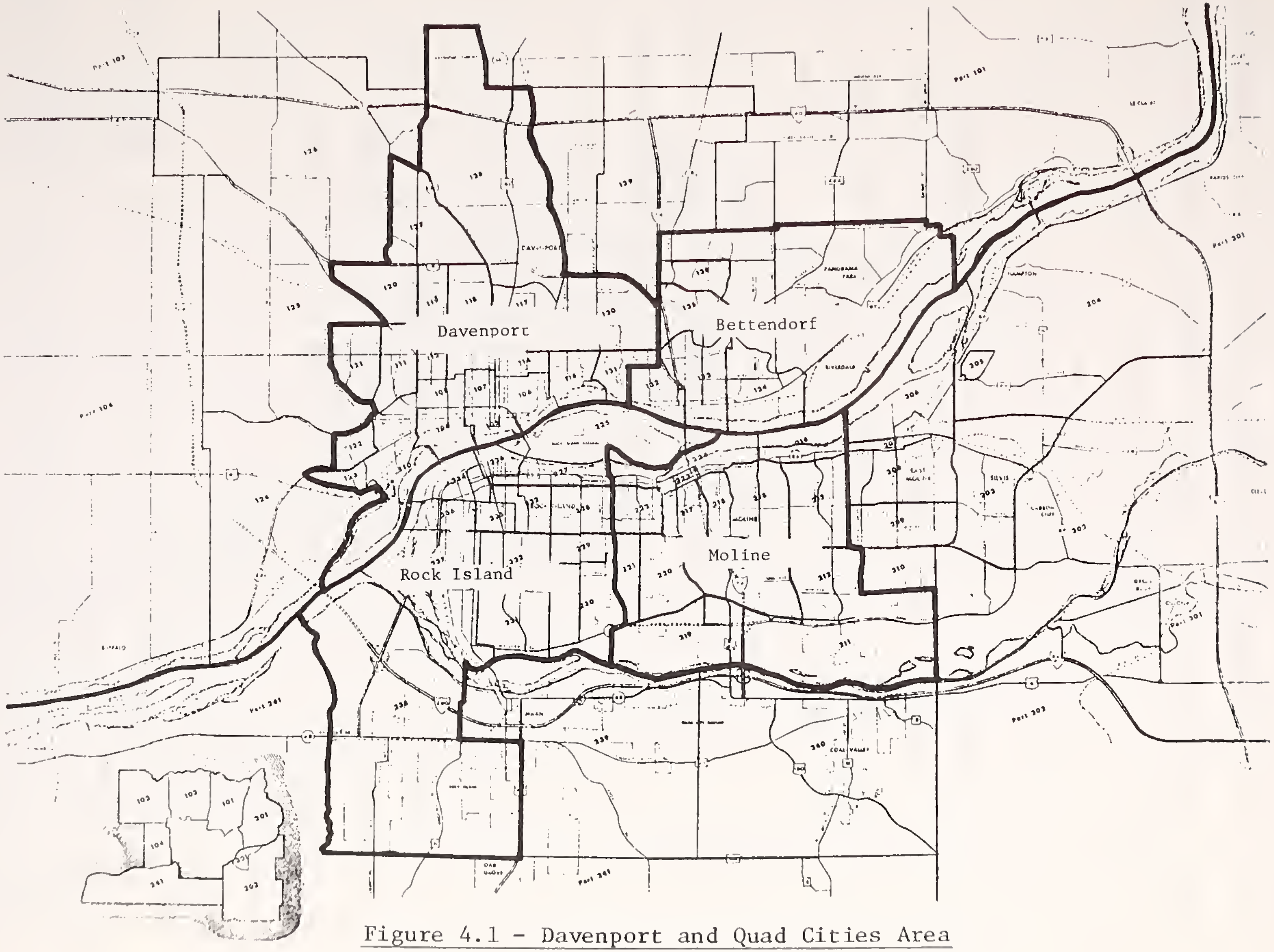


Figure 4.1 - Davenport and Quad Cities Area

ment of a service area zone system. DRT service is offered throughout the Quad Cities area; however, a check with the Royal Cab Co. revealed that a sizeable majority of the trips are in fact internal to Davenport. Thus, it was decided to first consider only the city of Davenport as the service area. A review of a map of the city and census data indicated that the outer census tracts of Davenport are very sparsely settled. Since the cost of running the model is highly sensitive to the number of zones used, it was decided, for the initial validation, to further limit the specified service area to the most densely populated area of Davenport. This included 23 census tracts, which were used as the zone system, and a total population of 86,769 (out of a total city population of 98,500), according to 1970 census figures. Subsequently, five additional "super zones" were created. The first included the central city Bettendorf area; the second was central city Rock Island; the third was central city Moline; and the fourth was the semicircular area north of the base service area, including parts of Davenport and Bettendorf and some suburban areas; and the fifth was the corresponding southern semi-circle consisting of parts of Rock Island and Moline, and their suburbs. Note that in this application these five zones are not external zones since DRT service includes these areas.* The base service area and the five surrounding zones are shown in Figure 4.2.

All of the necessary zonal data were obtained in the same way as

*For the purposes of the supply model, it would not be appropriate to consider these zones to be part of the service area. The supply model was based on an assumption of uniform travel patterns. Since the majority of trips are intra-Davenport, it is that area that should be used for the supply side.

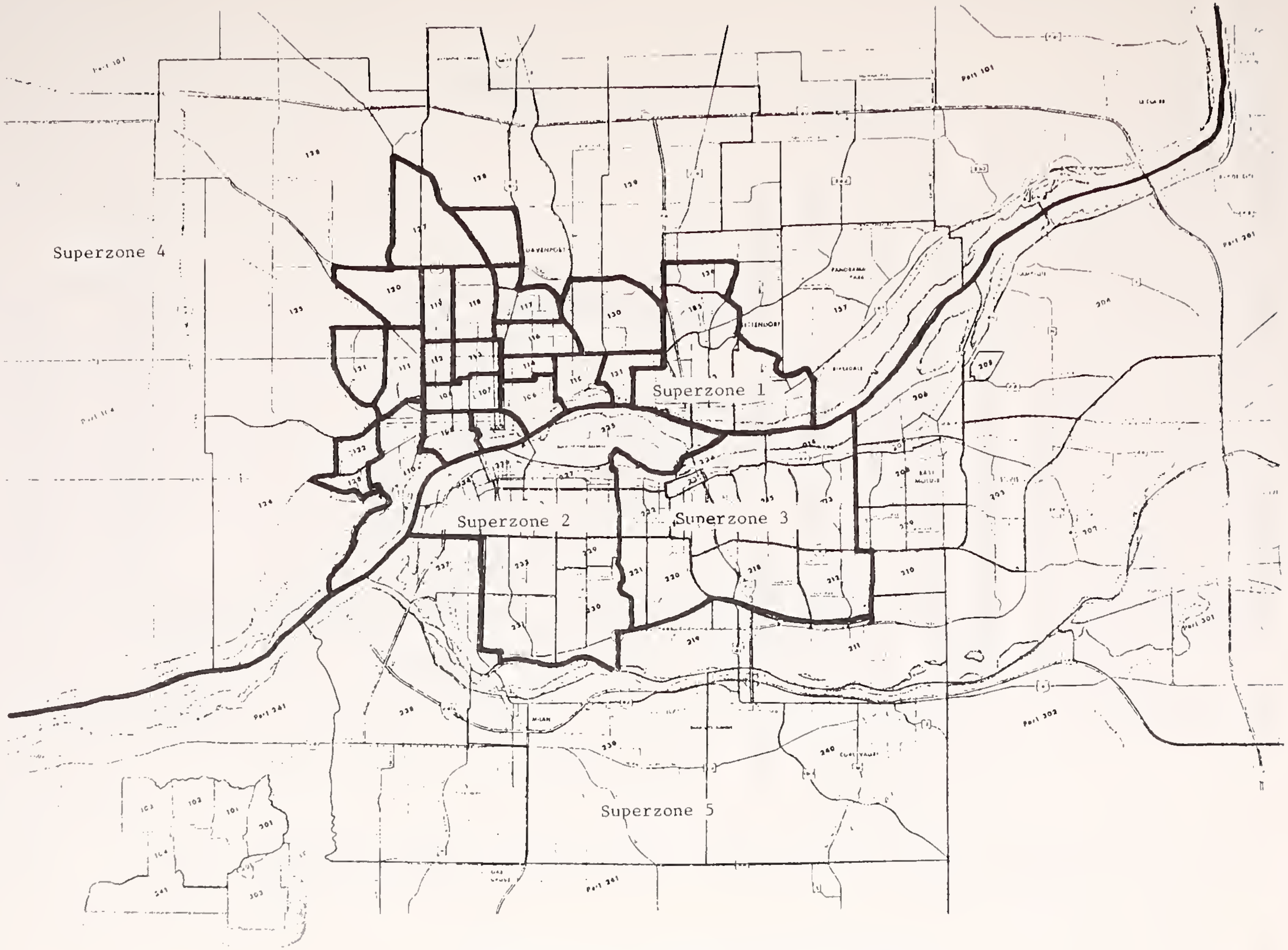
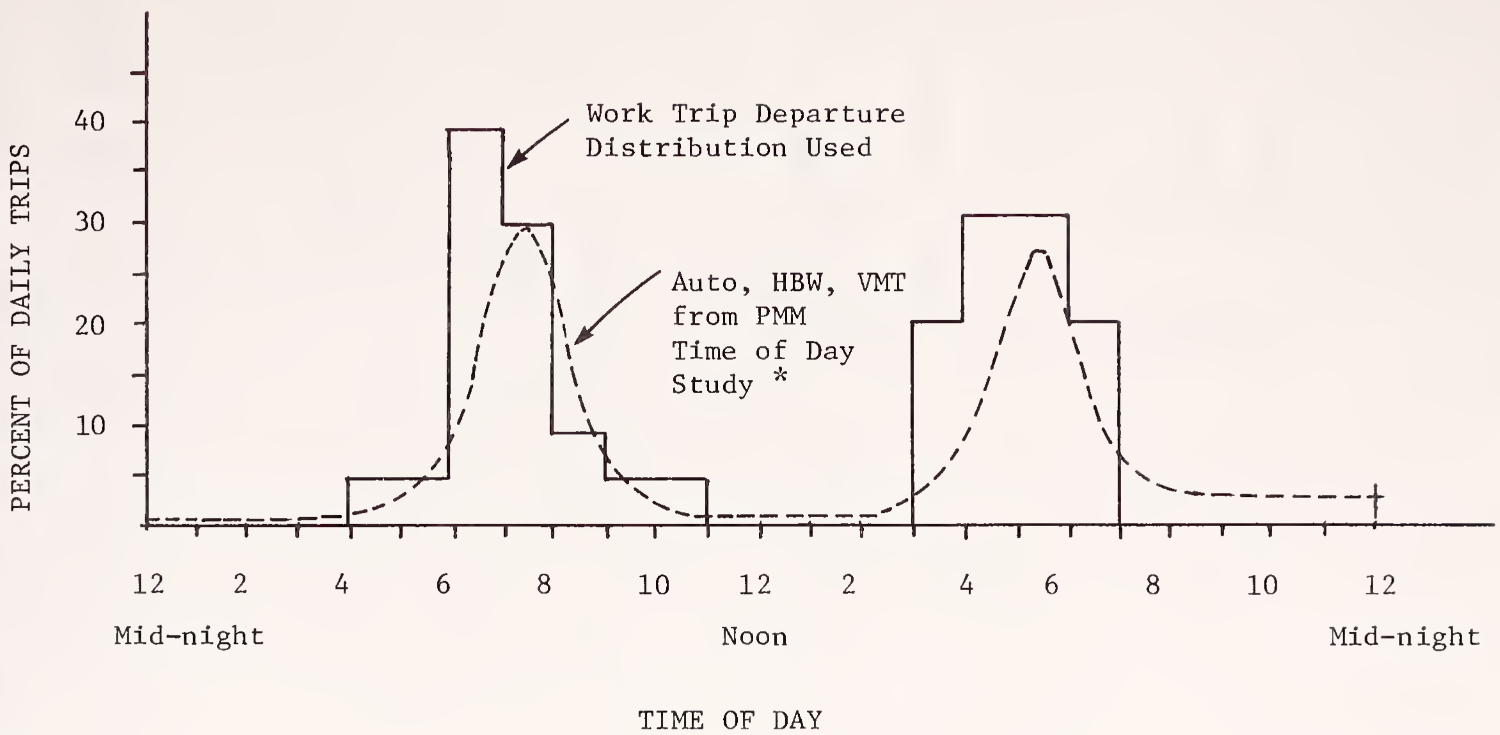


Figure 4.2 - Davenport Zone System

for the Irondequoit example in Section 3. The work trip matrix was obtained from the local planning organization, the Bi-State Metropolitan Planning Commission. The time of day work trip distribution was based on composite data from similar cities and is shown in Figure 4.3. All socioeconomic data were developed as in the Irondequoit example in Section 3. Estimates of in-vehicle and out-of-vehicle travel time for the extensive, fixed-route bus system serving the area was also obtained in the manner discussed earlier. Note that in a number of cases zones could have been subdivided into zones with bus access and zones without; however, it was felt that such subdivisions would create too many zones, so the method discussed earlier for estimating walk time was used.

Figure 4.3 -- Time of Day Distribution



* Auto, home-based vehicle miles traveled by time of day from study by Peat, Marwick, Mitchell & Co. (1972)

4.3 Davenport, Iowa: Operating Data

The best source of data on the Davenport DRT system is a study performed by the University of Tennessee Transportation Study Center.* Unfortunately, the parameters of the service have since changed because of the destruction of some of the vehicles. Consequently, validation had to be based on information obtained directly from the system operator. His estimate of total ridership over the course of the day was scaled down for our purposes by: first considering the ratio of trips in the 5:30 AM to 5:30 PM period (which was the time period modelled) to the total ridership, as available from the University of Tennessee study,** and second, multiplying this value by a factor which the operator estimated to be the percentage of total trips made within the designated service area. The data that was developed for validation are shown in Table 4.1. Note that an attempt was made to capture mean values only, but daily values can vary by as much as 15-25 percent from the mean.***

Bus ridership was obtained directly from the Rock Island County Metropolitan Transit District, which provides service in the Quad City area. They estimated that daily ridership on Davenport bus routes was between 3,000-3,500 per day. We estimated that approximately 35% of the total trips are made in each of the two peak periods (6:00-9:00 AM; 4:00-6:00 PM).

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*Davis et al, Economic Characteristics of Shared Ride Taxi Systems, August, 1974.

**The study covered ridership over a two-week period.

***The University of Tennessee study indicated that daily ridership varied from a low of 859 to a high of 1679 over the two-week period.

Table 4.1 - Davenport Operating Data

	Number of Vehicles	Trips	Passengers	Trip Purpose	Wait Time	Ride Time
5:30 AM-7:30 AM	7	40	43	work: 25 trips, 25 passengers other: 15 trips, 18 passengers	NA	NA
7:30 AM-9:00 AM	10	60	69	work: 15 trips, 15 passengers other: 45 trips, 54 passengers	NA	NA
9:30 AM-3:00 PM	9	27	322	work: 10 trips, 10 passengers other: 260 trips, 312 passengers	NA	NA
3:00 PM-5:30 PM	10	130	146	work: 50 trips, 50 passengers other: 80 trips, 96 passengers	NA	NA
TOTAL	--	500	580	work: 100 trips, 100 passengers other: 400 trips, 480 passengers	20 min.	12 min.

NA - Not available.

4.4 LaHabra, California: Site Description

LaHabra, California, is located in Orange County, California, and is part of the Los Angeles Metropolitan Area, as shown in Figure 4.4 LaHabra is southwest of Los Angeles proper, not far from the City of Anaheim. It is a relatively small city of just under seven square miles, with a total population of 41,350.

Many-to-many DRT service was established in LaHabra in 1973, as the first step by the Orange County Transit District toward the development of demand responsive services throughout the county. Since then, LaHabra has continued and other DRT services have been implemented in the county despite legal difficulties with the local taxi industry. The LaHabra system is county-owned, but managed by a professional DRT management firm.

The validation data for LaHabra were organized in much the same manner as in Davenport. The LaHabra case was much less time consuming, since the service area contained only fourteen zones, rather than the twenty-three zones used in Davenport. Establishment of service area boundaries in LaHabra was also much simpler, since the DRT service is provided only within the city limits of LaHabra. Two external zones, the northern and southern semicircles surrounding the city up to a radius of 10 miles from the city center, were also established. The LaHabra zone system is shown in Figure 4.5.

All other necessary information was obtained in much the same manner in LaHabra as in Davenport. Again, the same time of day work trip distribution was used because of a lack of local data.

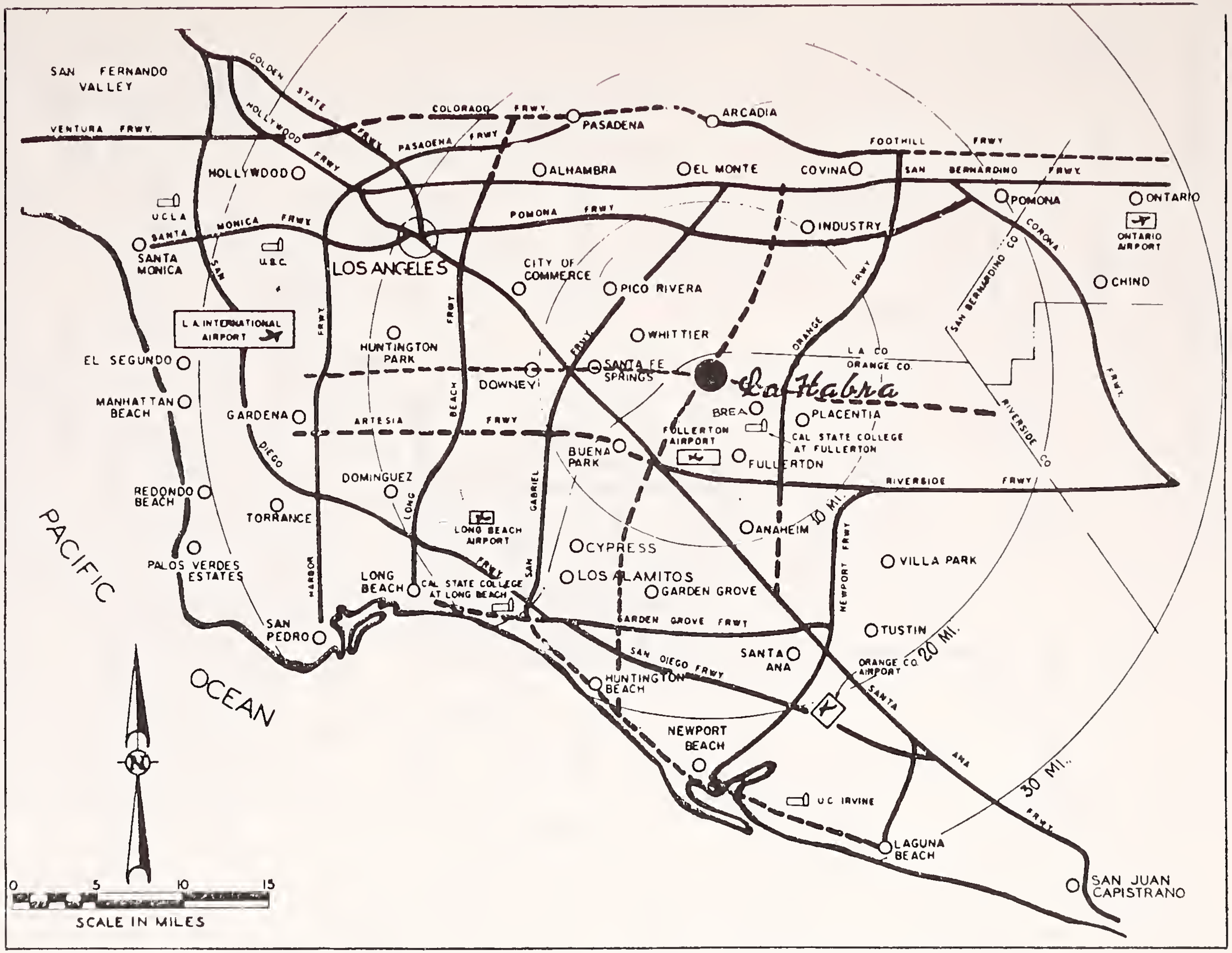

Figure 4.4 - Location of LaHabra in Los Angeles Metropolitan Area

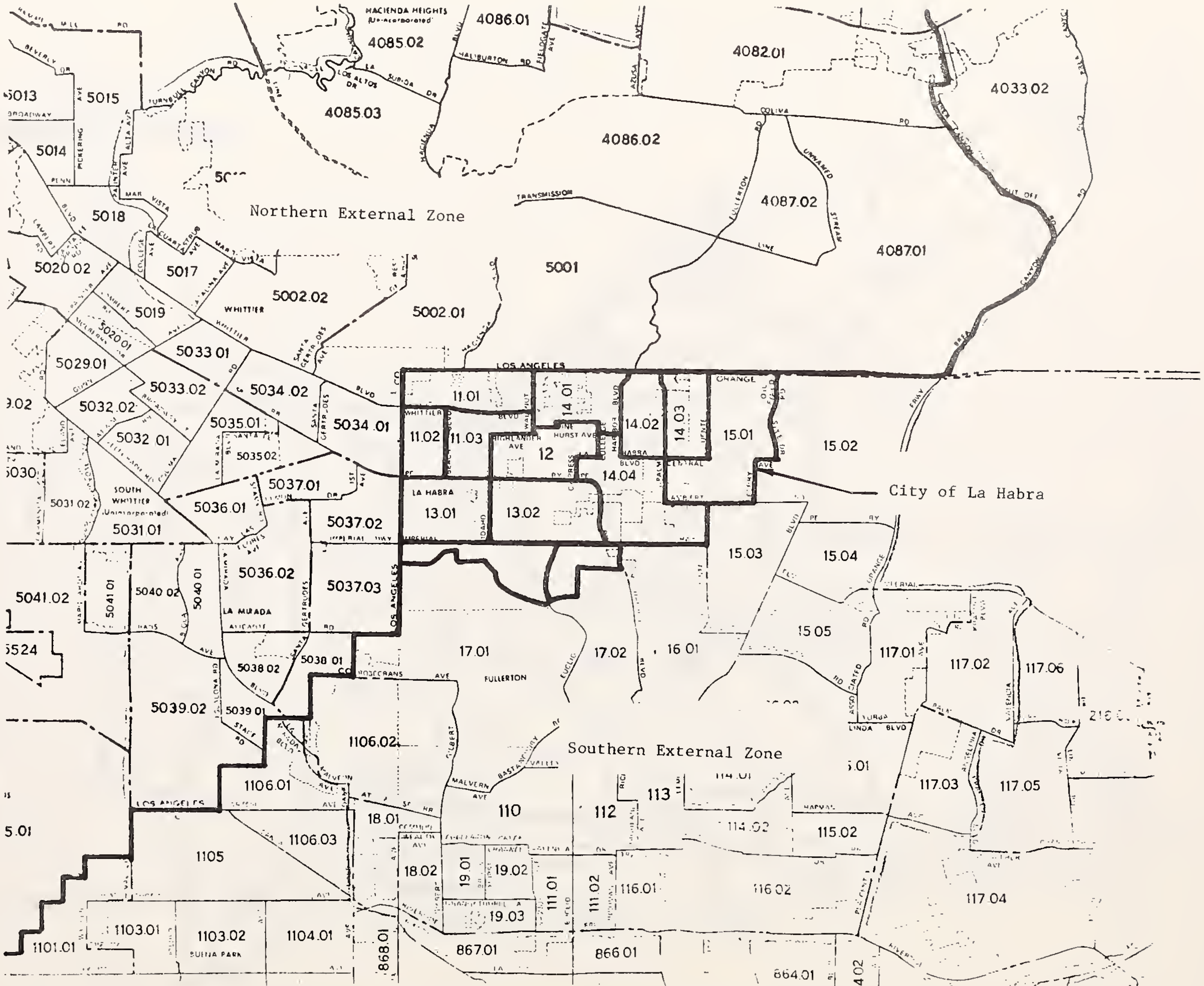

Figure 4.5 - LaHabra Zone System

4.5 LaHabra, California: Operating Data

A fairly extensive data base is maintained on the LaHabra DRT system by a private management firm. Daily ridership information was obtained for the months of June and December 1975.* In addition, for one day in both months the following information was provided:

1) ridership by hour
2) mean wait and ride times by hour
3) number of vehicles in service by hour
4) trip purpose distribution
5) vehicle speed.

Although the sample size is too small for any confidence on hourly travel volumes and service times, sufficient data are available to be fairly certain about daily ridership. Bear in mind, however, that daily ridership variations are substantial; for example, weekday ridership on the system in June 1975, ranged from 377 to 585. Thus, while the average ridership was 466, daily ridership fluctuated by 20-25% about the mean. The information available for validation is summarized in Table 4.2.

Fixed route bus ridership in the area was obtained from OCTD as well. Unfortunately, ridership data was not available for trips within LaHabra, since each of the bus routes serving LaHabra originated and ended outside the LaHabra boundaries. Bus ridership within LaHabra was estimated at 250-400 per day, based on the ratio of route miles in the city to total route mileage.

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*Updated ridership figures were provided in a telephone conversation with the Orange County Transit District (OCTD).

Table 4.2 - LaHabra DRT Validation Data

Time Period	Number of Vehicles in Service	Trips	Passengers	Estimated Trip Purpose	Mean Wait Time	Mean Ride Time
7:00 AM- 9:00 AM	5	57	80	work: 25 trips, 25 passengers school: 28 trips, 50 passengers other: 4 trips, 5 passengers	15 min.	10 min.
9:00 AM - 3:00 PM	5	160	200	work: 10 trips, 10 passengers school: 15 trips, 25 passengers other: 136 trips, 165 passengers	17.5 min.	12 min.
3:00 PM - 6:00 PM	5	91	113	work: 23 trips, 23 passengers school: 14 trips, 25 passengers other: 54 trips, 65 passengers	19 min.	12.5 min.
6:00 PM - 7:00 PM	3	6	7	work: 2 trips, 2 passengers school: 0 trips, 0 passengers other: 4 trips, 5 passengers	18 min.	9 min.
TOTAL	--	314	400	work: 60 trips, 60 passengers school: 56 trips, 100 passengers other: 198 trips, 240 passengers	17 min.	10.5 min.

4.6 Modelling the Fixed Route Bus Mode

As discussed in Section 2, both the work and non-work demand models were calibrated without fixed route bus available as an alternative, because there was insufficient data on which to develop an appropriate model. In performing the validation, however, it was decided to extend the original model to represent fixed route bus and to compare the predictions with actual ridership levels.

To do this, it is necessary to define a utility function for fixed route bus and a set of appropriate coefficients. Since fixed route bus is most like DRT in that neither requires a privately owned vehicle nor the ability to operate one, the DRT utility function was deemed the most appropriate starting point for "synthesizing" the fixed route bus utility function. For example, there is no obvious reason to assume that the fare for DRT and that of fixed route bus should not have identical coefficients.

It should be clear that a synthesized utility function for fixed route bus is not likely to perform particularly well in these validation tests, given the caliber of the bus data. Therefore, its success or failure to accurately predict bus patronage should not be viewed as an indication of the merits of the DRT patronage forecasting procedure. Rather, the inclusion of the synthetic bus utility in the validation tests was designed to test the feasibility of expanding the model's range of application through a very simple extension.

The assumptions made in developing the synthetic utility for fixed route bus are as follows:

1) For work trips, the fixed route bus utility function has the same coefficients as for DRT. (Note that this does not imply that the utilities themselves are equal; levels of service on fixed route bus and DRT are generally quite different.)

2) For non-work trips, the DRT and fixed route bus utility coefficients were also assumed to be equal, except that the DRT utility functions weight in-vehicle time and out-of-vehicle time equally, while for fixed route bus the coefficient of out-of-vehicle time was 2.5 times greater than the in-vehicle time coefficient. The rationale behind weighting in-vehicle and out-of-vehicle times equally in the DRT utility function was that most DRT wait time was incurred either at home or at some reasonably comfortable shopping center, doctor's office, etc. In contrast, out-of-vehicle time on fixed route bus trips is spent walking or waiting outside, often in inclement weather. The value of 2.5 reflects a general averaging of prior mode choice studies.

4.7 Validation Results: Daily DRT Ridership and Service

There are a number of different levels at which the validation forecasts can be compared with the actual observations. Perhaps the simplest and most relevant is to examine the daily DRT ridership. The prediction of this value is most important to decision-makers, since it relates directly to revenues, costs and profitability.

Table 4.3 compared the predicted and actual daily ridership for both Davenport and LaHabra. Note that the forecast values are accompanied by a range which reflects the sum of the possible errors in prediction for each operating period. As discussed in Section 2, it is recommended that the iterative equilibrium procedure be terminated when the upper and lower bounds are reasonably close to each other. This method saves a substantial amount of computer time. Furthermore, the use of more accurate convergence criteria is of little value since the error associated with models probably exceeds the difference between the solution approximated by the looser convergence criteria and the actual equilibrium value. In addition, for validation purposes, the ridership figures against which the forecasts are being compared are subject to significant measurement errors, so further accuracy in forecasting seemed unwarranted.

The range for the demand forecasts in any single operating period was developed by the forecasts at successive iterations. The last value of the vehicle productivity and its last upper and lower bounds (as described in Section 3) can be easily obtained from the output. In addi-

Site	Predicted Value Passengers/day	Actual Value Passengers/day
Davenport	730 $\pm$ 75	580
LaHabra	266 $\pm$ 45	400

Table 4.3 - Total Daily DRT Ridership Forecasts in Validation Sites

tion, by inspection of the output, it is possible to determine the corresponding upper and lower estimates of work and non-work trips associated with these bounds on productivity. The predicted numbers of work and non-work trips were taken as the midpoints of these ridership bounds and the bounds were used to indicate the range. The range for the total daily forecast was simply the sum of ranges for the individual periods.

From Table 4.3, the predicted Davenport DRT ridership is too high by 150 ± 75 passengers, while the LaHabra prediction is too low by 135 ± 45 travellers. These errors (evaluated without their corresponding ranges) reflect errors of about 26% and 33% for Davenport and LaHabra, respectively. Accounting for the ranges the errors could be as low as 13% in Davenport and 22% in LaHabra; they could be as high as 39% and 45% for Davenport and LaHabra respectively.

A second aspect of the validation is an examination of the average daily level of service for the DRT systems. While the ability to accurately predict level of service was not the major objective in the development of the model system, it is an implicit objective, since in the equilibrium structure of the models, errors in service predictions will produce errors in demand forecasts. The predicted and observed daily average values of DRT wait, ride and total time are summarized in Table 4.4. (Since the convergence criterion is based on the demand forecasts the model does not provide a range of possible service levels, although it is possible to compute these ranges manually from the demand variations.)

Site	Wait Time (minutes)		Ride Time (minutes)		Total Time (minutes)	
	Predicted	Observed	Predicted	Observed	Predicted	Observed
Davenport	26.1	20.0	12.7	12	38.8	32.0
LaHabra	15.5	17.0	8.0	10.5	23.5	27.5

Table 4.4 - Average Daily Level of Service Forecasts in Validation Sites

The level of service errors range from about 30% in the Davenport wait time forecast to less than 6% in the Davenport ride time forecasts. Comparable values for wait and ride time in LaHabra are 9% and 14% respectively. Total DRT service time forecasts for Davenport and LaHabra differ by about 21% and 15%,respectively, from the observed values.

Table 4.5 examines the individual forecasts of work and non-work daily patronage.* Perhaps the most notable entry in this table is the 261% error in the Davenport work trip forecast. One might speculate that the very high fare level in Davenport and the taxi-like operation of the service has produced a service viewed as unsuitable for work trip-making by Davenport residents and that this is not captured in the work trip demand model. The cost coefficient in the work trip mode split model was adapted from prior studies which used more typical transit services for calibration. It is therefore not surprising that an attempt to apply the work trip model to a situation in which fares are as much as an order or magnitude higher than the calibration data produces very high errors. Section 5 describes some potential solutions to this problem.

In comparison, when applied to LaHabra, the work trip model performs much better,with an average error of about 36%. The LaHabra service has fare levels which are within the range of the calibration.

*The reader is cautioned that the accuracy of the observed values for this validation test is questionable, since DRT operators do not take frequent on-board surveys to determine riders' trip purposes.

Site	Work Trips (passengers/day) Predicted	Observed	Non-Work Trips (passengers/day) Predicted	Observed
Davenport	361 ± 18	100	369 ± 57	480
LaHabra	103 ± 11	160*	163 ± 34	240

*includes school trips in work trip count

Table 4.5 - Daily Work and Non-Work Patronage Validation Results

The non-work forecasts differ by 23 and 32 percent from the observed values in Davenport and LaHabra respectively. However, some care should be exercised in interpreting the results in Davenport, since the overestimation of work trip patronage tends to cause the model to underestimate non-work demand. One can think of the extra work trips resulting in congestion,and the poor service quality then discourages non-work trip-makers from using DRT.*

*As discussed in Section 5, a comparison of two sketch planning runs, one with a DRT constant term of 2.085 and one of 0, produced a decrease of 57% in work trips with a corresponding increase in non-work of 163%, while total trips decreased by only 27%. This effect would tend to drive work trips down, and non-work trips up, both in the directions that would seem appropriate for both cities (if school trips are ignored in LaHabra). However, it is not clear what will happen to total trips. Therefore, primarily because of time and budget limitations, as well as the fact that the total trip model was performing reasonably well, no further changes were made in the model. The implications of this will be discussed more in the next section.

4.8 Validation by Period

Since the model system provides forecasts of DRT patronage and level of service for each period, it is possible to further disaggregate the validation results. Normally, the further one disaggregates a forecast, the greater will be the expected error in any component. However, it is useful to examine the results for each period to explore whether the model is more reliable in some periods than others.

Table 4.6 summarizes the predicted and observed ridership forecasts by time of day and trip purpose. As expected, the Davenport work trips are, with the exception of the third operating period, overpredicted; in the worst case, they are too high by a factor of six. Note that, however, in the Davenport third period (9:00 AM to 3:00 PM) when work trips are insignificant, the non-work trips are predicted accurately (that the predicted and observed non-work trips are numerically identical is less relevant than the fact that the range of non-work forecasts (312 $\pm$ 50) includes the observed value.) This supports the hypothesis that the 26% overprediction of total daily trips in Davenport is due principally to errors in the work trip model. The remaining periods show an overprediction of work trips and an underprediction of non-work trips; however, the latter is not surprising since, as discussed previously, the equilibrium structure of the model will tend to "balance off" overpredictions from one demand sector with underpredictions in the other.

The LaHabra forecasts, however, do not present a clear reason for

Site	Period	Predicted Ridership (passengers/day)			Observed Ridership (passengers/day)		
		Work	Non-Work	Total	Work	Non-Work	Total
DAVENPORT	5:30 AM - 7:30 AM	93 ± 5	2 ± 0	95 ± 5	25	18	43
	7:30 AM - 9:00 AM	93 ± 8	12 ± 2	105 ± 10	15	54	69
	9:00 AM - 3:00 PM	0	312 ± 50	312 ± 50	10	312	322
	3:00 PM - 5:30 PM	175 ± 5	43 ± 5	218 ± 10	50	96	146
	TOTAL	361 ± 18	369 ± 57	730 ± 75	100	420	580
LAHABRA	7:00 AM - 9:00 AM	28 ± 8	29 ± 3	57 ± 11	75	5	80
	9:00 AM - 3:00 PM	16 ± 1	98 ± 27	114 ± 28	35	165	200
	3:00 PM - 6:00 PM	53 ± 0	30 ± 3	83 ± 3	48	65	113
	6:00 PM - 7:00 PM	6 ± 2	6 ± 1	12 ± 3	2	5	7
	TOTAL	103 ± 11	163 ± 34	266 ± 45	160	240	400

Table 4.6 - Ridership Forecasts by Period

the underestimation of total daily forecast. Except for the insignificant demand in the last period, the forecast in each period underpredicts total trips.

Another perspective from which to examine the forecasts is to consider each period's percentage contribution to the total demand. This approach focuses on how well the model reflects the distribution of DRT demand over the day, ignoring overprediction and underprediction in the total. Table 4.7 summarizes these results for both validation sites; the range of forecasts is ignored in this table.

In the case of total trips (work plus non-work), the rank of each period's contribution to DRT patronage is perfectly reproduced in the forecasts. Furthermore, the consistency between the observed and predicted percentages is fairly good except for those periods with very small percentages. An example of high error in low demand periods is the 5:30 AM to 7:30 AM period in Davenport, which accounts for 7.4% of the actual DRT daily patronage, while the model predicts 13%. Similarly, in the fourth operating period in LaHabra the observed and predicted percentages are 1.8% and 4.5%, respectively. While these errors appear quite large in percentage terms, they actually represent extremely small numbers of trips. As such, they are relatively unimportant in the context of the actual DRT system design questions the model is intended to address.

When one examines the distribution of work and non-work trips separately, the agreement between the predicted and observed percentages is not as good. For example, the observed and predicted percentages of

Site	Period	Predicted Percentage of Patronage*			Observed Percentage of Patronage*		
		Work (%)	Non-Work (%)	Total (%)	Work (%)	Non-Work (%)	Total (%)
DAVENPORT	5:30 AM - 7:30 AM	25.8	.5	13.0	25	3.8	7.4
	7:30 AM - 9:00 AM	25.8	3.3	14.4	15	11.3	11.9
	9:00 AM - 3:00 PM	0	84.6	42.7	10	65.0	55.5
	3:00 PM - 5:30 PM	48.5	11.7	29.9	50	20.0	25.2
LAHABRA	7:00 AM - 9:00 AM	27.2	17.8	21.4	46.9	2.1	20.0
	9:00 AM - 3:00 PM	15.5	60.1	42.9	21.9	68.8	50.0
	3:00 PM - 6:00 PM	51.5	18.4	31.2	30.0	27.1	28.3
	6:00 PM - 7:00 PM	5.8	3.7	4.5	1.2	2.1	1.8

*totals may not equal 100% due to rounding

Table 4.7 - Percentage of Patronage by Operating Period

non-work trips in the 9:00 AM to 3:00 PM period in Davenport are 65.0% and 84.6%, respectively. It is difficult to assess whether or not this type of error is of major consequence. However, in more general terms there is only one case (the work trip forecast in LaHabra) in which the ranking of the percentage contributions differ in the observed and predicted values. The levels of service (wait time and ride time) by period were unavailable in Davenport, but in LaHabra some data was available. In general, the model tended to predict greater variation in levels of service (over the day) than was reported in LaHabra. For example, actual total travel times vary over the day from 25 to 31.5 minutes, while the predicted times range from 20 minutes in the 9:00 AM to 3:00 PM period, to 35.2 minutes in the 6:00 PM to 7:00 PM period. This is not unexpected, since an error in the demand prediction tends to produce similar errors in the travel time forecasts. If the forecast of total demand in a period is too high, for example, then the average travel time will also be overpredicted if the supply model is reasonably accurate.

4.9 Fixed Route Bus Ridership Forecasts

The use of a synthesized fixed route bus utility function was not successfully validated, in part due to a lack of confidence in the observed ridership values. The predicted fixed route bus volumes were, in most cases, a factor of two or more less than the "observed" daily volumes. For example, in Davenport, estimated daily ridership on the fixed route bus system was between 3,000 and 3,500 passengers per day, with approximately 800 of those trips made in each of the two hour peak periods. In contrast, the predicted total bus volume was only 1,754 passengers, with 782 made in the two-and-a-half hour evening peak period (from 3:00 PM to 5:30 PM).* The predicted ridership for the 7:30 to 9:00 AM period was only 386 passengers.

In LaHabra it was impossible to obtain reasonable data on fixed route bus volumes since transit routes in LaHabra tend to run across the city's boundaries into other jurisdictions. Attempts to infer bus ridership within LaHabra's boundaries produced estimates which were so questionable that no validation was attempted.

In summary, it appears that the model must be recalibrated or that adjustments to the synthesized coefficients to match some base year data must be made when accurate bus ridership forecasts are desired. However, the software is fully equipped to model the fixed route bus situation, and these modified fixed route bus utility functions can readily be entered through an optional set of input parameters.

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*The periods used to validate the DRT service do not match the peak hours for which bus volumes were available. It was deemed more important to maintain consistency with the available DRT data in the validation tests than to match peak hour data for the fixed route bus system.

4.10 Summary of Validation Results

The model appears to be accurate in predicting total daily ridership with an error of between 25 and 35 percent. However, given this general range of expected errors in total daily ridership forecasts, a number of qualifications must be made:

1) The work trip DRT patronage model is not accurate in situations such as the Davenport, Iowa, system where fares are much higher than those used in estimating the work trip model. Predicted work trips in this situation were unacceptably high.

2) The more detailed the level of forecast examined, the greater the expected percentage error. Thus, the forecasts by period have much higher errors than the total daily ridership forecasts. The validation results indicate, however, that the actual distribution of DRT ridership by period (expressed as the percentage of daily DRT ridership within each period) is well represented by the model forecasts.

3) The average level of service forecasts (wait time and ride time) are as accurate as the total daily ridership figures. However, in comparison with the LaHabra data by period, the forecasted level of service varies more than the observed values.

4) Attempts to use a "synthesized" fixed route bus utility function were unsuccessful. Users of the model will have to either calibrate a separate set of fixed route transit coefficients or adjust the coefficients to match some existing base year data. This latter alternative might be accomplished by altering the constant term (the so-called "pure alternative" effect) in the fixed route utility.*

While (subject to the above reservations) the validation results for all day forecasts are relatively encouraging, only two sites were analyzed. These two cities differ significantly from those used to calibrate the models, but still only constitute a small percentage of existing DRT

*Readers interested in this method may wish to review a paper by Atherton and Ben-Akiva (1976) which discusses the question of transferring disaggregate model coefficients from one urban area to another.

systems operating in the U.S. Clearly, more experience with the model is ultimately needed before a definitive statement about the validity of the model can be made. In the course of developing a simplified sketch planning version of the model, we were able to make several additional preliminary comparisons with six different U.S. DRT systems with encourating results. These comparisons are described in the following section.

SECTION 5

SENSITIVITY ANALYSIS AND PRELIMINARY DEVELOPMENT OF A SIMPLIFIED SKETCH PLANNING MODEL

5.1 Objectives

Following the validation of the model system, an additional series of model runs were made using data from a set of hypothetical cities. The results of these runs were then compared with data from DRT systems with characteristics similar to those of some of the input cities. The runs were developed for the following purposes:

1) To provide a further test of the models predictive capability, this time over a wider range of inputs.

2) To determine how DRT ridership can be expected to vary with changes in certain inputs.

3) To test how well these runs can serve as the basis of a preliminary sketch planning tool, enabling the user to obtain a "first cut" approximation of ridership without developing a site specific data file.

5.2 Input to the Runs

Given the wide range of data inputs required by the model, and hence given the large number of possible permutations of system characteristics, it was necessary to try to isolate a few major determinants of ridership. Ranges for these factors then served as the input parameters and were varied from run to run. The variables selected as key determinants of demand were:

1) Vehicle density (vehicles per square mile)

2) Population served

3) DRT fare.

Obviously, other factors will influence DRT ridership (e.g., the number of persons who do not own an automobile), but the selected variables used are the primary factors affecting DRT patronage. The set of input values for those variables used in the 18 experiments are shown in Table 5.1 and were chosen to include most existing DRT systems.

Simple zone systems were established for these runs. Five zones were used for the 6 square mile areas, as shown in Figure 5.1, while a 9 zone system was used for the 20 square mile areas, as shown in Figure 5.2.

The levels of zonal population, zonal wholesale and retail employment, and zone to zone work trips used as inputs to these runs are shown in Tables 5.2 - 5.7. These breakdowns were developed somewhat arbitrarily, based on intuitive notions on how such factors would be distributed in an "average" situation.* Clearly the actual values in a given site would depend on the specific characteristics of the site. Thus, a service area of 25,000 persons which is part of a larger urban area is likely to have a very different work trip distribution than a service area comprising an entire city with a population of 25,000. The data was intended to be more representative of the latter situation, since most many-to-many DRT systems implemented in recent years have been implemented

*Note that the number of work trips in each community totals approximately 25% of the population. This figure can be expected to vary from service area to service area. The 25% figure is very close, however, to the figure estimated for the Davenport and La Habra service areas.

Table 5.1 - Major Inputs

Run	Area(Mi^2)	Population	Number of Vehicles	Fare ($)	Vehicle Density (veh/s.m.)
1	6	10,000	3	$.50	.5
2	6	10,000	6	.50	1.0
3	6	10,000	12	.50	2.0
4	6	25,000	3	.50	.5
5	6	25,000	6	.50	1.0
6	6	25,000	12	.50	2.0
7	20	50,000	10	.50	.5
8	20	50,000	20	.50	1.0
9	20	75,000	10	.50	.5
10	20	75,000	20	.50	1.0
11	6	25,000	6	.25	1.0
12	6	25,000	6	1.00	1.0
13	20	50,000	20	.25	1.0
14	20	50,000	20	1.00	1.0
15	20	75,000	20	.25	1.0
16	20	75,000	20	1.00	1.0
17	20	50,000	40	.50	2.0
18	20	75,000	40	.50	2.0

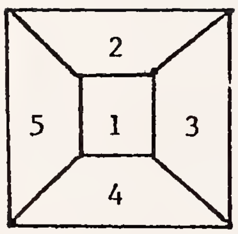


Figure 5.1

Zone System
6 square mi area

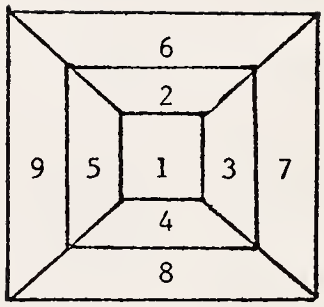


Figure 5.2

Zone System
9 square mi area

Table 5.2 - Zonal Population and Wholesale/Retail

Employment 5-Zone System

Zone	Population 10,000		Population 25,000	
	Population	Retail & Wholesale Employment	Population	Retail & Wholesale Employment
1	1000	800	2000	2550
2	2250	350	6500	550
3	3000	250	5000	750
4	2000	250	6800	350
5	1750	350	4700	800

Table 5.3 - Zonal Population and Wholesale/Retail

Employment 9-Zone System

Zone	Population 50,000		Population 75,000	
	Population	Retail & Wholesale Employment	Population	Retail & Wholesale Employment
1	3000	2700	4500	4300
2	8000	750	6500	1600
3	6000	1450	14500	2000
4	9500	1000	12000	1500
5	8000	1100	12000	1750
6	4500	800	10000	850
7	4000	850	6000	1000
8	2400	650	6000	1200
9	4600	700	3500	800

Table 5.4 - Work Trip Matrix for Population 10,000

Origin Zone

From \ To (Destination Zone)	1	2	3	4	5
1	360	25	5	15	25
2	200	110	75	75	90
3	260	110	110	70	80
4	160	85	65	70	80
5	140	55	55	50	100

Table 5.5 - Work Trip Matrix for Population 25,000

Origin Zone

From \ To (Destination Zone)	1	2	3	4	5
1	500	20	30	20	35
2	900	350	150	130	180
3	600	200	300	150	250
4	700	300	300	100	300
5	500	150	160	80	300

Table 5.6 - Work Trip Matrix for Population 50,000

From \ To	1	2	3	4	5	6	7	8	9
1	250	40	175	125	80	20	20	20	20
2	550	385	350	250	250	100	100	85	85
3	350	125	500	175	175	70	70	70	50
4	600	200	425	500	250	125	125	100	100
5	600	175	350	200	500	100	100	80	100
6	350	50	125	80	85	85	60	50	60
7	300	40	125	80	85	60	100	60	65
8	175	20	75	40	40	40	40	50	35
9	200	70	125	80	85	100	100	40	85

Table 5.7 - Work Trip Matrix for Population 75,000

From \ To	1	2	3	4	5	6	7	8	9
1	350	85	175	65	125	20	40	40	20
2	475	425	185	125	125	70	80	85	80
3	1025	625	850	350	350	125	175	210	210
4	850	550	385	600	350	100	140	185	185
5	850	550	385	300	640	100	150	185	185
6	800	300	350	210	250	200	110	125	175
7	470	125	125	85	85	40	85	60	60
8	470	125	125	85	85	40	40	110	85
9	340	40	40	40	40	20	20	40	85

in smaller cities. However, the runs were conducted in part to determine the sensitivity of the model to input parameters such as the work trip matrix, and to determine how well the model performs using general, rather than site specific, inputs.

Other inputs to all runs included:

auto ownership distribution - 8% 0 cars; 48% 1 car; 36% 2 cars; 8% 3 or more cars

household size distribution (persons over the age of 16) - 15% 1; 55% 2; 19% 3; 8% 4; 3% 5 or more

percent over the age of 65 assumed equal to 12%

persons over the age of 16 and not working - set at 28% of the total population

work trip time of day distribution - same one as was used for the validation runs

model constants - set to the default value.

All runs were made under the assumption that no transit service exists in the community. Three time periods: 6 AM - 9 AM (peak); 9 AM - 3 PM (off-peak); 3 PM - 6 PM (peak) were used in all cases; one thousand entities were simulated in the non-work model. Unlike the validation runs, where an attempt was made to estimate the range around the final equilibrium value based on the results of each iteration, for these runs the last (fifth) iteration was selected in each case as the final value. Based on the results of the validation described in the previous section, this approach probably introduces an additional error of about 10% in the model results.

5.3 Results of the Eighteen Runs

The key results of the eighteen runs are summarized in Table 5.8. The implications of these results for population, fare and vehicle density changes are discussed below.

Impacts of Population

Clearly a key determinant of ridership is service area population. Table 5.9 summarizes the impact on ridership of increased population, for a constant area size, vehicle density, and system fare. These results, shown graphically in Figure 5.3, indicate that ridership will not increase linearly with population, since supply will serve to somewhat constrain DRT patronage. The most extreme example of this appears to be in the change from a 50,000 to 75,000 population with a vehicle density of .5, where only a 5% increase in ridership is generated because of tightly constrained supply. The number of new trips per capita (of new persons eligible for service) will increase with increasing vehicle density.

Impact of Fare Changes

Because the model is an equilibrium model, it is not a straightforward matter to determine the elasticity of demand with respect to fare, i.e., to identify the impact of fare changes alone on demand since changes in fare will cause changes in both demand and supply which in turn will affect demand further. However, the model produces what might be referred to as an equilibrium elasticity (as opposed to a pure elasticity) which is very important in planning DRT fare levels. The results of fare changes which are shown in Table 5.10 and Figure 5.4 lead to the following observations:

Table 5.8 - Results of the Additional Runs

Run #	Average Wait Time	Average Ride Time	Ridership Work	Ridership Non-Work	Ridership Total	Productivity
1	17.8	7.4	122	92	214	5.9
2	12.8	6.4	276	177	453	6.3
3	8.4	5.5	607	273	880	6.1
4	22.9	8.0	157	123	280	7.8
5	17.4	7.1	366	248	614	8.5
6	12.2	6.2	850	457	1307	9.1
7	26.3	14.4	453	333	788	6.6
8	18.4	11.8	1078	549	1627	6.8
9	29.0	15.7	519	307	826	6.9
10	20.6	12.3	1295	897	2192	9.1
11	19.6	7.3	343	331	674	9.4
12	15.2	6.8	371	147	518	7.2
13	20.6	11.5	1039	843	1882	7.8
14	15.6	11.0	1007	365	1372	5.7
15	23.7	12.3	1190	1174	2364	9.8
16	18.6	12.0	1149	444	1593	6.6
17	11.4	9.8	2386	1167	3553	7.4
18	13.5	10.9	2753	1621	4374	9.1

Table 5.9 - Impact of Population on Ridership

Base Population	Vehicle Density (No. of Vehicles)	Change in Population	% Change in Population	Change in Ridership	$\frac{\Delta \text{ Ridership}}{\Delta \text{ Population}}$	% Change in Ridership
10,000	.5 (3)	15,000	150%	66	.004	30.8%
10,000	1.0 (6)	15,000	150%	161	.011	35.5%
10,000	2.0 (12)	15,000	150%	427	.028	48.5%
50,000	.5 (10)	25,000	50%	38	.002	4.8%
50,000	1.0 (20)	25,000	50%	565	.023	34.7%
50,000	2.0 (40)	25,000	50%	821	.033	23.1%

Figure 5.3 - Ridership vs. Population

(Vehicle Density, Vehicle Fleet Size, Fare Constant)

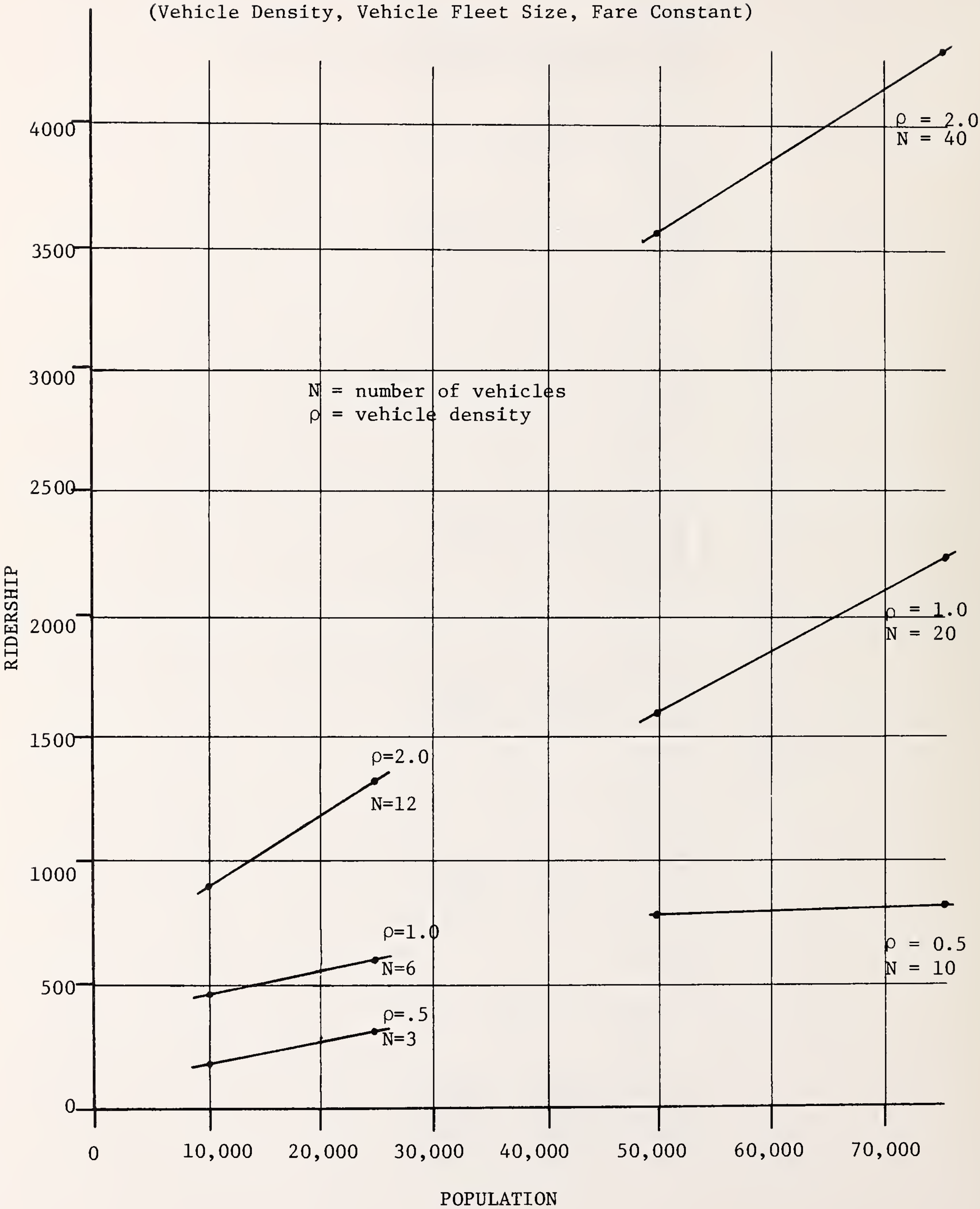
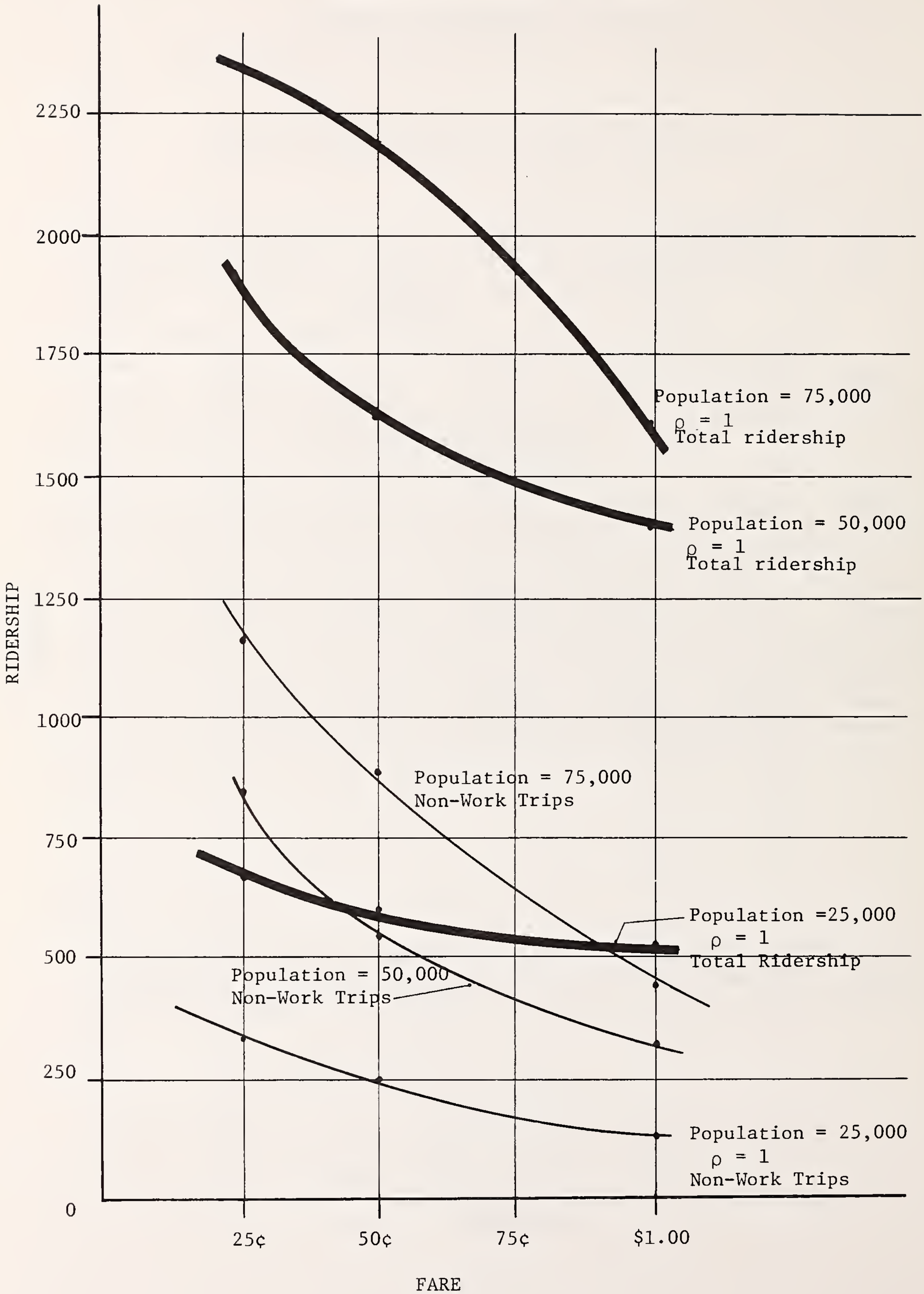


Table 5.10 - Impact of Fare Change on Ridership

Base Fare	Population	% Change in Fare	% Change in Work Trips	% Change in Non-Work	Implied* Elasticity of Non-Work Trips	% Change in Total Trips	Implied* Elasticity of Total Trips
.25	25,000	+100%	+ 6.7%	-25.1%	-.251	- 9.8%	-.098
.25	50,000	+100%	+ 3.8%	-34.9%	-.349	-13.5%	-.135
.25	75,000	+100%	+ 8.8%	-23.6%	-.236	- 7.8%	-.078
.50	25,000	+100%	+ 1.4%	-40.7%	-.407	-15.6%	-.156
.50	50,000	+100%	- 6.6%	-33.5%	-.335	-13.5%	-.135
.50	75,000	+100%	-11.3%	-50.5%	-.505	-27.3%	-.273
.50	25,000	-50%	- 6.7%	+33.5%	-.670	+ 9.7%	-.194
.50	50,000	-50%	- 3.6%	+53.5%	-1.070	+15.7%	-.314
.50	75,000	-50%	- 8.1%	+30.8%	-.616	+ 7.8%	-.156
1.00	25,000	-50%	- 1.3%	+68.7%	-1.374	+18.5%	-.370
1.00	50,000	-50%	+ 7.1%	+50.4%	-1.080	+18.6%	-.372
1.00	75,000	-50%	+12.7%	+102.0%	-2.040	+37.6%	-.752

*These are not true elasticities; rather, they represent the percentage change in patronage resulting from a one percent increase in DRT fares, given a constant supply, but not necessarily constant service quality.

Figure 5.4 - Ridership vs. Fare



1) In most cases the demand for non-work trips is so much more sensitive to fare than the demand for work trips, that a decrease in non-work trips (resulting from an increase in fares) actually causes an increase in work trips. This again points out the dynamics of the work trip/non-work trip interaction in the model. This result is reasonable, since non-work trips have been shown to have a higher fare elasticity than work trips in previous studies.

2) Demand (for non-work trips) is more sensitive to fare changes at higher fare levels. This has also been demonstrated in previous research on other urban transit services.

3) The resulting implied non-work trip fare elasticities range from -.24 to -.50 for fare increases. These values bracket the value of -.33, (the so called Simpson-Curtin value) commonly used as a typical transit fare elasticity. Previous research has suggested a somewhat higher fare elasticity for DRT service, at least when fares are decreased. Table 5.10 also suggests significantly higher elasticities for fare reductions.

Impact of Vehicle Density

The impact of vehicle density on demand is shown in Table 5.11 and Figure 5.5. These results suggest that, at the demand levels being considered, the supply actively constrains demand; a doubling in supply will result in a virtual doubling of demand. This is somewhat counter-intuitive and, indeed, there is no evidence available to indicate that it will occur. On the other hand, there is also little in the way of hard evidence to refute it, since few DRT systems have experienced a doubling in vehicle fleet size with no other changes. Furthermore, few DRT systems operate at vehicle densities of 2, with the corresponding high service levels. Thus, it is difficult to conclude from the runs performed to date how well the model predicts the impact of vehicle density changes.

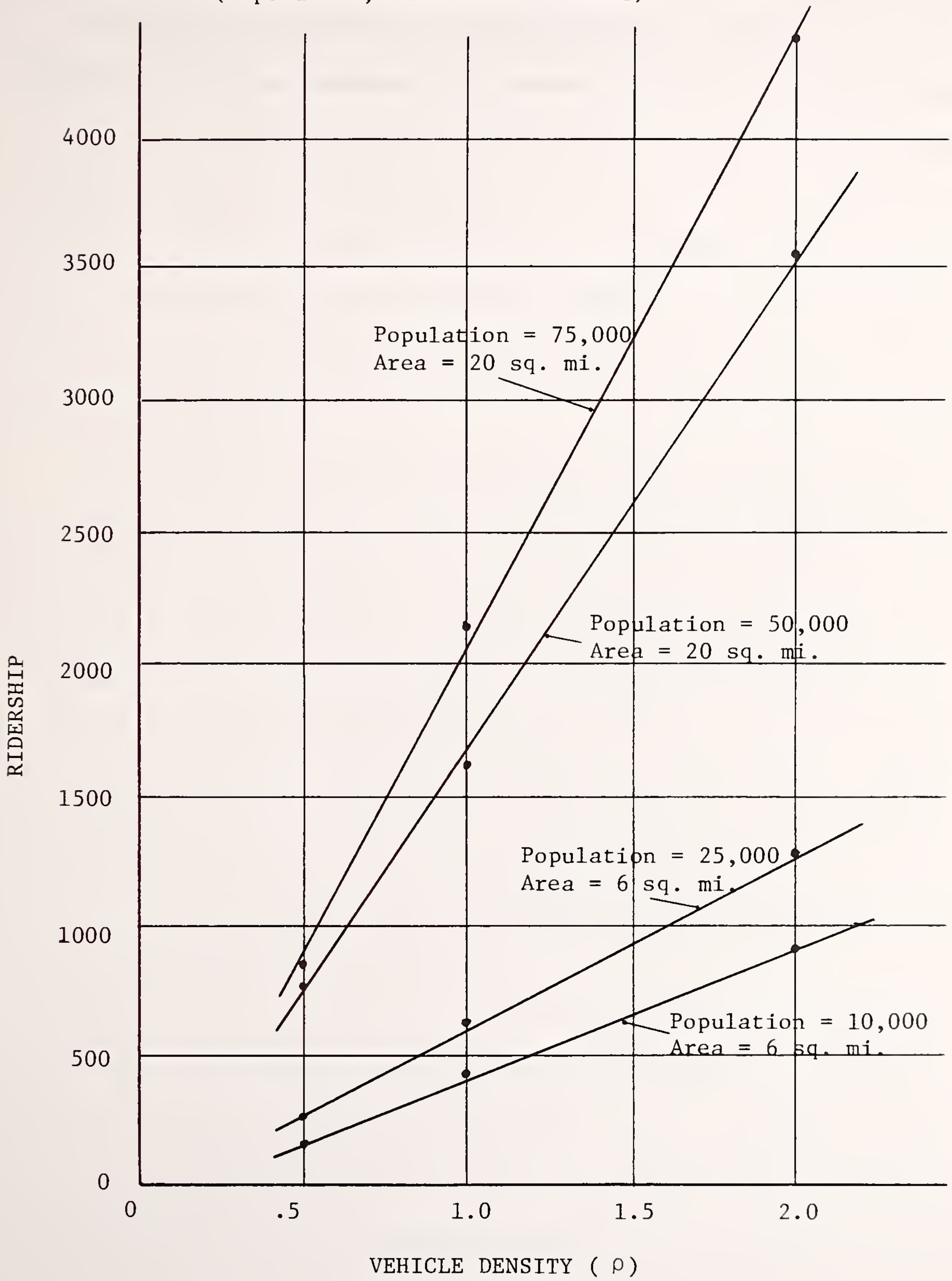
It is important to note that the experiments with vehicle density

Table 5.11 - Impact of Vehicle Density on Demand

Population	Vehicle Density	Number of Vehicles	Total Ridership
10,000	.5	3	214
10,000	1.0	6	453
10,000	2.0	12	880
25,000	.5	3	280
25,000	1.0	6	614
25,000	2.0	12	1307
50,000	.5	10	788
50,000	1.0	20	1627
50,000	2.0	40	3553
75,000	.5	10	826
75,000	1.0	20	2192
75,000	2.0	40	4374

Figure 5.5 - Ridership vs. Vehicle Density

(Population, Area Held Constant)



of 2 are significantly beyond the range of calibration and validation. Thus, it is difficult to assess the model's performance under these conditions. It is strongly suggested that the model should only be used with extreme caution, if at all, at such vehicle densities.

5.4 Utilization of Model Results

In this subsection a procedure is developed to predict the patronage of a DRT system which does not have characteristics exactly like those of any of these hypothetical systems. This procedure is based on a series of interpolations, using the tables and curves presented in the previous subsection. The procedure has been tested by comparing the forecasts derived using this procedure with actual ridership data for six DRT systems. The results of these tests and their implications are discussed later in this section.

The suggested procedure starts with selecting the set of results for the hypothetical system which most closely resembles the system for which forecasts are to be made. Of course, in some cases it may be difficult to determine which is the closest case; however, in those cases the starting point should not prove critical.* One by one. adjustments are made to the results to account for differences between the actual and hypothetical system characteristics. The step-by-step procedure is intended to provide a first cut approximation of system patronage. The suggested sequence of steps is presented below.

1. Adjustments for Hours of Service

One clear difference that can exist between the hypothetical systems and the one under consideration is service hours. The hypothetical systems were analyzed for the period 6 A.M. to 6 P.M. This approximates the service hours of a majority of DRT systems; however,

*This issue will be discussed further later in this section.

some systems operate longer or shorter hours. It is not possible to use the results to estimate ridership outside these hours, but it is possible to estimate ridership for systems with fewer hours of service.

If a DRT system operates with fewer hours, it is possible to adjust for starting times which are an hour or two later than 6 AM and/or ending times an hour or two earlier than 6 PM. Based on the results of the model presented earlier, almost all trips during these two periods will be work trips; thus, it is these trips which must be considered. Recall that the time of day distribution used for all runs was shown in Figure 4.3. If one assumes that the time of day distribution for DRT work trips is identical to the overall work trip distribution, one can simply scale down predicted trips based on the percentage of trips made during the service hours. For example, consider that 10% of all work trips beginning at home are made before 6 AM. Thus, the hypothetical systems can draw from a market of work trips which includes 90% of all trips made. (Note that since 10% of the workers cannot receive DRT service in the morning, 10% are excluded from the afternoon market of workers even if the service were to continue past 7 PM in the evening.) Now consider a system which starts operation at 7 AM. According to Figure 4.3, only 50% of all work trips are made after this hour. This system could draw from only 50% of the total market, or 5/9 of the market served by the hypothetical system. If the hypothetical system closest to the one being analyzed served 100 work trips, the latter system would be expected to serve 5/9 x 100 or 55 trips. Note that the hypothetical system is assumed to have served 50 trips during the morning and 50 during the afternoon; the new system therefore serves 28 during the morning and 28 during the afternoon.

Table 5.12 uses the time of day work trip distribution of Table 4.3 to develop factors by which the total number of work trips should be adjusted for a shorter service day.

The equilibrium nature of the model implies that a reduced number of work trips during the afternoon will result in an increased number of non-work trips for the same size system. Thus, if our hypothetical system were to have 28 work trips during the afternoon period, rather than 50, one would expect that some of these twenty-two trips that have been eliminated (both morning and evening) because of a late starting time will be replaced by non-work trips. Obviously, this will occur only in the afternoon period. As a first approximation, the procedure suggested here is based on the assumption that 100% of all work trips eliminated during the afternoon period would be replaced by non-work trips, if the system were in operation throughout the evening peak. If, however, service on the DRT system being modelled ends before 6 PM, then some of these new non-work trips will also not be made by DRT. Suppose that in the above example (in which 22 work trips lost in the afternoon peak are assumed to be replaced by an equal number of non-work trips), the DRT system ended service at 5:15 PM rather than 6:00 PM. If one considers 4:00 to 6:00 PM to be the afternoon peak, and assumes that the non-work trips in that time are uniformly distributed, then service is available for only 75 minutes out of 120 minutes in the peak. This implies that only 75/120, or 62.5% of the 22 possible non-work trips will actually be made on DRT. That is, work trips will decline by 22 and non-work trips will increase by 14.

Table 5.12 - Factoring of Work Trips Based on Service Hours

Starting with X work trips:

If Service Starts at:	Reduce A.M. and* P.M. Totals by:	If Service ends at:	Reduce A.M. and P.M. Totals by:
6:00 A.M.	0	4:00 P.M.	.75 $(\frac{x}{2})$
6:30	.223 $(\frac{x}{2})$	4:30	.562 $(\frac{x}{2})$
7:00	.445 $(\frac{x}{2})$	5:00	.375 $(\frac{x}{2})$
7:30	.611 $(\frac{x}{2})$	5:30	.187 $(\frac{x}{2})$
8:00	.778 $(\frac{x}{2})$	6:00	0
8:30	.833 $(\frac{x}{2})$		

* Non-work trips should be increased by same amount during P.M. period if service is available to 6 P.M. These non-work trips should be considered evenly distributed between 4 P.M. and 6 P.M. If the service ends earlier, the total non-work trips added should be factored down proportionately.

To summarize the proposed procedure, the following steps must be taken if the system in question begins after 6 AM or ends before 6 PM:

a) reduce work trips: Refer to Table 5.12 to determine the factor by which work trips are to be reduced. Remember that either a late start or an early closing will affect work trips in both the morning and evening. If the system both starts late and ends early, then two separate factors must be applied.

b) adjust non-work trips: A reduction in evening work trips due to a late start in the morning will result in an increase in evening non-work trips. It is assumed that evening non-work trips will replace lost evening work trips on a one-to-one basis if the system operates throughout the evening peak. If the system is closed during part of the 4 PM to 6 PM period, then the addition of new non-work trips is reduced by the proportion of the 4 PM to 6 PM period for which the system is not operating. Note that a late start, for example, does not affect the total number of evening trips (work plus non-work) unless the system also closes early.

2. Vehicle Density and Vehicle Fleet Size

Vehicle density clearly plays some role in determining ridership. Experiments with the supply model have indicated that travel time is a function of vehicle density at a given productivity level. Thus a system with eight vehicles operating in four square miles will exhibit approximately the same travel time as a system with 16 vehicles in eight square miles, if the productivity and trip lengths are the same in both systems. However, it is difficult to translate this fact into a relationship between productivity and ridership. The results for the hypothetical systems are somewhat limited in this regard, since a doubling of vehicle density in most cases also involved a doubling of vehicle fleet size, making it difficult to distinguish between the impacts of the two. Intuitively, it would seem that higher vehicle fleet densities should allow improved service levels, and hence serve to increase ridership.

Tables 5.8 and 5.11 allow some preliminary relationships to be developed. In the pairs of runs in which vehicle density was doubled, the impacts on productivity varied somewhat with the average change over all runs being 9.1%. Until additional data are available, it is suggested that the average of these impacts be used. This implies that for a 100% increase in vehicle density, one would expect a 9.1% increase in productivity. To compute the total ridership one would then multiply the productivity by the total number of vehicles and the number of service hours. As part of this process, the ratio of work to non-work trips resulting after Step 1 would remain the same.

3. Population

The impact of population on ridership was shown in Table 5.9. The user should select the row in Table 5.9 which corresponds closest, in terms of factors such as population and vehicle density, to the system being considered. The adjusted ridership should then be estimated by multiplying the calculated ridership from Step 2 by the following factor:

$$1 + \left(\frac{\text{True Population} - \text{Population of Hypothetical Case}}{\text{Population of Hypothetical Case}}\right) \cdot k$$

where k is the ratio $\frac{\text{\% change in ridership}}{\text{\% change in population}}$ taken from Table 5.9.

4. Fare

Finally, ridership would be adjusted to account for fare difference using the elasticities shown in Table 5.10. Again, as a first order approximation, a simplification is suggested. Since non-work trips have been shown to be much more sensitive to fare than work trips, and since the impact of fare on work trips is dependent upon the dynamics of the model, it is suggested that fare be assumed to impact non-work trips only. The user would find the base population and base fare closest to the system under consideration, and apply the implied elasticity of non-work trips to fare to estimate the adjusted ridership.

To summarize the steps in the sketch planning procedure:

Step 1. Select most similar system: Select the set of results in Table 5.8 for the system most closely resembling (in terms of area size, vehicle fleet size, vehicle fleet density, population, and fare) the system under consideration. Initial values for work and non-work ridership are taken directly from Table 5.8. Denote these initial values as follows:

$$\text{work ridership} = \text{wrid}_1$$

$$\text{non-work ridership} = \text{nrid}_1$$

Step 2. Adjust for Differences in Operating Periods: If the system operates for a shorter period than 6 AM to 6 PM, use Table 5.12 to scale down the number of work trips. If service starts later than 6 AM, the total number of non-work trips will be increased by the number shown in Table 5.12. If service ends before 6:00 PM, this number is adjusted by the fraction of the 4:00 PM to 6:00 PM period during which DRT service is available. Denote the resulting values as wrid_2 and nrid_2 for work and non-work trips respectively.

Step 3. Adjust for Differences in Vehicle Density: If the vehicle density of the system under consideration is X% higher (lower) than the vehicle density of the hypothetical system, increase (decrease) the productivity by .091 (X%). The base productivity to use for this step is the productivity obtained after Step 2 is completed (based on the number of vehicles in the test run). This should be very close to the productivity in the test run.

Step 4. Compute Total System Ridership: Total ridership is now obtained by multiplying productivity by vehicle fleet size by service hours. The ratio of work to non-work trips should remain the same as it was after Step 2, and both ridership figures should be estimated. Denote the resulting values as wrid_4 and nrid_4 for work and non-work trips respectively.

Step 5. Adjust for Differences in Population: If the population of the system is different from that of the hypothetical system being used, ridership should be changed by:

$$\text{wrid}_5 = \left(1 + \frac{\text{Pops} - \text{Poph}}{\text{Poph}} \cdot (k) \right) \text{wrid}_4$$

$$\text{nrid}_5 = \left(1 + \frac{\text{Pops} - \text{Poph}}{\text{Poph}} \cdot (k) \right) \text{nrid}_4$$

Where:

$wrid_5$ = work ridership after Step 5
$nrid_5$ = non-work ridership after Step 5
Pops = Population of the service area
Poph = Population of the hypothetical service area
k = Ratio of ridership to population increase from the most appropriate row in Table 5.9

Step 6. Adjust for Differences in Fare: If the fare of the system under consideration is different than the fare of the hypothetical system, non-work ridership only should be adjusted by using the formula:

$$nrid_6 = \left(1 + \frac{FareS - FareH}{FareH} \cdot (Elas)\right) nrid_5$$

Where:

$nrid_6$ = Non-work ridership after Step 6
FareS = System fare
FareH = Hypothetical system fare
Elas = The most appropriate implied elasticity of non-work ridership with respect to fare from Table 5.10. (Base fare, population, and direction of fare difference are the factors that determine which elasticity to use)
$wrid_6$ = Work ridership after Step 6 = $wrid_5$

5.5 Application of Suggested Procedure

The procedure suggested in the previous subsection has been used to forecast ridership in six existing DRT systems. To illustrate its use, a step by step description of its application is provided for each example.

The characteristics of the systems considered are compared with the characteristics of the hypothetical systems most resembling these systems in Table 5.13.* The first two lines for each row contain the information for the city and the run having the characteristics closest to that city. The third line contains the resulting revised ridership predictions after the application of the suggested procedure. The arrow in each case indicates the comparison that should be made between each city's observed ridership and the adjusted run forecast.

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*Data on these systems were obtained primarily from Ewing, R.H. and N.H.M. Wilson, "Innovations in Demand-Responsive Transportation," M.I.T. Research Report, October, 1976. Additional data on Rochester was obtained from the Rochester SMD demonstration staff at M.I.T.; additional data on El Cajon and Merced were obtained from the UMTA Small City Transit Reports on those cities.

Table 5.13 - Comparison of Results with Actual Systems

Location	Area (mi^2)	Popu-lation	# of Veh.	Service Hours	Base Fare	Daily Ridership					Produc-tivity	WT	RT
						Work	School	Other	Total w/o School	Total w/ School			
Merced, CA	10	23,000	3.5	7:15AM-5:15PM	.25	40	130	170	210	340	9.7	25	16
Run 4	6	25,000	3	6AM-6PM	.50	157	-	123	280	280	7.8	23	8
4 w/adjustments						34	-	220	254	254	7.25		
Ludington, MI	3.2	9,000	2.6	6AM-6PM	.25	65	*	175	240	240	7.8	10	10
Run 2	6	10,000	6	6AM-6PM	.50	276	-	177	453	453	6.3	13	6
2 w/adjustments						114	-	100	214	214	6.8		
El Cajon, CA	12	52,000	9	24 hrs.	.50	5	*	555	560	560	5.2	15	12
Run 7	20	50,000	10	6AM-6PM	.50	453	-	333	786	786	6.6	26	14
7 w/adjustments						428	-	314	710	742	6.9	--	--
Niles, MI	5.2	13,000	3.7	6AM-6PM	.25	80	*	180	260	260	5.9	30	15
Run 1	6	10,000	3	6AM-6PM	.50	122	-	92	214	214	5.9	18	7
1 w/adjustments						163	-	166	317	329	7.1		
Oneonta, NY	12.7	16,000	3.4	6AM-6PM	.25	95	40	215	310	350	8.6	20	18
Run 1	6	10,000	3	6AM-6PM	.50	122	-	92	214	214	5.9	18	7
1 w/adjustments						162	-	163	289	325	7.1		
Rochester, NY	15	70,000	4.4	8AM-6PM	1.00	40	*	180	220	220	4.2	25	14
Run 9	20	75,000	10	6AM-6PM	.50	519	-	307	826	826	6.9	29	16
9 w/adjustments						49	-	133	182	182	3.5		

* signifies no information available on number of school trips included in total

Merced, California

Step 1. The Merced system is most similar to the system represented by Run Number 4. Starting ridership values therefore are:

Work ridership = $wrid_1$ = 157 Non-work ridership = $nrid_1$ = 123

Step 2. The Merced system starts at 7:15 AM and ends at 5:15 PM. Referring to Table 5.12, the number of work trips (AM and PM) should be reduced by .528 x 157 = 82 because of the late AM start (.528 is midway between the factors which would be used for 7:00 AM and 7:30 AM starts), and by .281 x 157 = 44 because of the early end of service. Afternoon non-work travel would be increased by 82/2, or 41 trips, if service extended to 6 PM. Because it extends until 5:15 PM only (i.e. service is available for only 75 minutes out of the 120 minute afternoon peak period), non-work ridership is increased by .615 x 41, or 26. Thus:

$wrid_2$ = 31 trips $nrid_2$ = 149 trips

Step 3. The vehicle density in Merced is .35 vs. the vehicle density in run 4 of .5. For the 30% decrease in vehicle density, productivity is decreased by 30 x .091 or 2.7%. The productivity after Step 2 is given by

$$\frac{31 \text{ work trips} + 149 \text{ non-work trips}}{10 \text{ hours X } 3 \text{ vehicles}} = 6 \text{ trips/vehicle hour}$$

Thus the productivity after Step 3 is 5.8 trips/vehicle hour.

Step 4. Total ridership = 5.8 trips/vehicle hour X 3.5 vehicles X 10 hours = 203 trips.

Retaining the same ratio of work to non-work ridership:

$wrid_4$ = 35 work trips $nrid_4$ = 168 non-work trips

Step 5. The population of Merced is slightly lower than that of run 4. Turning to Table 5.9, the most appropriate value of ratio k is .205, for a system with three vehicles and a population of 10,000. Applying the formula:

$$wrid_5 = (1 + \frac{-2000}{25,000} (.205))35 = 34 \text{ work trips}$$

$$wrid_5 = (1 + \frac{-2000}{25,000} (.205) 168) = 165 \text{ non-work trips}$$

Step 6. The Merced fare is 25¢, rather than the 50¢ fare used in run 4. Based on Table 5.10, the most appropriate implied elasticity (base fare of 50¢, population of 25,000) is -.670. Using the formula:

$$wrid_6 = wrid_5 = 34 \text{ work trips}$$

$$nrid_6 = (1 + \frac{-.25}{.50} (-.670)) 165 = 220 \text{ non-work trips}$$

Total Ridership = 254 trips

Ludington, Michigan

Step 1. The Ludington, Michigan system is most similar to the system represented by run 2.

$wrid_1$ = 276 work trips $\qquad$ $nrid_1$ = 177 non-work trips

Step 2. Service hours are identical to the base run, and no adjustments are therefore necessary.

$wrid_2$ = 276 work trips $\qquad$ $nrid_2$ = 177 non-work trips

Step 3. Vehicle density is .8125 rather than 1.0 in the base case, so

Revised productivity = (1 - .017) 6.3 = 6.2 trips/vehicle hour

Step 4. Vehicle fleet size is 2.6, so

Total ridership = 2.6 x 12 x 6.2 = 193 trips

$wrid_4$ = 117 work trips $\qquad$ $nrid_4$ = 76 non-work trips

Step 5. Population is 10% lower. A value of k of .236 applies in this case (see Table 5.9 for vehicle density of 1 and a population of 10,000)

$$wrid_5 = \left(1 + \frac{-1000}{10{,}000}(.236)\right) 117 = 114 \text{ work trips}$$

$$wrid_5 = \left(1 + \frac{-1000}{10{,}000}(.205)\right) 76 = 74 \text{ non-work trips}$$

Step 6. The fare is 25¢ rather than 50¢ for Run 2. Elasticity of -.67 applies again (see Table 5.10).

$wrid_6$ = 114 work trips

$$nrid_6 = \left(1 + \frac{-.25}{.5}(-.67)\right) 74 = 100 \text{ non-work trips}$$

Total Ridership = 214 trips

El Cajon, California

Step 1. The El Cajon system is most similar to the system represented by Run 7.

$wrid_1$ = 453 work trips $nrid_1$ = 333 non-work trips

Step 2. Service is provided all day in El Cajon; the figures presented are for the 6 AM to 6 PM period; thus no adjustments are necessary

$wrid_2$ = 453 work trips $nrid_2$ = 333 non-work trips

Step 3. Vehicle density = .75 in El Cajon vs. .5 in Run 7.

Revised productivity = (1 + (.091)(.5)) 6.55 = 6.85 trips/vehicle hour

Step 4. Vehicle fleet size = 9

Total ridership = 9 X 12 X 6.85 = 739 trips

$wrid_4$ = 426 work trips $nrid_4$ = 313 non-work trips

Step 5. Population is 4% higher. A value of k of .096 applies

$$wrid_5 = \left(1 + \frac{2000}{50{,}000}(.096)\right) 426 = 428 \text{ work trips}$$

$$nrid_5 = \left(1 + \frac{2000}{50{,}000}(.096)\right) 313 = 314 \text{ non-work trips}$$

Step 6. Fare is the same, therefore:

$wrid_6$ = 428 work trips $nrid_6$ = 314 non-work trips

Total ridership = 742 trips

Niles, Michigan

Step 1. The Niles system is most similar to the system represented by Run 1.

$wrid_1$ = 122 work trips $nrid_1$ = 92 non-work trips

Step 2. Service hours are the same; no adjustment necessary

$wrid_2$ = 122 work trips $nrid_2$ = 92 non-work trips

Step 3. Vehicle density is .71 in Niles vs. .5 in Run 1

Revised productivity = (1 + (.42)(.091)) 5.9 = 6.1 trips/vehicle hour

Step 4. Vehicle fleet size = 3.7

Total ridership = 271 trips

$wrid_4$ = 154 work trips $nrid_4$ = 117 non-work trips

Step 5. Population is 30% higher; a value of k of .205 applies.

$wrid_5$ = (1 + (.3)(.205) 154 = 163 work trips

$nrid_5$ = (1 + (.3)(.205) 117 = 124 non-work trips

Step 6. Fare is 25¢ in Niles vs. 50¢ for Run 1. An elasticity of -.67 applies.

$wrid_6$ = 163 work trips

$nrid_6$ = (1 + (-.5) (-.67)) 124 = 166 non-work trips

Total ridership = 329 trips

Oneonta, New York

Step 1. The Oneonta system is most similar to the system represented by Run 1.

$wrid_1$ = 122 work trips $nrid_1$ = 92 non-work trips

Step 2. Service hours are the same. No adjustments necessary.

$wrid_2$ = 122 work trips $nrid_2$ = 92 non-work trips

Step 3. Vehicle density is .268 in Oneonta vs. .5 in Run 1.

Revised productivity = 1 - (.46)(.091) 5.9 = 5.7 trips/vehicle hour

Step 4. Vehicle fleet size = 4.7

Total ridership = 253 trips

$wrid_4$ = 144 work trips $nrid_4$ = 109 non-work trips

Step 5. Population is 60% higher. A value of k of .205 applies.

$wrid_5$ = (1 + (.6)(.205)) 144 = 162 work trips

$nrid_5$ = (1 + (.6)(.205) 109 = 122

Step 6. Fare is 25¢ in Oneonta vs. 50¢ in Run 1. An elasticity of -.67 applies.

$wrid_6$ = 162 work trips $nrid_6$ = 163 non-work trips

Total ridership = 325 trips

Rochester, New York*

Step 1. The Rochester system is most similar to the system represented by Run 9.

$wrid_1$ = 519 work trips $nrid_1$ = 307 non-work trips

Step 2. The Rochester system began providing many-to-many service at 8 AM, continuing to 10 PM. (The figure in the Table 5.13 is the 8 AM to 6 PM ridership.) Referring to Table 5.13, combined AM and PM work trips should be reduced by 403 for the start. Afternoon non-work travel should be increased by 403/2, or 201 trips.

$wrid_2$ = 116 work trips $nrid_2$ = 508 non-work trips

Step 3. The vehicle density in Rochester is .293 vs. .5 in Run 9.

Revised productivity = (1 - (.41)(.091)) 6.24 = 6.0 trips/vehicle hour

Step 4. Vehicle fleet size = 4.4.

Total ridership = 264 trips

$wrid_4$ = 49 work trips $nrid_4$ = 215 non-work trips

Step 5. Population is 6.67% lower in Rochester. A value of k of .096 applies.

$wrid_5$ = (1 - .067 (.096)) 49 = 49 work trips

$nrid_5$ = (1 - (.067)) 215 = 214 non-work trips

Step 6. The average fare in Rochester is 87.54¢ (since additional passengers travelling together pay only 5¢). Based on the results in Table 5.10, the most appropriate elasticity is -.505.

$wrid_6$ = 49 work trips

$nrid_6$ = (1 - (.75)(.505)) 214 = 133 non-work trips

Total ridership = 182 trips

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* The ridership data for Rochester in Table 5.13 was obtained one year after the data used for calibrating the model system. Some parameters of the DRT operation changed during that time period.

5.6 Selection of a Starting Point

One of the more difficult elements of the analysis is selecting the appropriate starting point. Because of the limited number of sample points, it is at time difficult to identify a hypothetical system which is very similar to the system being considered. The following basic guidelines can be offered for selecting the appropriate starting point:

1) Since population is a service area characteristic not under the control of the analyst, and since the impact of population on ridership is not at all intuitive, matching population figures as closely as possible is of highest priority in choosing a base run.

2) The second most important attribute of a DRT system to match with a base run is vehicle density.

3) Service area size and vehicle fleet size of the hypothetical system are more or less given after vehicle density is determined. The only other data item to consider is then fare.

To test the impact of the choice of starting point on the procedure, the Ludington analysis was performed three times using logical starting points. The results of these tests are presented in Table 5.14.

Table 5.14

Results of Ludington Analysis with Different Starting Points

	Area (Square Mi.)	Population	Veh. Fleet	Veh. Density	Fare	Total Ridership
Ludington	3.2	9,000	2.6	.81	.25	240
Run 2 as starting point	6	10,000	6	1.0	.50	214
Run 1 as starting point	6	10,000	3	.5	.50	215
Run 11 as starting point	6	25,000	6	1.0	.25	242

The results indicate that the choice of a starting point does not have a major impact on the results. The spread between the upper and lower bound was only 12% (of the upper bound). While these results for only one city cannot be considered conclusive, they do suggest that one need not be overly concerned about selecting the "best" starting point.

5.7 Evaluation of the Results

An examination of the results in Table 5.13 seems to indicate that the runs reported in this chapter, together with the suggested procedure for manipulating the results of those runs, can be used to predict total DRT ridership fairly accurately. Table 5.15 summarizes the percentage error in total ridership estimation for each of the cities.* These errors, which range from -17.3% to 32.5% for trips excluding school trips, and -25.2% to 32.5% including school trips, with an absolute level range from 4.8% to 32.5%, are well within the bounds established by the validation runs for the entire model system. Furthermore, as was the case with the validation runs, the errors are not consistently positive or negative. This provides further evidence that the model can provide a reasonable forecast of DRT demand. It suggests further that the results and procedures presented in this chapter can be used as the basis of a preliminary sketch planning model, which provides a first cut approximation of total DRT ridership.**

A closer examination of the results, however, seems to confirm a tentative conclusion reached after the validation runs; namely, that the work model is a consistent overpredictor of demand. The overpre-

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* Since, as noted earlier, it is not clear whether predictions should be compared with figures which include school trips, the error has been calculated both including and excluding school trips (wherever data on school trips were available).

**Note that once demand estimates have been made, the supply equations presented in Appendix B can be applied by hand to estimate level of service.

Table 5.15 - Percent Errors in Prediction

Location	Error in Total Trips Excluding School	Errors in Total Trips Including School
Merced	21.0%	-25.2%
Ludington	-10.8%	-10.8%
El Cajon	32.5%	32.5%
Niles	26.5%	26.5%
Oneonta	4.8%	-7.1%
Rochester	-17.3%	-17.3%

diction again appears to be in the range of 2 to 1 for three of the six cities; in one case (El Cajon), however, the prediction for work trips is 428, while actual work trips is 5.* This large difference may be in part understandable when one looks more closely at the El Cajon system. El Cajon is a shared-ride taxi system geared largely to the elderly. As noted in the Davenport case, a taxi system, even if it operates in a shared-ride mode, might not be used for the work trip for psychological reasons not directly considered by the model.

For non-work trips, Table 5.13 indicates that the model seems to be fairly consistently underpredicted, but as discussed in Section 4, this is due in part to the overprediction of work trips.

Given this additional information on the amount of overprediction from the sketch planning runs, one suggested change to the model system would be a further adjustment of the constant of the work trip model to better reflect the data from these additional cities. While there were differences in the validation cities between observed and predicted trips, it was not clear if the model would consistently overpredict work trips or not, primarily because of the school trips component which was not being explicitly modelled. Therefore, no change was recommended at that point in time. However, based on the 18 runs and the comparison with six additional cities, indications are that an adjustment of the work trip constant may be appropriate. To test the sensitivity of work trips to changes in the constant and the resulting effect on non-work

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*In two cases, Merced and Rochester, both of which began DRT service later than 6 AM, the work trip forecasts are exceptionally accurate.

trips, one additional run was carried out using Run 1 as the base. Table 5.16 summarizes the results of an arbitrary decrease in the DRT mode constant from 2.085 to 0.0, predictions for wait time, ride time, ride distance and for work, non-work and total trips are given. As expected, work trips decrease, and in this specific case by 57% (29 trips), while non-work trips increase by 163% (13 trips) and the effect on total trips is an overall decrease of only 27% (16 trips).

While these results are only preliminary, they do serve to indicate a useful direction to explore in making further improvements to the model system. Because of time and budget limitations, however, no further comparison or adjustments were made.

Table 5.16 - The Effect on Work and Non-work

Trips with Varying DRT Constants

					Trips		
	Productivity	Wait Time	Ride Time	Ride Distance	Work	Non-Work	Total Trips
DRT Const = 2.085	7.0	21.1	8.8	1.4	51	8	59
DRT Const = 0.0	4.9	14.5	6.6	1.2	22	21	43

5.8 Conclusions

The results presented in this chapter suggest that the additional model runs, and the sketch planning procedure can be used to provide first level approximations of total DRT ridership. The expected reliability of this approach, based on six examples, seems to be accurate within ±30% of the actual value. This level of accuracy certainly represents an improvement over existing sketch planning tools. However, the results at this time are presented as only a preliminary sketch planning tool. It is felt that there have been too few runs made so far to fully develop the sketch planning procedure. With few data points available, the interpolations that must be made are quite major, and there may be too many equally good (or poor) starting points when applying the procedure. Furthermore, a number of the data points appear to be based on system characteristics beyond the range of most existing systems. More runs would be desirable to reduce the number of interpolations needed, to develop better and easier-to-use graphics, and to obtain a better estimate of the impact of certain factors, such as vehicle density. Users planning to use the model results as a sketch planning tool are cautioned that the sketch planning procedure is in the preliminary stages of development.

If the sketch planning procedure is used, the resulting projections will, in some cases, be sufficient for preliminary estimation and preliminary sizing of systems. In other cases, a planner might use the results of this type of analysis to help decide whether more detailed analysis using the entire model system is warranted. For both cases, the sketch planning tool can eliminate the need to develop the extensive data base required to run the full model system and/or perhaps reduce the number of runs required by the full system in testing alternative designs.

SECTION 6

CONCLUSIONS

6.1 Summary of Study

This report has described the design, development, implementation and validation of a detailed patronage forecasting model for demand responsive transportation (DRT) systems. The model system utilizes disaggregate travel demand models for predicting both work and non-work trips in conjunction with a level of service prediction capability.

Preliminary specifications of the demand models were based on data from Haddonfield, New Jersey and a suburb of Rochester, New York. Because of unsatisfactory results in both cities, the final work trip model was estimated only on Rochester data (because of larger sample size and more reasonable results). The final model was then constrained to incorporate one variable (the cost coefficient) that was insignificant in virtually all estimations, but which was deemed essential for forecasting purposes. The coefficient selected was derived from prior studies of work trip mode choice.

The non-work trip model represents a significant methodological advance over prior models. It explicitly allows for variations over the day in the propensity of people to travel and also includes complex tours; existing models used in practice only represent simple tours, i.e. trips which leave home, visit one location and return home. The non-work model not only represents a traveller's choice of mode, but also the choice of destination. Thus, the model is capable of forecasting how DRT service will alter the pattern of non-work travel in an urban area. The entire set of demand model components and their interrelationships are documented in detail in Appendix A.

The level of service, or supply, model is a set of equations which predict period by period DRT average systemwide wait time and ride time on an origin - destination basis. These equations (described in Appendix B) were estimated using data generated with the MIT simulation model, which in turn was validated using data from the Haddonfield DRT system. While originally intended for use in the overall model system, the service prediction equations can be used as simple, stand alone forecasting models.

Demand and level of service models are solved simultaneously to obtain the equilibrium travel pattern. This solution involves an iterative procedure that attains an approximate equilibrium very close to the true equilibrium. The number of iterations is user-controlled, and experiments indicate that little additional accuracy is gained after four to six iterations. Because the entire model involves a stochastic simulation, using more iterations tends to produce random fluctuations around the true equilibrium that provide little additional information.

The model system has been implemented in a computer software package (documented in Appendix C) and applied in a set of highly simplified prototypical cities representing a wide range of DRT systems. The resulting forecasts serve as a sketch planning tool which can be used by planners who lack the time or resources to use the detailed model system. It requires a simplified description of the area being served, the DRT system design including fleet size, fare, service area size, and service area population.

Validation tests indicate that both the detailed and sketch planning models predict total daily ridership (passengers per day) reasonably well (within approximately 30% of actual ridership levels). The observed errors are much greater when patronage forecasts are disaggregated into work and non-work travel; with the model consistently overpredicting work trips by a factor of two.

Forecasts from the sketch planning model were compared with data from six additional existing DRT systems in the U.S. As in the validation of the detailed, computer-based model system, the total daily patronage forecast was reasonably accurate (again, the error was less than or equal to $\pm$ 30%). However, the percentage of DRT work trips forecast appears to be high (again) by a factor of two, reflecting the same shortcoming of the work trip demand submodel isolated in the earlier validation efforts. A comparison of the non-work model by itself on data that was available for two of these six cities indicated that the non-work sketch planning model showed errors of less than 30% and suggest that it might also be used as a first approximation for off-peak design and evaluation.

6.2 Use of the Results of this Study

The detailed model and the sketch planning version provide planners of potential DRT systems with a method for forecasting demand for alternative systems. Obviously, final planning decisions will also depend on local conditions such as wage rates, other costs, the availability of funds for subsidies which are outside the scope of the model. <u>The model results should be used outside the range over which the model was estimated only with extreme caution. It should be used only to provide a reasonable initial estimate of potential DRT patronage.</u>

The following issues relate to the use, misuse and limitations of the model.

1) The model is based on an assumption of long term equilibrium which is not likely to be valid in the first year of DRT system operation during which time patronage is likely to rise relatively rapidly. In this phase, knowledge of the system is still spreading among the service area population by advertising, news media reports and word of mouth. DRT planners should not expect the ridership that is forecasted to be attained in this early phase.

2) Ridership levels can often be altered by tapping transportation markets which are not explicitly included in the model. For example, many DRT systems offer charter and school service in the off-peak hours to utilize vehicles which would otherwise be idle.

3) Attitudinal studies such as those conducted by Gustafson and Navin (1972) have indicated that DRT patronage may be influenced by many factors which are difficult to quantify. On-board surveys have often indicated that travellers find friendly and courteous drivers and a perception of physical security to be quite important. These effects are included in the model in the sense that user perceptions in Rochester are reflected in the coefficient estimates. Cities with more or less personalized services may be able to produce travel environments which are perceived as considerably better or worse than this case; demand levels will in all likelihood reflect such differences. Users of the model should apply their own judgment of the local potential for better DRT services in using the model's forecasts.

4) The models have a limited range of validity, and are unlikely to

prove useful in service areas which are extremely densely or sparsely populated, too large or small, have a great number of vehicles or otherwise vary in some major way from the calibration site. Attempts to utilize the models in such situations may produce unrealistic forecasts.

5) No model yet developed can be applied in many different geographic areas with consistent success. It is always possible to find cases in which a model "doesn't work", and there is always a non-zero probability that the models will be in error in any situation. For this reason, users of the model are advised to compare forecasts with data on prior bus usage, taxi ridership and DRT patronage levels from cities that are similar to the one being studied as a check on the reasonableness of the forecasts. Differences between the model's forecasts and the other sources should be at least qualitatively explainable in terms of fare differentials, variations in service levels or amenities and other factors.

6) Sensitivity analysis should be included in any application of the models. For example, if a five vehicle fleet is planned, users should consider at a minimum how four and six vehicle fleets would perform. Users may also wish to explore how varying assumptions about the service area population, work trip time of day distribution, the socioeconomic distribution, etc. affect the final patronage forecast.

7) In some cases the DRT service concept used may differ from the pure, many-to-many concept used in the model calibration. Use of both the detailed and sketch planning models in these situations will require simplification of the proposed DRT system (as discussed in Section 3) and some judgment in interpreting the resulting forecasts.

6.3 Future Research

As with virtually all studies which seek to develop an entirely new model, the research described in this report has opened a number of important research areas which have been only briefly considered. Further efforts at improving the usefulness of the model to practicing planners, developing more accurate demand and level of service models, validating the model in other cities, incorporating the capability to forecast bus trips, and improving the computational efficiency of the software all offer potentially high yield.

Specific research areas can be logically grouped into three categories as follows:

1) minor improvements to the usefulness of the existing model system and software package;

2) further validation of the model and making necessary adjustments on an ad hoc basis;

3) estimating new model components and implementing them in the model system.

In the first category, the following improvements in the usefulness of the existing model system and software package are most needed:

1) development of more detailed user documentation including additional examples and more extensive guidelines on data preparation;

2) use of the model by planning agencies to identify which aspects of the model and its associated documentation are least understandable; this would lead to revisions in the model and the documentation as well as a "case study" report for use by other planning agencies;

3) further analysis of the level of service forecasting models as potential "stand alone" aids to DRT system design.

The following additions to model validation are suggested:

1) testing the detailed model on additional DRT sites; for example, a system such as Irondequoit discussed in Section 3 offers a more complex service than either Davenport or LaHabra;

2) sensitivity analysis to determine how errors that may exist in the model affect the patronage and level of service forecasts;

3) further tests of the level of service submodel against data from existing DRT systems.

Finally, the following new model development tasks are suggested:

1) estimation of a fixed route bus mode utility function in both the work and non-work demand models; this may require some new data collection and a restructuring of the travel demand models to reflect interdependency between DRT and fixed route bus modes;

2) improvement of the work trip mode choice model;

3) re-estimation of the demand models to specifically reflect variations in travel behavior across specific socioeconomic groups, or market segments, such as the elderly or poor;

4) estimation of the existing models in another city to assess the transferability of the coefficients;

5) improvements in the level of service models so that the effective vehicle fleet (accounting for breaks due to driver shift changes) could be forecast and alternative dispatching algorithms could be better represented.

6) incorporation of travel time reliability in both the demand and supply submodels.

Each of these research tasks can potentially improve the usefulness and accuracy of the detailed model system. However, further development and testing of the sketch planning procedures (including improvements suggested in Section 5 to more realistically reflect work trip usage of DRT) would be of greatest value to most planning professionals, particularly those in smaller cities. We believe that this last research area should receive the highest priority, since it will be both relatively inexpensive and of major importance to the local planning community.

APPENDIX A

DEMAND MODEL: TECHNICAL DOCUMENTATION

A.1 Introduction

In the main body of this report, a brief, non-technical overview of both the work and non-work trip demand model is presented. This appendix is a detailed description of these submodels, and provides the interested user with a more substantial description of the basis for the demand forecasts produced by the model.

The next subsection is a brief description of choice theory, the general methodology used in the demand modelling effort; readers familiar with this subject may wish to skip this section. Subsection A.3 is a description of the data used for model calibration and a discussion of how choice-based samples were utilized to estimate the models. The following two subsections, A.4 and A.5, describe the work and non-work demand models respectively, including the coefficient estimates of the final models and some general discussion of the alternative specifications tried and why they were ultimately rejected in favor of the models presented.

A.2 Disaggregate Choice Model Theory*

Until relatively recently, travel demand models were generally oriented towards representing the behavior of groups of travellers, i.e.,

*More detailed reviews of disaggregate choice theory and choice models can be found in a variety of references including: Luce and Suppes (1965), McFadden (1973 and 1974), Ben-Akiva (1973), Lerman (1975), Domencich and McFadden (1975) and Richards and Ben-Akiva (1975).

residents of a particular traffic or analysis zone. However, in a study of choice of mode, Warner (1962) suggested and applied a far sounder approach which focused on the behavior of individual travellers. This approach, currently termed disaggregate choice modelling or disaggregate behavioral modelling, has since been the central thrust of travel demand research.

Disaggregate choice models are based on the decisions of individual households or travellers; hence, they eliminate the need for aggregating various segments of the population either geographically or demographically.* Disaggregate choice models can be estimated using very small samples and hence offer the potential for significantly reducing data collection costs. However, most importantly, disaggregate choice models are based on a clear, credible and consistent theory of how decision makers choose among available alternatives.

Choice theory is concerned with the behavior of an individual decision-maker confronted with a mutually exclusive set of alternatives from which one and only one can be selected. The individual decision-maker, n, associates some level of utility with each available alternative, denoted by i. Denote this utility as U_{in}. We denote the set of alternatives available to individual n as A_n.

Following the development of Lancaster (1966), each alternative and decision-maker can be characterized by a set of attributes. Thus, the utility of the i-th feasible alternative to decision-maker n can be expressed as follows:

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*Studies of data about one facet of travel demand, trip generation, by Fleet and Robertson (1968) and McCarthy (1969) indicate that the aggregation of behavior at the zonal level may so reduce the variability in the data that most of the behavioral sensitivity of trip-making to transportation level of service is lost.

$$U_{in} = U_{in}(X_i, S_n)$$

where:

U_{in} is the utility of alternative i to individual n;

X_i is a vector of attributes describing alternative i;

S_n is a vector of attributes describing decision-maker n.

A more convenient expression for the utility function can be developed by defining a vector $Z_{in} = g(X_i,S_n)$, where g is some vector valued function. Thus we can now write $U_{in} = U_{in}(Z_{in})$.

Each decision-maker is assumed to evaluate the attributes of every alternative and select the one yielding the greatest utility. However, since some of the attributes are unobserved, variables are improperly measured, or utility relationships are mis-specified, it is in general impossible for an observer to ever determine precisely which alternative any decision-maker will select. However, with suitable assumptions about the distribution of the unobserved elements in the utility function, it is possible to predict the probability with which any alternative will be selected. When each utility is a random variable, the probability that alternative i is selected from any set of alternatives A_n is:

$$\Pr\,(i|A_n) = \Pr(U_{in}(Z_{in}) \geq U_{jn}(Z_{jn}) \text{ for all } j\varepsilon A_n).$$

Within the class of random utility model forms, the most generally applicable have been what Manski (1975) defines as LPAD, linear in the parameters with additive disturbances. In this case, it is assumed that

$$U_{in} = \beta Z_{in} + \varepsilon_{in},$$

where:

β is a vector of parameters and ε_{in} is a random variable.

The LPAD form selected for this study is the multinomial logit model. This particular model was chosen for a variety of practical and theoretical reasons, including the lack of alternative methods for modelling decision problems with large choice sets and the substantial base of successful prior applications which exists. The logit model relies on the assumption that the ε_{in}'s are independently and identically distributed as double exponentials, i.e.,

$$P\ (\varepsilon \leq \omega) = \exp\ (e^{-(\alpha + \omega)})$$

Using this distribution, McFadden (1973) demonstrated that

$$P\ (i | A_n) = \frac{e^{\beta Z_{in}}}{\sum_{j \varepsilon A_\pi} e^{\beta Z_{jn}}}$$

The parameters of this model can be estimated by maximum likelihood. Such estimates are consistent, asymptotically normal and asymptotically efficient. McFadden also demonstrates that under relatively weak conditions such estimates exist with probability approaching unity and are unique.

Note that the set of available alternatives, A_n, can vary from decision-maker to decision-maker. For example, a traveller without a driver's license or an available automobile would not generally be viewed as having the alternative of driving alone available.

The initial applications of this modelling technique to travel demand were for travellers' choice of mode (e.g. Warner, 1962; Lisco, 1967; Lave, 1969; McGillivray, 1972; and Peat, Marwick and Mitchell, 1973). The first extension of disaggregate models to a problem involving other travel choices was made in a study by Charles River Associates (1972) for the Federal Highway Administration. In this study, the logit model was applied to the choices of frequency, destination and mode for shopping travel. However, these choices were modelled in a sequence, thereby imposing a strong, and statistically unsupported structure on these decisions.*

Ben-Akiva (1974) extended the application of choice theory to include various combinations of travel choices by applying the multinomial logit model to shopping destination and mode choice. In this approach, each feasible combination of modes and destination was treated as a distinct alternative, one of which is chosen. Adler and Ben-Akiva (1975) extended this work by including the possibility of not travelling at all in the set of alternatives.

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*Note that it is possible to estimate a logit model of a joint process using a sequentially applied estimator. However, such estimates are less efficient than the more usual maximum likelihood estimates.

A.3 A Notational Convention

In order to describe the model estimation results, the utility of every alternative will be defined as

$$V = \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3 + \ldots \beta_K Z_K$$

where every alternative has the same set of k coefficients $(\beta_1 \ldots \beta_K)$ When there are some coefficients which pertain to the utility of one alternative but not others, the value of Z for that variable will be defined as alternative specific, i.e., having a value of zero in all alternatives except the relevant one.

A simple example will illustrate this convention. Suppose we wished to define a utility function for the drive alone mode which had the k^{th} variable equal to autos per household member over 16 years of age. The term in the utility function would therefore be

$$\beta_k Z_k = \beta_k \left(\frac{\text{autos in household}}{\text{number in household over 16}} \right)$$

Suppose further that we did not want this term to appear in any other utility. By the proposed convention, the kth variable in the utility of every alternative would be defined as

$$Z_k = \begin{cases} \dfrac{\text{autos in household}}{\text{number in household over 16}} & \text{for drive alone mode} \\ 0 \text{ otherwise} & \end{cases}$$

By using this convention, we can easily express even very complicated utility relationships. As a shorthand notation, it will be convenient to subscript variables to denote the alternatives to which they pertain. In this simplified form, the subscripts DA, SR and DRT will denote driving alone, sharing a ride and using DRT (either for access or directly) respectively. When it is necessary to distinguish the direct from the access DRT modes, the subscript DIRECT and ACCESS will be used. For example, if we were to define the number of automobiles per household member over 16 years of age as AA16, then the notation $AA16_{DA}$ would define a variable as follows

$$AA16_{DA} = \begin{cases} \text{autos per household member over 16 in the drive} \\ \text{alone utility} \\ \text{0 otherwise} \end{cases}$$

Variables without any subscript will be by definition generic or non mode specific. Thus, a variable for in-vehicle time, denoted as IVTT, without a subscript would take values as follows:

$$IVTT = \begin{cases} \text{in-vehicle time by drive alone mode in the drive} \\ \text{alone utility} \\ \text{in-vehicle time by shared ride mode in the shared} \\ \text{ride utility} \\ \text{in-vehicle time by DRT mode in the DRT utility} \end{cases}$$

In contrast, the notation $IVTT_{DA}$ would denote a variable

$$IVTT_{DA} = \begin{cases} \text{in-vehicle time by drive alone mode in the drive} \\ \text{alone utility} \\ \text{0 in other modes} \end{cases}$$

Table A.1 lists all the variable definitions used in the work and non-work models. Note that some of the variables were used only in early model

Table A.1

Notation for Models

CONST	A 0, 1 constant term (always subscripted)
AA16	Autos per household member over 16 years
AALIC	Autos per household member with a drivers' license
AGE1	1 if under 16 years old, 0 otherwise
AGE2	1 if over 65 years old, 0 otherwise
INCOME	Household annual income in dollars
HHSIZE	Household size
SEX	1 if male, 0 if female
IVTT	In-vehicle time (in minutes)
OVTT	Out-of-vehicle time (in minutes)
OPTC	Out-of-pocket cost (in cents)
DIST	Distance of trip (in miles)
POP*	Total population of zone
TOTEMP*	Total employment of zone
RWEMP*	Retail and wholesale employment in zone
RWEST*	Number of retail and wholesale establishments
AREA*	Zonal area, in square miles

* used in non-work models which involve destination choice

specifications described in later sections of this appendix and do not appear in the final model forms. Other variables which describe the attributes of destinations are used only in the non-work model, where choice of destination is part of the choice model structure.

Variables in this table can easily be combined to define new variables. For example, the notation IVTT + OVTT defines the sum of in-vehicle and out-of-vehicle time or total trip time. AGE1 + AGE2 is a socioeconomic variable which takes a value of one if a traveller is either under 16 or over 65 years of age.

In the logit model all of the socioeconomic variables (as well as the constants) must of necessity be defined with a subscript. Treating socio-economic characteristics as generic (i.e., as appearing in the utility function for all modes with the same coefficient) results in a model which can not be estimated.

As a final convention, each model reported in the following sections will be followed by five summary statistics:

1) number of observations - the count of trips actually used in the estimation of the reported coefficient estimates;

2) number of cases - the total number of alternatives available to all the observations minus the number of observations used in the model estimation (this equals the number of degrees of freedom in the estimation results);

3) $L^*(0)$ - the value of the log likelihood function when all the coefficients are zero;

4) $L^*(\hat{\beta})$ - the value of the log likelihood function at the maximum likelihood estimates;

Where appropriate, model coefficients will be presented with their corresponding "t"-statistics. (In theory, these values are only asymtotically normal, but in reasonably large samples they can be used as true t-values without significant error.) Due to the use of choice-based sampling, these values differ slightly from the correct t-statistics in some preliminary runs. In these cases, they still serve to indicate the general significance of the coefficients. In the final non-work model summaries, the + - statistics were corrected by use of a procedure documented in Manski and Lerman (1977).

A.4 The Calibration Data Set

All the modes estimated in the course of the study were based on data from one of two DRT service areas: Haddonfield, New Jersey and Rochester, New York. For reasons discussed in Subsection 2.1 of the main report, the final models were all based on the Rochester data.

Each of the two data sets included three basic classes of information:

1) a survey - Both data sets included the results of a home interview survey of DRT service area residents. In the case of Haddonfield, this survey was the third of three home interview surveys performed by the MITRE Corporation as part of the monitoring of the Haddonfield service. The key shortcoming of this survey was that all trips leaving the service area had their destination noted only as a single code, to indicate that they were external. This factor, along with non-reporting of either origin or destination, eliminated 1756 of the 3213 trips made by the Haddonfield survey respondents. Other problems with the data included non-reporting of information (29.8% of the households did not respond to the income question) and the existence of four distinct and very different subsamples: a random home interview sample, a sample of known DRT users, a sample of bus users and a sample of taxi users.

For Rochester, a general home interview survey of the metropolitan area was conducted in 1975, including a sample of 610 residents making a total of 1759 trips in the DRT service area. However, of these 1750 trips, only four were reported as made by DRT. In order to estimate any useful model, it was necessary to perform an on-board survey of DRT users and augment the random, home interview survey sample with the additional observations of DRT users.* The on-board survey provided a total of 401 survey responses taken on two separate days.

2) level of service data - This data includes wait times, in-vehicle times and costs by DRT, driving alone and ride sharing for every relevant origin-destination pair. In Haddonfield, DRT level of service was obtained by keypunching and processing summary statistics generated by the computer dispatching system. These summaries provided an estimate of zone-to-zone DRT travel times and average wait times for service. In addition, the available summaries made it possible to trace vehicle tours on a stop-by-stop basis with the times at each stop and between stops known. By assuming that DRT vehicles move at roughly the same speed as private automobiles, the data about these tours made it possible to estimate the direct driving times for most origin-destination pairs.

At the time the data for this study was collected, the Rochester DRT system was not computer dispatched, and it was therefore impossible to obtain level-of-service information from existing sources. The data ultimately used was obtained by conducting a set of measurements of the level-of-service concurrently with the administration of the on-board survey. As in Haddonfield, this data was also used to construct vehicle tours and thereby infer direct origin-destination driving times.

In both data sets, driving time for shared ride trips was estimated by imposing an in-vehicle and out-of-vehicle time penalty on direct driving times.

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*This type of sampling procedure is termed choice-based. The statistical theory required to use such samples is developed in Lerman and Manski (1976) and Manski and Lerman (1977).

The values of these penalties for work trips were two and four minutes for in-vehicle and out-of-vehicle time respectively. These were based on surveys of persons who share rides to work described by Attanuci (1974). The same values were used for non-work trips.

In both study areas, driving cost data was estimated by assuming an operating cost model which gave an average cost of 3.8 cents per mile and using direct driving distances derived from centroid coordinates. Parking costs are negligible in both service areas.

DRT fares for the average traveller were derived from reports by the service operators (Note that because of various discounts for multiple passenger groups sharing an origin and destination, it is not possible to simply use the nominal fare). The resulting values were $0.30 and $0.90 for Haddonfield and Rochester respectively.

The detailed zone systems used to originally code home interview surveys in both Haddonfield and Rochester had to be collapsed to a smaller number of zones. This was done primarily to reduce the number of cells in the travel- and wait-time matrices for which no observations were available. In addition, the reduction in the number of zones made the development of the zonal data described below much easier.

3) zonal data - The non-work models require measures of zonal attraction, including population and employment. These were developed from existing sources, all of which were originally derived from the U.S. Census data. In the case of Rochester, a special tabulation of zonal information at the traffic

analysis zone level was provided by the New York State Department of Transportation. For the Haddonfield area, the population and employment data were used at the original census tract level.

A.5 The Work Trip Demand Model

As discussed in Section 2 of the main report, the work trip models are multinomial logit mode choice models. A maximum of three alternatives is available to any one traveller: driving alone, sharing a ride, and either taking DRT directly to work or using DRT access to line haul transit.*

Table A.2 presents the best of the three Haddonfield models. The other two were estimated using a slightly smaller sample, but yielded roughly similar results except the coefficient of out-of-pocket cost was insignificant and positive rather than insignificant and negative. The specification of level of service using cost, total time, and the ratio of out-of-vehicle time to work trip distance is adapted from one by Koppelman (1975) and is based on the theory that the value of out-of-vehicle time, while always greater than the value of in-vehicle time, tends to approach the latter as trips get very long.

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*Note that because the destination of trips to external zones was not coded in the Haddonfield survey data this access to line haul transit option was not included in the work trip models for Haddonfield. All work trips used to estimate the Haddonfield models of necessity had both their origin and destination within the DRT service area.

Table A.2

Haddonfield Work Trip Model

Variable	Estimate	"t" statistic
$CONST_{DA}$	.934	.36
$CONST_{SR}$	-.140	-.06
OPTC	-.0133	-.18
$AA16_{DA}$	1.27	.70
$AA16_{SR}$	1.47	.84
$AGE1_{DRT}+AGE2_{DRT}$	1.27	.60
IVTT+OVTT	-.0791	-.77
OVTT÷DIST	-.00811	-.15

No. of observations = 130

No. of cases = 250

$L^*(0) = -144.3$

$L^*(\hat{\beta}) = -82.41$

The estimated "t"-statistics were uniformly very low in all the Haddonfield work trip models. This is probably due to the low amount of variability in the data sample, since only intra-service area work trips could be used. Such trips were typically quite short. Compounding this problem, workers in Haddonfield making these trips probably have little heterogeneity in their socioeconomic characteristics.

As a result of these problems, attempts at estimating a useful set of work trip models in Haddonfield were abandoned in favor of developing the Rochester data. The first series of work-trip models estimated on Rochester data were of the functional form in Table A.2. Various specifications of the level of service variables were tested, each producing at least one counter-intuitive sign. All these work-trip model specifications were restricted to only three socioeconomic variables: auto ownership; household size over 16 years old; and the age of the traveller were used. This was done to minimize the amount of input data required to forecast with the overall model system.

A further series of specifications were estimated to test the effect of introducing wait- and travel-time reliability measures. Included in these runs were variance of wait time, the standard error of wait time, the ratio of the standard error of wait time to the actual time, and two comparable series which used the same measures except for ride time and total time respectively. All these efforts failed to produce a credible model, with wrong signs, and/or low t-statistics, occurring in a number of variables.

The plausible reasons for this apparent lack of sensitivity to trip-time reliability (assuming, of course, that reliability is indeed important) include the following:

1) lack of true variation in DRT wait time - As later simulation experiments confirmed, DRT wait-time reliability tends to vary most across DRT systems rather than within a single system. While our observations of the variance of DRT wait time showed some variability, this may well have been due to inherent randomness in wait time over the sample period rather than systematic changes in average-time reliability. If this is the case, then over any long period, wait-time reliability is uniform over the DRT service area, and as a consequence, acts as a constant and presumably negative effect on the utility of the DRT mode. As such, it would be impossible to distinguish between the alternative-specific constants and DRT wait-time reliability.

2) multicollinearity between ride-time variance and average ride time - Unlike wait-time variance, there is significant variation in the variance of ride time over the DRT service area. For both the DRT and auto modes, longer trips tend to have higher variances than do shorter trips. However, the ratio of the standard error of ride time to the average ride time is, like wait time for DRT, fairly constant.

Thus, when measures such as the variance or standard error of ride time were introduced into the model, their high collinearity with in-vehicle time resulted in either one or both of the measures being statistically insignificant; frequently, one of the two variables' coefficients had a counter-intuitive sign. When the ride-time reliability variables were normalized by ride time, the lack of significant variability in the measure resulted in a statistically insignificant coefficient.

3) measurement problems - Obtaining accurate estimates of time variance requires extensive observations on actual trip times. The only way such repetitions could be obtained for even a few specific origin-destination pairs was to use all trips that began and ended in the correct zones.

This procedure tends to overstate time variance, since two trips with the same zones of origin and destination will in general have some difference in ride time even if the DRT system were perfectly reliable because the two trips may simply be of different length.

The extent of this upward bias in the estimated variance of ride time is difficult to determine, since it depends on the geometry of the zone as well as the distribution of origins and destinations for each zonal pair. However, it is likely that the use of zonal data, even for relatively small zones, tended to make the estimation of useful time-reliability coefficients more difficult.

The discouraging results of the work-trip models with limited socioeconomic effects and/or with reliability effects led to the conclusion that the development of such models <u>for work trips</u> was not feasible given the available resources. The strategy ultimately adopted was to introduce both a richer description of socioeconomic characteristics and to eliminate reliability from the model.

Table A.3 presents the best model obtained from these efforts. These results, while far from ideal, were the best of more than twenty five specifications. The alternative specific variable INCOME - 800 * HHSIZE represents an estimate of the discretionary income of the household; this variable has been used in a number of previous studies of work mode choice, yet appears to be relatively insignificant here. Other, more important variables from the perspective of designing a DRT also have weak significance, and in the case of out-of-pocket travel cost, have the wrong sign.

In summary, the basic shortcomings of this model are: (1) the counter-intuitive though statistically insignificant, sign of the out-of-pocket cost; (2) the inclusion of a large number of socioeconomic variables which would increase the input requirements of the model system; (3) the low level of statistical significance of many coefficients.

Rather than continue what appeared to be a fruitless effort which would exhaust all the study resources remaining for non-work model estimation, software development and model validation on this single subtask, it was decided to adjust the results in Table A.3 into a useable model by performing the following transformations:

(1) eliminating the extra socioeconomic variables - In order to reduce the needed data inputs required to actually execute the model, income, sex and household size were removed from the model by evaluating the utility functions at the average values of these variables and adding the sum into the constant.

(2) constraining the out-of-pocket cost coefficient - The out-of-pocket cost coefficient in Table A.3 has an insignificant coefficient with a counter-intuitive sign. This was modified by using the results of a number of previous estimation efforts. Empirical evidence, such as that described by Ben-Akiva and Atherton (1976), for the high degree of transferability of disaggregate choice models provides some support for this procedure.

Table A.4 describes the adjusted work trip mode choice model which was included in the final model system. The two travel time coefficients appear to be consistent with a great deal of existing empirical evidence (e.g., models estimated on other cities such as New Bedford, Mass.; Washington, D.C.; Milwaukee, Wisconsin; and Los Angeles, California). For both in-vehicle and out-of-vehicle time, the adjusted coefficients are at the high (in absolute magnitude) end of the range of prior values, though not at the extreme. This provides some additional confidence in their values, even though the t-statistic for the in-vehicle time coefficient is quite low.

Table A.3

Rochester Work Model as Estimated

Variable	Coefficient	"t"-statistic
$CONST_{DA}$	-1.483	-.41
$CONST_{SR}$	.1557	.04
$CONST_{DIRECT}$	2.085	.55
$AALIC_{DA}$	6.642	2.17
$AALIC_{SR}$	4.4608	1.52
SEX_{DA}	3.352	1.81
SEX_{SR}	2.413	1.31
$(INCOME-800*HHSIZE)_{DA}$	-.1162	-.78
$(INCOME-800*HHSIZE)_{SR}$	-.006	-.05
$(1/DIST)_{DIRECT}$	.753	.17
$DIST_{SR}$	-.2716	-1.01
IVTT*INCOME	-.0029	-.32
OVTT*INCOME/DIST	-.013	-2.19
OPTC	.011	.16

Number of Observations = 236

Number of Cases = 408

$L^*(0)$ = -118.9

$L^*(\beta)$ = -75.2

Table A.4

Final Rochester Work Model After Adjustments

Variable	Coefficient	"t"-statistic
$CONST_{DA}$	-3.51	NA
$CONST_{SR}$	.0507	NA
$CONST_{DIRECT}$	2.085	NA
$AALIC_{DA}$	6.642	2.17
$AALIC_{SR}$	4.608	1.52
SEX_{DA}	3.352	1.81
SEX_{SR}	2.413	1.31
$(1/DIST)_{DIRECT}$	.7529	.17
$DIST_{SR}$	-.2716	-1.01
IVTT	-.0508	NA
OVTT/DIST	-.2275	NA
OPTC	-.010	NA

Note: NA implies that t -statistic is not valid here due to model adjustments.

A.6 Structure of the Non-Work Trip Demand Model

As discussed in Section 2, the non-work trip demand model involves several different submodels. Each of the simulated individuals in the model transitions through a series of probabilistically determined trips and dwell times over the course of the day. The tracing of this behavior (for a sufficient number of simulated individuals), provides a forecast of total non-work trip-making for the DRT service area.

Figure A.1 is a schematic state-transition diagram for any one individual. Each person who does not work is presumed to begin the day at home. There is a distribution of dwell times at this initial state which describes how long the person remains there. (Some fraction of all travellers do not leave home on a given day; these persons are accounted for in the prediction process by adjusting the relative weight of each simulated individual.)

Assume for the moment that the distribution of first dwell time at home is sampled, and the simulated individual will leave home within the operating period under consideration. Now the relevant question becomes the prediction of where the traveller will go and how he or she will get there. While all possible destinations reached by auto, shared ride, DRT direct or DRT as access to line haul transit are in fact available, these are represented schematically in Figure A.1 by two possibilities.

The actual simulated choice of destination is determined by first computing the various destination choice probabilities from a joint-choice model of mode and destination, and then sampling randomly from the resulting distribution. Then, as described in Section 2, the various mode-choice probabilities conditional on the choice of destination are used to assign

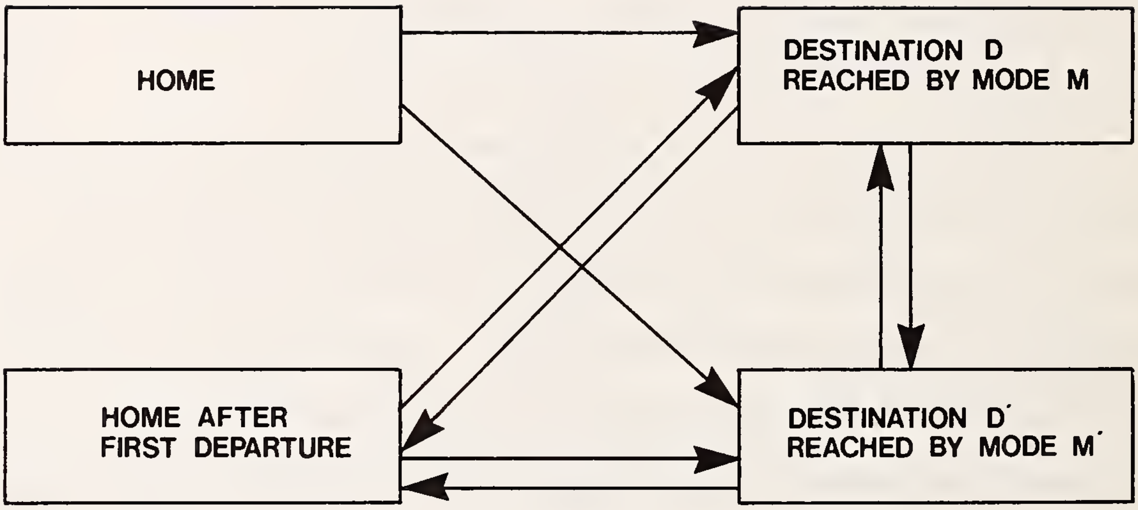

FIGURE A.1

STATE TRANSITION DIAGRAM

fractions of trips in the predicted trip tables.

The simulated individual is then "moved" to the selected destination. The total travel time is determined by a random draw from the conditional mode choice probabilities. Then, a second dwell-time distribution, the time away from home at any destination, is sampled. Once again, if the resulting time is still within the operating period, a destination choice is determined by using a joint choice model. However, this time a different model which includes returning home as a relevant destination is used.

The same process of determining fractional modal trips and travel time is again applied. If the randomly drawn destination is away from home, the non-home dwell time distribution is again sampled, and the process continues as above until the simulated time is beyond the operating period. If, however, the simulated individual returned home, a third dwell time distribution is applied. This one describes the time at home given that the person has left home and returned at least once. After a draw from this distribution, the process continues as above.

At the end of one operating period, the locations and departure times for all individuals become an initial condition for later periods. Thus, in the sense of a simulation, the model "keeps track" of where the residents of an area are over the entire day.

This simulation process allows for an explicit, though somewhat simplified, representation of trip chaining and mode switching. It also includes trips which go beyond the service area to external zones, and thereby captures the diversion of trips from outside the DRT area to within it. Such trips can be made directly by auto, ride sharing or bus, but may also be made by

DRT access to line haul transit. This generality allows the model user to predict the contribution of DRT to the line-haul transit system directly.

A full specification of the model requires the following five elements:

1) <u>home-origin trip model</u> - predicts the probability of going from home to some mode/destination combination md out of a set of such combinations MD.

2) <u>non-home-origin trip model</u> - predicts the probability of going from some non-home destination to mode/destination combination md out of a set of such combinations, MD (MD in this case includes the special destination of returning home).

3) <u>first dwell time at home</u> - the distribution of the time of first departure from home to mode/destination combination md.

4) <u>subsequent dwell times at home</u> - the distribution of the time of departure from home (other than the first departure) to mode/destination combination md.

5) <u>non-home dwell time</u> - the distribution of the time of departure from places other than home to mode/destination combination md.

Each of these elements is either a joint-choice model or a distribution over time. Both of the choice models will be considered in the subsection below, and the three dwell-time distributions will be described in a subsequent subsection.

A.7 Non-Work Choice Models

Unlike simple mode choice models, the non-work trip choice models include both mode and destination decisions. For this reason, the variables in the models must describe not only travel times and costs but also measures of the relative attraction of the alternative destinations.

In the final models used, the measures of attraction were restricted to functions of population, employment and zonal area. These attraction variables are far from optimal from the perspective of calibrating the best possible behavioral model; variables such as retail employment, service employment, recreational services and population by social class, income, or life style group would be more descriptive of true destination attractiveness. (Some of these variables were tested in exploratory models estimated with the Haddonfield data). The restriction to the simpler descriptors was imposed, however, in order to keep the data requirements of the model system within reasonable bounds.

In order not to be tied to any one zoning system, models involving destination choice must be specified to satisfy the property of <u>homogeneity</u>. Intuitively, homogeneity implies that the forecasts of the model are invariant (to the greatest extent logically feasible) with respect to the zone system used. For example, suppose one were using three zones (A, B and C), and the choice model predicted P(A:ABC), P(B:ABC) and P(C:ABC) as the choice probabilities for selecting destination zones A, B and C respectively from the set of available alternatives, ABC*. Suppose further that all the variables describing zones A and B are of equal observed utility, so that the user of

*For the purposes of this example, mode choice has been ignored.

the model wished to combine the zones into a single one, denoted as A + B. For the model to make behavioral sense, the sum of the probabilities for zones A and B separately (i.e., $P(A:ABC) + P(B:ABC)$) should equal the choice probability for the combined zone (i.e., $P(A+B:ABC)$). In other words, the probability that a person goes to either A or B should not depend on whether zones A and B are treated separately or combined into one zone. This is what is meant by homogeneity*.

It can be shown that in order to maintain this homogeneity condition in the multinomial logit model, all variables which measure zonal attraction and depend on the size of the zone (so-called "size" variables) should appear in the utility function as natural logarithms, with a coefficient contrained to one. For example, the size variable used in this study is zonal area, so the utility for any zone should be

$$V = Z'\beta + \ln(\text{AREA}),$$

in order to satisfy the homogeneity condition. Note that variables such as population density are not size variables, since their values are not functions of zonal size but of zonal composition; combining two zones of equal population density will not result in an aggregate zone with different density. On the other hand, a variable such as population is size-related.

In both the final home-based and non-home-based models, the condition of homogeneity was imposed by constraining the size-related coefficient to unity. However, the corresponding unconstrained models were also estimated, and the resulting coefficients are also reported.

Table A.5 describes four of the early models which were developed for exploratory analysis on the Haddonfield data base. (Because the

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*A more theoretical treatment of this property in terms of the utility of groups of alternatives is presented in Lerman (1975).

Table A.5

Non-Work Models: Haddonfield Data

	(1)		(2)		(3)		(4)	
	Home-Origin Trips		Home-Origin Trips		Home-Origin Trips		Non-Home-Origin Trips	
VARIABLE	Coefficient	"t"	Coefficient	"t"	Coefficient	"t"	Coefficient	"t"
$CONST_{DA}$	-1.866	-1.30	-1.769	-1.11	-1.703	-1.06	-.736	-.86
$CONST_{SR}$	-1.191	-.94	- 1.158	0 .84	-1.087	- .79	.370	.51
$AA16_{DA}$	4.428	3.27	4.659	2.98	4.660	2.08	3.472	2.42
$AA16_{SR}$	3.616	2.76	3.814	2.50	3.814	2.50	3.078	2.18
$AGE1_{DRT}$	1.628	1.96	.0891	.81	.890	.81	--	--
IVTT	- .113	-2.63	- .0982	-2.17	- .101	-2.21	--	--
OVTT	- .0679	- .78	- .0592	- .60	- .0565	- .56	--	--
OPTC	- .0172	-2.64	- .0759	-2.69	- .0740	-2.62	- .00572	-.20
RWEST	.00783	3.30	--	--	--	--	--	--
RWEMP	--	--	.00202	5.12	.00187	4.47	--	--
POP	--	--	--	--	.0000484	1.20	--	--
$CONST_{HOME}$	--	--	--	--	--	--	3.657	22.29
1/RWEMP	--	--	--	--	--	--	-.0021	-2.36
1/POP	--	--	--	--	--	--	.0000165	.45
IVTT + OVTT	--	--	--	--	--	--	-.145	-2.6
Number of observations	279		262		262		284	

Haddonfield data lacked external trips it was deemed inappropriate for use in the final models.) Note that size variables such as the total population and the number of retail employees were not used in logarithmic form and their coefficients were unconstrained. This is primarily because the goal of these estimations was not to achieve a final model but to assess the general feasibility of the general model structure.

The variable $CONST_{HOME}$ in Table A.5 denotes a variable which has a value of one in the utility of returning home by any mode and is zero otherwise. All other variables are as defined in Table A.1.

These models used a wide range of attraction variables, including retail and wholesale employment (RWEMP), the number of retail and wholesale establishments (RWEST) and some transformations of these variables. The results of these experiments were used to guide the final specification of the models estimated on the Rochester data.

The general empirical results were deemed encouraging, particularly for the home-origin trip model. The critical level-of-service parameters consistently had the expected sign and, except for out-of-vehicle time, were statistically significant. The employment-related attraction measures (retail/wholesale employment and number of retail establishments) were both significant. Population and DRT-specific age variables appear to be insignificant.

In the most interesting Haddonfield non-home origin trip model, in-vehicle and out-of-vehicle time were combined into a total time variable. This was motivated by the high standard error in the out-of-vehicle time coefficient in the home-based trip models . In this model, the return home constant ($CONST_{HOME}$) is by far the most significant. Out-of-pocket cost has a very small, insignificant coefficient, indicating that the individuals who have already left home and are travelling may well be very cost insensitive.

Table A.6 presents the final models estimated from the Rochester data in both constrained and unconstrained forms. A number of changes were made in developing these models based on the Haddonfield results.

(1) In-vehicle and out-of-vehicle travel time were combined into a single variable. This implies that they are evaluated by travellers as having equal disutility; while such an assumption may be untenable for work trips or for conventional transit, it is quite plausible for non-work DRT trips in which wait time is incurred at home or in a store rather than an outdoor bus stop.

(2) Out-of-pocket cost is entered into the model in logarithmic form. Earlier models without this transformation were overly cost sensitive and severely under predicted for high fare DRT systems such as Davenport, Iowa. This transformation is necessary because unlike conventional transit, DRT is typically more expensive than the auto mode and the range of possible fares is much greater than usually encountered in modal choice models. (It may well be that such a transformation would be necessary in mode choice for conventional transit if one were interested in a wider range of fares; given the current low variability in transit fares, whether one uses a linear or logarithmic form is probably of little practical importance.)

(3) The constraining of the coefficient for the logarithm of zonal area to unity makes little difference in the home origin model, but significantly affects the non-home origin estimates.* This was true for all variants of the model specification tested, and may pose some potential problems. The constrained version was selected for the final model despite this difficulty in order to preserve homogeneity in forecasting with the model.

*The Cambridge Systematics Logit Estimation Program has the capability to perform this particular type of constrained estimation.

Table A.6

Final Non-Work Models: Rochester Data *

VARIABLE	Home-Origin Unconstrained		Home-Origin Constrained		Non-Home Origin Unconstrained		Non-Home Origin Constrained	
$CONST_{DA}$	-6.992	-3.44	-7.223	-3.47	-1.687	-.35	-3.035	.62
$CONST_{SR}$	-7.134	-3.63	-7.338	-3.62	-1.806	-.38	-2.991	-.61
$AA16_{DA}$	7.381	1.73	7.450	1.64	8.440	.82	8.608	.80
$AA16_{SR}$	7.507	1.78	7.577	1.68	8.010	.78	8.178	.76
IVTT + OVTT	-.133	-3.65	-.141	-3.93	-.0223	-.77	-.0573	-2.01
ln(OPTC)	-1.462	-6.21	-1.484	-6.33	-.883	-4.76	-.934	-4.85
POP/AREA	$-.824 \times 10^{-4}$	-2.82	$-.768 \times 10^{-4}$	-2.62	$-.606 \times 10^{-4}$	-2.33	$-.250 \times 10^{-5}$	-.09
TOTEMP/AREA	$.218 \times 10^{-4}$	2.39	$.236 \times 10^{-4}$	2.58	$-.137 \times 10^{-5}$	.15	$.118 \times 10^{-4}$	1.21
$CONST_{HOME}$	--	--	--	--	1.979	9.76	2.663	13.49
ln(AREA)	.901	6.28	1.000	*	.234	1.85	1.000	*
Number of observations	211		211		277		277	
Number of cases	5145		5145		7497		7497	
L*(0)	-495.2		-495.2		-867.4		-867.4	
$L^*(\hat{\beta})$	-344.2		-344.2		-558.4		-577.8	
Percent Right	23.2		23.2		32.9		31.4	

*Each Unconstrained and Constrainted model is summarized for each variable by the value of the variable coefficient and its "t" statistic.

(4) The statistical significance of one of the two density measures (POP/AREA and TOTEMP/AREA) in the non-home origin model is very low, though the insignificant coefficient depends on whether or not the model is constrained. Both variables were kept in the models to maintain some logical consistency between them.

(5) The coefficient of population density (POP/AREA) is negative in both models, perhaps reflecting the possibility that such zones are highly residential in character and are therefore even less attractive as destinations than their employment density would otherwise indicate.

A.8 Distribution of Departure and Dwell Times

The final set of distributions for first departure time from home, time between subsequent returns and departures, and non-home dwell times are described in the model by eight distinct distributions. All distributions were derived from an analysis of the Rochester data. Initially, each distribution was tabulated for every group in a cross-classification based on auto ownership (0, 1, 2+) and age of resident (less than 65 years, greater than 65 years). The resulting 18 distributions (3 distribution types x 3 auto ownership levels x 2 age groups) was aggregated into the final eight by use of a series of simple t-tests to determine whether or not the hypothesis of equivalent distribution means for various socioeconomic groups can be rejected.

The use of only eight distinct distributions implies some fairly strong assumptions about the trip frequency of various socioeconomic groups. Simply because the means of two distributions are not significantly different at some level of confidence does not necessarily imply the two are identical. However, since some of the samples were extremely small, some pooling of socioeconomic groups was essential. In other cases, the means of the distributions were fairly close, so that pooling them did not change the forecasting results significantly anyway.

Two types of probability distributions were then fitted to the actual data to simplify the sampling process. The first, used to represent the time of first departure from home, is a shifted and truncated gamma distribution, which is defined as follows:

$$f(t_F) = \begin{cases} 0 \text{ if } t_F \le t_{crit} \\ f_\gamma\,(t_F - t_{crit}) / \int_{t_{crit}}^{t_{max}} f_\gamma(t_F - t_{crit}) \text{ if } t_{crit} \le t_F \le t_{max} \\ 0 \text{ otherwise} \end{cases}$$

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*This distribution is defined as the time of first departure from home in minutes after midnight <u>given that a trip is made</u>.

t_F = time of first departure from home (in minutes) given that a trip is made

t_{crit} = the time of the first possible trip during the day (in minutes)

t_{max} = the end of the trip-making period of the day

$f_\gamma(t_F)$ = the gamma distribution, i.e.,

$$f_\gamma(t_F) = \frac{\rho(\rho t)^{\alpha-1} e^{-\rho t}}{\int_0^\infty e^{-u} u^{\alpha-1} du}$$

The other two distributions, the second dwell time at home and the non-home dwell time, are described as modified exponentials. Thus,

$$f(t) = \begin{cases} \dfrac{\lambda e^{-\lambda t}}{\int_0^{t_{max}} \lambda e^{-\lambda t} dt} & \text{if } 0 \leq t \leq t_{max}. \\ 0 \text{ otherwise} \end{cases}$$

Table A.7 presents a summary of the final distributions, listing the variable described, the socioeconomic group to which it applies, the type of distribution (gamma or exponential), the mean of the sample, t_{crit} (if applicable), t_{max}, and the parameters of the distribution.

A second set of data to execute the non-work trip model is the fraction of residents who do not leave home in a given day. This fraction is used to determine the number of people who do not travel at all for non-work purposes.

Table A.8 presents these fractions for the various socioeconomic groups. These groups do not correspond one-to-one with those used for the final distributions, since the propensity to travel may differ even though some of the distributions for those who travel are identical.

Table A.7

Time Distribution for Non-Work Trip Model: Rochester Data

Distribution	Socioeconomic Group	Type of Distribution	Mean (min)	Standard Error (min)	t_{crit} (min)	t_{max} (min)	Parameters	Number of observations
1st Departure from Home	>65 years all auto ownership levels	Gamma	713.6	184.18	360	1440	α=3.68482 ρ=.01042	274
"	65 years 1 auto	Gamma	654.2	230.1	360	1440	α=1.63475 ρ=.00557	158
"	65 years 1 auto	Gamma	616.5	235.0	300	1440	α=1.81389 ρ=.005731	838
"	65 years 2+ autos	Gamma	571.8	194.3	240	1440	α=2.91613 ρ=.008789	1629
2nd Departure from Home	all ages all auto ownership levels	Exponential	147.0	143.4	0	1440	λ=.0068027	2221
Non-home Dwell Time	all ages 0 autos	Exponential	184.1	168.3	0	1440	λ=.0054318	344
"	all ages 1 auto	Exponential	135.5	165.6	0	1440	λ=.00738	2618
"	all ages 2+ autos	Exponential	127.2	158.5	0	1440	λ=.0078616	3000

The fraction of the population who do not travel for non-work purposes is slightly greater for the elderly than the non-elderly. This difference, while small, may reflect the low labor force participation rate of the elderly population. (While roughly 31% of the non-elderly population in the sample made a work trip, only 7.6% of the elderly population did). Thus, it appears that, at least in the Rochester sample, though the elderly make very few work trips they travel fairly often for non-work purposes.

Note that while all the above distributions are built into the software, each can be changed by the user if so desired. Thus, these values are defaults for the user rather than inflexible model parameters.

Table A.8

Fraction Not Departing From Home During Day: Rochester Data

Group	Fraction Not Departing From Home During Day	Sample Size
$\geq$65 Years 0 autos	.72	202
$\geq$65 Years more than 0 autos	.48	439
$\leq$65 Years, 0 autos	.78	827
$\leq$65 Years, 1 auto	.62	2418
$\leq$65 Years 2+ autos	.53	3693

APPENDIX B

SUPPLY MODEL: TECHNICAL DOCUMENTATION

B.1 Initial Attempts at Model Development

Before describing the final supply model and its development, several preliminary, unsuccessful attempts at developing a DRT supply model will be briefly described. As indicated by the Study Design developed at the outset of the project, it was not originally intended to develop a descriptive supply model.* Although it was recognized that a descriptive model, if constructed carefully, could serve as a powerful tool, the limitations of a model not based on an underlying theory were considered to be more important factors. As such, it was decided to attempt to develop a causal, analytic supply model which would be consistent with the development of the behavioral demand model. It was understood, and stated in the study design, that the budget available for supply model development might not be sufficient to allow the development of an analytic model. Thus, the development of a descriptive model was considered from the outset as the potential backup approach.

B.2 Queuing Theory

Some previous attempts to develop an analytic DRT supply model for many-to-many service (e.g., Lerman and Wilson, 1974) were based on queuing theory. Many-to-many DRT service clearly involves a queuing process, albeit a rather complex one. The initial approach undertaken in this project was to extend some models based on queuing theory developed by Yamamoto at M.I.T.. The models appeared to produce reasonable results although they had not been fully tested. These preliminary successes offered the hope that an analytic model could be developed within the initial budget.

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*The term descriptive is used here to describe a model developed principally by empirical observation rather than theoretical considerations.

Yamamoto developed separate models for predicting the mean wait time and ride time in a DRT system. Wait time was defined as the mean time between the service request and the arrival of a bus, and ride time as the time from boarding the bus to arrival at the destination. In the wait time model, the DRT system was treated as a multi-server queuing system with N (number of vehicle) servers in parallel. A service in random order (SIRO) queue discipline was assumed. The queue was considered to be composed of persons waiting to be picked up and persons already on board waiting to be dropped off. The start of service was defined as the time a vehicle began to provide dedicated service to a passenger, i.e., started heading directly towards his or her origin or destination.

Passenger wait time is broken into two components: 1) the time until a vehicle begins heading towards the pickup location, i.e., the time spent waiting in a queue; and 2) the time it takes the vehicle to travel to the pickup location, i.e., the service time.

Let us deal with this latter component first. The service time is essentially the time it takes a vehicle to travel from one stop to the next; the average service time is the "mean interstop travel time." The estimation of interstop travel time has been important in all efforts at using queuing theory to model dial-a-ride systems. Lerman and Wilson (1974 and 1975) resorted to a regression equation for estimating interstop distance. Yamamoto used probability theory to estimate average interstop distance; however, his approach was considered to be unsuitable, and this was one of the areas of his model for which improvements were planned under this project. At the outset the Lerman-Wilson formulation of interstop travel time was employed as an element of the Yamamoto wait-time model.

Using multiserver queuing theory, the first component of passenger wait time can be obtained as the wait time in the queue. Thus, given a method for estimating the mean interstop travel time, mean passenger wait time can be estimated. The results of this modelling approach, however, did not prove satisfactory, for the following reasons:

1) This representation assumes that a passenger could be assigned to the first free vehicle. Typically a passenger would only be assigned to one of a subset of vehicles, those heading in the appropriate direction. Thus, the model should consistently underestimate wait time.

2) The model treats passengers on board vehicles as if they were in the same queue as persons waiting for a vehicle. Since persons on board a vehicle can only be served by the vehicle they are on, they really should not be considered in the same queue as those waiting for any vehicle.

3) Service in random order may not be the appropriate queue discipline. Clearly passengers who have been waiting longer or travelling on board the vehicle for a while will have some priority over new passengers.

Attention was next focused on the Yamamoto ride time model, a Markov reliability model, in which a passenger's trip was represented by a series of system states. These states correspond to the number of passengers other than the "passenger of interest" on board the vehicle, and whether or not the vehicle was in motion. The arrival of a passenger at his or her destination was defined as the "absorption state," analogous to the failure state in a standard reliability model. The passenger's ride time could then be estimated as the mean time to failure. State transition probabilities were based on assumptions of Poisson arrivals with mean λ, exponential interstop travel time with mean $1/\mu_1$ (equal to the mean interstop travel time), and exponential "deviation" time distribution with mean $1/\mu_2$, with deviation time defined as the time it takes to pickup or drop off a passenger not on the direct route of the passenger of interest.

A full description of this model can be found in a paper by Yamamoto (1975). The model did not produce satisfactory results for the following reasons:

1) A more realistic representation of system states would consider the number of persons waiting for service as well as the number of persons on board.

2) The assumption of exponential interstop travel time (as well as exponential deviation time) is not realistic. Interstop time could probably be better represented by a gamma distribution.

3) There was no satisfactory method developed for estimating mean deviation distance.

4) This representation still assumes service in random order.

Given the apparent difficulties with the Yamamoto formulation, it was decided to seek alternative approaches towards developing the supply model.

B. 3 A "Pseudo" Semi-Markov Model

The problems encountered in attempting to extend the Yamamoto ride-time model led to the next approach at developing a supply model. This model was termed a "pseudo" semi-Markov model because of its resemblance to a semi-Markov model (in the use of system states and state transition probabilities).

In this model a single vehicle is again considered. System states are determined by the number of persons on board the vehicle and the number of persons assigned to the vehicle and waiting to be picked up. Specifically, state x,y is attained when there are:

x people assigned to the vehicle, waiting to be picked up, and

y people on board the vehicle waiting to be dropped off.

A SIRO (service in random order) queue discipline was assumed as an initial approximation. State changes occur when a vehicle arrives at a stop and picks up or drops off passengers. The average time it takes to change states is the mean interstop travel time plus the mean load/unload time.

Consider that a passenger arrives in the system at state x,y (i.e., the "passenger of interest" is the xth person assigned to the vehicle), and we are trying to predict his or her expected wait time. If the vehicles next stop is a pickup, there will be y + 1 passengers on board at the next state. The number of passengers waiting for service will be x-1 only if no passengers were assigned to the vehicle during the state transition time period. However, there is a probability associated with one or more passengers being assigned to the vehicle during that time period. Likewise, when a passenger is dropped off there will be one less person on board the vehicle, but there may be more persons waiting. Recalling the SIRO queue discipline, the probability of a drop off being the next stop is given by $\frac{y}{x + y}$, while the probability of a pickup is given by $\frac{x}{x + y}$. The probability of the passenger of interest being picked up is given by $\frac{1}{x + y}$ (because of the SIRO assumption). In general, the following probabilities hold:

1) $p(x,y \rightarrow x+n-1,y+1) = p(n) \frac{x - 1}{x + y}$

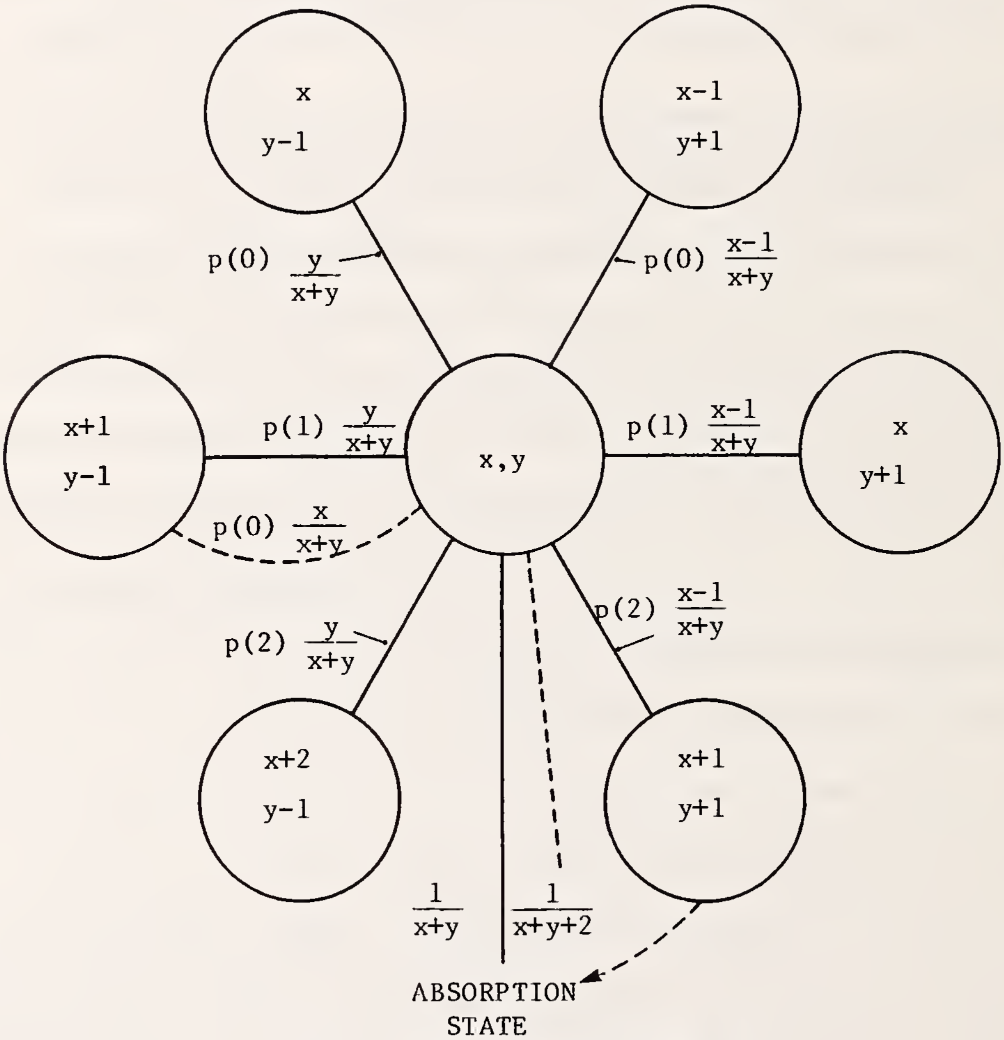
2) $p(x,y \rightarrow x+n,y-1) = p(n) \frac{y}{x + y}$

3) $p(x,y \rightarrow \text{passenger of interest pickup}) = \frac{1}{x + y}$

Where the first term is the probability of going from state x,y to a pickup of someone other than the passenger of interest, with n other passengers assigned to the vehicle in that time period; the second term is the probability of going from state x,y to a drop off with n other passengers being assigned, and the third term is the probability that the passenger of interest is picked up. Define p(n) as the probability of n arrivals in the state transition time period T_i, assumed constant.*

*Assuming calls for service arrive according to a Poisson distribution with mean λ (per vehicle) p(n) is given by $\frac{(\lambda T_i)^n}{n()!}$ exp $(-\lambda T_i)$.

To help visualize the process, consider the following portion of a state transition diagram.



(ie., passenger is picked up)

The estimation of expected wait time was based on the calculation of the probabilities associated with k interim stops between the time a passenger is assigned to a vehicle and the time he or she is picked up.

The results of this modelling effort also proved to be unsatisfactory. The problems with the model that have been identified include the following:

1) Similar logic could be used for estimating expected wait and ride times; thus, there was no reason for the model not to predict identical values for wait and ride time. This was based on a number of factors, including the lack of consideration of trip length.

2) Because ride time prediction was based on the number of interim stops and the interstop travel time and not on actual trip length, it was possible for the model to predict a ride time that was shorter than the direct ride time.

3) The assumption of a constant state transition time introduces difficulties. Clearly the state transition time (mean interstop time) is a function of the number of persons on the system.

4) The SIRO assumption still may not be an accurate representation of the system.

The basic approach outlined above was still considered to be promising, and work began on modifying the approach in order to remedy the problems. Among the changes being considered were:

1) Modification of the model to a continuous time semi-Markov process representation using network flows in place of transition probabilities.

2) Development of a state dependent interstop travel time estimate.

3) Adjusting the state transition probabilities to account for the number of interim stops, thus modifying the SIRO assumption.

4) Make the transition to the absorption state in the ride time model dependent upon distance travelled.

However, before significant progress could be made on any of these concepts, it was determined that the budget could not support further work and still retain sufficient funds to allow the development of a descriptive model in case further efforts did not produce results. Thus, attention was turned to the development of a descriptive model, described in the following section.

B.4 The Descriptive Supply Model Methodology

The approach taken in formulating the descriptive model was to first develop the bounds for wait and ride time and then formulate models that were (1) bounded correctly, and (2) demonstrated the observed empirical relationships between the input parameters and the travel time.* Calibration of the models was based on a series of simulation experiments. The simulation model used was the M.I.T. model which had previously been validated with data from the Haddonfield, New Jersey, DRT system and has since been validated with data from the Rochester, New York, system. A primary objective of the supply model development was accuracy within ± 10% of mean system performance as measured by the simulation model, since fluctuation between systems caused by factors not modelled would be at least at this level.

*The basic input parameters considered at the outset of the model development are discussed in Chapters 2 and 3 of the main report, and listed below:

1) Productivity (λ) $\dfrac{\text{demand rate (trips per hour)}}{\text{vehicle fleet size}}$
2) Vehicle fleet size (N)
3) Service area size (A)
4) Street network adjustment factor (fa)
5) Vehicle speed (V)
6) Load, unload times (l,u)
7) Trip length (L)

V_{eff} is defined as $\dfrac{(60 - \lambda)(1+u)V}{60}$

The remaining input parameters were considered at a later point in the model development, and will be discussed later in this section.

The projected sequence of model development steps was to first develop models for estimating system-wide wait and ride time averages, then to develop models for estimating the wait and ride time of individual trips, and finally to develop models of wait- and ride-time reliability. By the time the last step was reached, wait- and ride-time reliability had been eliminated from the demand model specifications (see Appendix A) and so this supply model was not developed.

Two factors that could influence the performance of a DRT system were not considered implicitly within the model formulation. The first factor is vehicle capacity. Experience and research have both indicated that level of service is sensitive to vehicle capacity only over a small range of vehicle sizes. The reason for this is that for vehicles with capacities of perhaps seven or more, the desired service quality more actively constrains the number of passengers that can be picked up than does physical capacity. Because of this characteristic of DRT systems, it was decided that the most effective approach would be to develop separate models for the DRT operating scenarios most closely related to vehicle capacity. The basic model would represent traditional DRT service which uses vans or small buses that seat 10 passengers or more. A second model would be developed to represent a shared-ride taxi system with a vehicle capacity of four or five.

The second major factor that could influence level of service is the type of dispatching system used. Two factors prevented incorporating dispatching within the initial model formulation. The first was the inherent difficulty of attempting to parameterize the many possible dispatching schemes, while the second was the fact that the simulation model could provide a consistent predictor of computerized dispatching only. It was decided that the impact of dispatching systems would not be considered in the model formulation, but the model would be later adjusted to account for dispatching options.

The steps in the overall model development are described in the following section.

B.5 Formulation of Model Bounds

System bounds for DRT systems are developed below.

1) As vehicle productivity approaches zero, i.e., when there are very few passengers in the system, wait and ride time approach their minimum values. The minimum ride time is simply the direct ride time, or:

$$\overline{RT} = \frac{f_a \overline{L}}{V}$$

where RT = mean system ride time
f_a = ratio of street distance to airline distance
$\overline{L}$ = mean trip length (airline distance)
V = vehicle speed

Note that for very low demand levels, V is equivalent to V_{eff}. The (minimum) wait time is the time it takes for the closest vehicle to reach the passenger. Assuming that the vehicles are randomly distributed throughout the area, the expected distance that the vehicle will travel is the expected distance between a (random) point and the closest of N randomly distributed points in an area of size A. It can be shown that this value is given by:

$$\frac{f_a}{2} \sqrt{\frac{A}{N}}\ *$$

so that the minimum wait time is:

$$\overline{WT} = \frac{f_a}{2V} \sqrt{\frac{A}{N}}$$

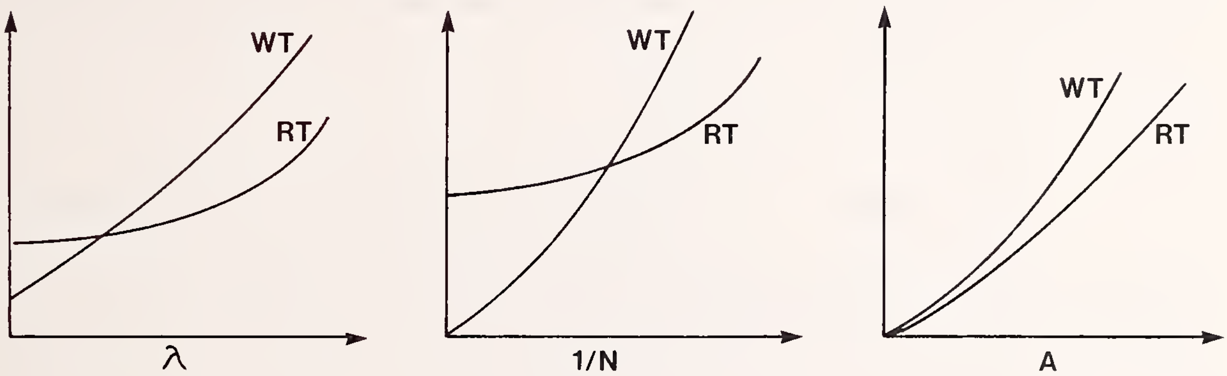
2) As demands per vehicle become very large, both wait and ride time approach infinity. In the real world, of course, there is a saturation point, beyond which no additional passengers can be carried (per hour), although they may be waiting for service. In practice, high wait times result in cancellation of service requests. This serves as a regulator, eliminating infinite service queues.

3) As the area becomes very large, wait time and ride time approach infinity.

*The derivation of this expression can be found in a number of texts, including Kendall and Moran (1963).

B. 6 Model Form

Observations of actual DRT systems, and simulation experiments, suggested that wait and ride time are related to productivity, vehicle fleet size, and area in the following manner:



From the diagram, it appears that these relationships could well be represented by exponential functions which is not surprising given the complex queuing process representation of DRT service. The use of an exponential form lends itself to the development of properly bounded models. Furthermore, while the models would not be causal, the use of proper bounds and a model form that reflects the underlying queuing process would seem to offer a fairly powerful base for the model.

A number of different formulations were tested (by hand) prior to actual calibration. The functional forms that seem to best fit the data were:

$$\overline{WT} = \frac{f_a}{2V_{eff}} \sqrt{\frac{A}{N}} \exp\left(k_1 \times \sqrt{\frac{A + k_5}{N + k_6}} \lambda^{k_2}\right)$$

$$\overline{RT} = \frac{f_a \times L}{V_{eff}} \exp\left(k_3\left(\frac{A \times \lambda}{N}\right)^{k_4}\right)$$

A series of 31 simulation runs were used to provide data for calibration.* Calibration was performed with log-linear regression; however, because of the limitation of readily available software, the regressions were designed to estimate k_1 and k_3 only: constants k_2 and k_4 were preset, and the regression results for different runs using different values of k_2, k_4, k_5 and k_6 were compared to select the best function.

Final estimated values for the six parameters were as follows:

$k_1 = .219$

$k_2 = .9$

$k_3 = .0843$

$k_4 = .7$

$k_5 = 4$

$k_6 = 12$

---

*Calibration was over the following range of inputs:

A (area) = 4 mi.^{2} - 20 mi.^{2}

N (vehicle fleet size) = 4 - 34

f_a (street network adjustment factor) = 1.2 - 1.4

V (vehicle speed) = .2 - .3 miles/minute

l,u (load, unload time) = .375 - 1.25 min.

λ (productivity) = 4 - 12.7 passenger trips/vehicle flow

Demands per square mile per min. = 2 - 4.5

B.7 Model Results

Table B.1 compares the predictions of the descriptive model with the results of the simulation model for the 35 runs. Some statistics on these results are shown in Table B.2.

In interpreting these results, consider that the RMS error is a measure of the mean difference between the descriptive model and simulation results; RMS error differs from standard error in that it does not correct for degrees of freedom. Both the t-test and the chi-square test could not reject the hypothesis that the two distributions (simulation and descriptive model results) were the same.

B.8 Shared-Ride Taxi Version of the Model

In a shared-ride taxi system, where vehicle capacity is typically four or five, level of service would be expected to be different than it would be in a system where larger vehicles are used. Since vehicles reach capacity more quickly, some passengers will have to wait longer for a vehicle. On the other hand, since the maximum number of passengers on board the vehicle is lower, one would expect the mean system ride time to be lower. Both of these impacts would be expected to be more severe at higher demand levels.

Because shared-ride taxi service is identical to DRT service with the exception of vehicle capacity, it was hypothesized that the same model formulation could be used, with the model recalibrated against simulation experiments that considered a vehicle capacity of 5. Following this procedure with a series of 10 simulation experiments, the wait time model was recalibrated with k_1 and k_3 re-estimated as:

Table B.1

Comparison of Descriptive Model with Simulation Results

Area	Inputs: Vehicle Fleet Size	Inputs: Productivity	Simulated WT	Estimated WT	Simulated RT	Estimated RT
9.	8	6.0	7.65	7.79	13.54	13.01
9.	8	6.0	8.27	7.27	10.99	12.14
9.	8	12.0	13.85	15.65	15.82	14.80
9.	10	12.0	13.47	12.96	14.58	14.17
12.	8	10.0	13.55	15.93	16.70	15.88
12.	14	6.0	6.94	5.93	12.68	12.74
12.	10	8.0	9.08	9.84	13.39	13.96
16.	10	8.0	12.95	13.11	17.35	16.74
20.	14	6.0	8.01	8.92	17.27	16.68
20.	14	8.0	12.44	12.52	19.01	18.63
12.	14	6.0	5.94	5.84	12.78	12.56
20.	14	6.0	11.00	10.40	19.69	19.38
9.	8	6.0	6.25	6.67	10.32	11.15
9.	8	8.0	8.67	8.67	11.57	11.95
4.	6	6.0	4.61	5.14	7.86	7.90
4.	6	4.0	3.20	4.00	6.64	7.29
4.	4	6.0	5.41	6.58	7.28	8.29
4.	4	4.0	3.72	5.05	6.78	7.44
4.	8	6.0	3.89	4.29	7.86	8.09
4.	8	8.0	5.41	5.41	8.59	8.75
9.	8	4.0	4.90	4.95	10.83	10.77
9.	8	10.0	11.95	11.83	14.64	13.38
6.	6	6.0	6.28	5.84	9.19	9.27
6.	4	6.0	7.72	7.58	10.24	10.58
10.	8	8.0	11.81	11.04	15.04	14.37
14.	10	6.0	11.02	9.36	16.39	15.96
18.	10	6.0	10.48	10.45	16.47	18.00
16.	12	5.0	8.46	7.46	15.91	15.25
9.	18	10.0	6.46	6.25	12.11	11.23
6.	22	12.7	5.56	5.07	9.61	9.42
18.	16	8.5	11.55	10.94	18.58	18.24
12.	34	9.0	4.91	4.13	12.47	11.63

Table B.2

Some Statistics on Calibration Results

	Wait Time Model	Ride Time Model
Predicted Mean/Actual Mean	8.29/8.32	12.84/12.78
Standard Error	1.05	.723
Root Mean Square (RMS)	.88	.626
Percentage RMS Error	10.72%	4.88%
T-Statistic/Confidence Level	3.85/99.5%	3.39/99.5%
X-Square Statistic	2.92	1.51

$k_1 = .20$

$k_3 = 1.0$

Note that, as expected, these results suggest that the wait time difference between shared-ride taxi and dial-a-ride service would be very small at lower demand levels (where the lower value of k_1 and the higher value of k_3 would counteract each other), but increase with increasing demand. Interestingly, for the 10 observation, the shared-ride taxi version of the model appeared to offer a better "fit" with a percentage RMS error of less than 6%.

The results of the ride time model calibration were somewhat surprising. The best results were obtained with the same constants estimated earlier. Thus, it appears that vehicle capacity does not significantly impact ride time. A possible reason for this is based on the fact that the mean number of passengers on board a vehicle will be well below five for most DRT systems, except in cases of very high demand levels. Although a vehicle capacity of five constrains the maximum number of passengers who can be on board at one time, it will have little impact on the overall average occupancy. Thus, the mean ride time is not significantly different. This may not hold true for very high demand levels; however, for the purposes of this project, a single ride-time formulation was accepted for both DRT and shared-ride taxi service.

B.9 Individual Ride Time and Wait Time Models

The next step in the model development process was to develop models for predicting wait time and ride time for an individual trip. It was hypothesized that for a given system, ride time for a particular trip is linearly proportional to trip distance; in other words, the expected ride time of a person whose trip distance is four miles would be twice that of the person whose trip is two miles. Based on this assumption, the model that was developed for predicting mean system ride time should be able to predict the ride time of an individual trip. To test this hypothesis, the model was recalibrated against the simulated individual travel time data for the runs used for the earlier calibration. The results were comparable to the earlier calibration; the k_2 term was almost identical (.086 instead of .0843) and, although the standard deviation of error was understandably greater given the greater variance in travel time for individual trips, the results seemed to support the hypothesis. Thus, the ride-time model can be used as shown earlier to estimate the expected ride time of a particular trip.

The initial hypothesis about the expected wait time of a particular trip was that it would be a function of the popularity of the zone of origin, as well as the location of that zone. If many trips are made to or from a particular zone there would seem to be a high probability that a vehicle will be in the zone, or headed towards it. Therefore, one would expect the wait time in that zone to be fairly low. Furthermore, one would expect vehicles to pass through zones near the center of the service area more frequently than through zones located at the extremities. Thus passengers waiting at central zones could expect shorter wait time.

On the first pass it was determined that it would be too difficult to account for zone location, but that the impact of zone popularity could be considered. The following model form was hypothesized:

$$WT_i = \frac{\bar{O} + \bar{D}}{O_k + D_i} \quad \bar{WT}$$

where

WT_i = Expected wait time for trips originating in zone i.

$\bar{O}$ = Mean number of origins per zone *

$\bar{D}$ = Mean number of destinations per zone *

O_i = Number of trips originating in zone i

D_i = Number of trips ending in zone i

$\overline{WT}$ = Mean system wait time

Comparison of the predictions of this model with simulation results suggested that this model was not capturing the impact of zone popularity; the simulation model did not suggest that wait time was inversely proportional to the number of trips to and from the origin zone.

As a next step, the popularity of the destination zone was incorporated in the formulation. This was based on the assumption that a passenger going to an unpopular destination may have to wait longer for a vehicle, i.e., he or she may have to wait until there is another call for a trip to or from that zone. (Likewise passengers going to a popular destination may be picked up fairly quickly). Again the results did not support this hypothesis. Tests were set up in which up to 35% of all trips were directed to a single zone, with the results indicating that the mean wait times for trips to and from that zone were not significnatly different from the system mean. Regressions indicated that zonal wait-time deviations from the mean wait-time were simply random deviations about the mean, or at least not explainable by any of the variables being considered. Based on these results, it was decided that the mean system wait-time model would be at least as good as the other model variations tested for predicting zonal wait time.

---

[1]Note that $\bar{O} = \bar{D} = \frac{\text{total trips}}{\text{number of zones}}$

A word of caution in interpreting these results. Although the evidence suggested that zonal wait-time differences from the mean system wait time were caused by random variations about the mean, these results are counter-intuitive. A possible reason for these results is the extremely high variance of zonal wait time. The runs simulated up to four hours of service. During that time period there may have only been two to four trips between particular zone pairs. Further research into this area is necessary before any final conclusions are drawn.

B.10 The Impact of Different Dispatching Systems

As noted earlier, the simulation model with which the descriptive model was calibrated simulates a computer dispatching system. It has been widely assumed that computer dispatching would have a significant impact on service levels. To date, only a single system, the Haddonfield, New Jersey system, has successfully experimented with computer dispatching, so that there is limited data available to support or refute the hypothesis.* In Haddonfield, the introduction of computer dispatching resulted in a 20% decrease in mean wait time, improvement in wait- and ride-time reliability, and no change in ride time. Although these results are clearly not conclusive, they provide the only basis for determining how the descriptive model can be used for forecasting the level of service of a manually dispatched DRT system.

Before describing the suggested modifications to the model to enable it to forecast manually dispatched DRT system performance, other dispatching system considerations must be introduced. Perhaps the most important

*A computer system has since been implemented in Rochester, New York. As of this writing the system is operating, but other operational difficulties have made it difficult to truly compare system performance under computer and manual dispatching.

consideration is the way in which the dispatching system makes assignment decisions. In general, dispatching assignments are based on providing the best overall service. In the Haddonfield assignment algorithm, the same algorithm used by the simulation model, an "objective function" is used to synthesize impacts of a specific assignment. This objective function includes a measure of passenger dissatisfaction which incorporates wait time and ride time. In Haddonfield, wait and ride times were assumed to be equally onerous to passengers, and hence were weighted equally within the objective function. Simulation experiments have indicated that the equal weighting of wait and ride time will result in minimum total system travel time (sum of wait plus ride time), although substantial changes to this weighting were found to increase total time by less than 10%.

However, an equal weighting of wait and ride time cannot be assumed for all DRT systems. Indeed, observations of manually dispatched systems such as the one in Rochester, New York, have suggested that dispatchers have a tendency to weight ride time more heavily than wait time because they perceive passengers waiting for service as not yet on the system. Furthermore, drivers have been known to disregard instructions to pick up passengers before dropping off others, since their contact is only with passengers already on board the vehicle.

As a vivid illustration of the way these dispatching options can impact wait and ride time, consider the following comparison of the model results with data obtained from the Rochester DRT system while it was under computer control. At that time the algorithm in Rochester weighted ride time 50% more heavily than wait time, partly in response to problems the system was having, and partly in response to suggestions from the dispatcher. The results of this comparison are shown in Table B.3.

Table B.3

Comparison of Descriptive Model with Data from Rochester*

	Mean System Wait Time	Mean System Ride Time	Mean Total Travel Time
Rochester Data	30.5 min.	16.0 min.	46.5 min.
Model Results	19.4 min.	23.6 min.	43.0 min.

*Data is for one evening of service. At the time this test was made the computer system had been successfully used for evening service only. Data represents a 4.6 hour period during which 62 demands were served. Five instances of "no shows" were treated as half-demands. Effective vehicle speed, accounting for street adjustment factors was measured at 11.3 miles per hour. Mean trip length was L=2.2 miles, and the service area was A=17.5 square miles.

The model, calibrated with an algorithm that weights wait and ride time equally, underpredicts wait time by 30% and overpredicts ride time by 47%, Note, however, that total travel time is underpredicted by only 7.5%; recall that different weightings of wait and ride time do not significantly impact the sum of these two measures.

Other dispatching options may also impact level of service. For example, dispatching strategies that allow trip purpose or passenger prioritization would be expected to impact wait and ride time differently than a strategy that treats all trips equally. However, it was decided that at most the model could be expected to account for two issues: manual vs. computer dispatching, and wait versus ride time trade-off.

Let us first consider the dispatching issue. There is no way to obtain additional information on the differences between manual and computer dispatching until the Rochester system is fully operational or other computer systems are implemented. Haddonfield remains the only data and so the only reasonable approach is to use it to make a very simplistic modification to the model. It was decided to introduce a user supplied adjustment factor to the wait time model only. By setting this factor greater than zero, the model will predict a wait time that is higher than the wait time expected for a computer dispatched system. Based on the Haddonfield results, a range of .1 to .3 is suggested for this factor, with a higher value suggested for higher demand levels.

Although the impact of the wait/ride time trade-off could have been analyzed through further simulation experiments, it was decided to use a fairly simplistic approach to account for this factor as well because of the limited budget remaining for supply model development. Since total travel time is relatively insensitive to the weighting of wait- and ride-time, an obvious approach was to introduce an adjustment factor that changes wait and ride time by the same amount.

The resulting models for wait and ride time prediction are as follows:

$$WT_a = (1 + \alpha + \beta)\ WT$$

$$RT_a = RT - \frac{L}{\bar{L}} \beta WT$$

where

WT_a = Wait time adjusted for dispatching system

RT_a = Ride time adjusted for dispatching system

α = An indication of whether the system is computer dispatched

β = A measure of the trade-off between wait and ride time

L = Length of trip

$\bar{L}$ = Mean trip length

Note that under this formulation the total travel time does not change, and ride time remains proportional to trip length. This relationship may break down for short trips or for high values of β, since the model may try to drive ride time below the minimum direct ride time. The model system software has been designed to test for this, and will not allow ride time to go below the minimum level. Because of this feature, the model system (i.e., the equilibrium model) may predict a mean ride time that is higher than would be predicted if the ride time model was executed alone with a mean system travel distance. Since the unadjusted model probably underestimates total travel time for a system that does not utilize equal wait/ride time weightings, this does not appear to be a problem.

To illustrate the impact these modifications have, return to the Rochester example. α would be set to 0, since the system was computer dispatched. Since ride time was weighted 50% lower than wait time, we might set $\beta = .5$. The results are shown in Table B.4.

Clearly, these modifications to the model are still in a preliminary form. The determination of the impact of different dispatching systems on DRT performance is an area where additional research is necessary.

B.11 Final Model Adjustments

Two final adjustments to the model were developed. The first is based on the concept of "effective vehicle fleet size," a concept developed during the validation of the simulation model. It was discovered that when vehicles leave and then re-enter service, (for example, for driver reliefs), the system operates as if it had fewer vehicles in operation than it actually has. Since passengers waiting for service cannot be assigned to vehicles scheduled to leave service, the mean system wait time is greater than it would be if there were a constant vehicle fleet size. As far as system wait time is concerned, the "effective" vehicle fleet size is smaller than the actual fleet size. Ride time, however, does not appear to be similarly affected. Although a backlog of passengers will appear before a vehicle re-enters service, resulting in a longer than average ride for these passengers, those passengers on board a vehicle scheduled to leave service will be dropped off directly, and thus receive a shorter than average ride. These two factors appear to offset each other.

Effective vehicle fleet size appears to be a function of the number of vehicles in service, the number of times vehicles enter and leave service, and

Table B.4

Modified Models vs. Rochester Data

	Actual Data	Unmodified Model	Modified Model
WT	30.5 min.	19.4 min.	29.1 min.
RT	16.0 min.	23.6 min.	13.9 min.
WT + RT	46.5 min.	43.0 min.	43.0 min.

the point where driver reliefs are made in relation to the service area. Simulation experiments have suggested that the effective vehicle fleet size may be as much as 20-25% smaller than the actual vehicle fleet size in cases where vehicles leave service frequently.

To develop a model of effective vehicle fleet size as a function of the factors noted above would require extensive simulation experiments. Once again, budgetary constraints did not allow such an effort, and for the purposes of this supply model it was decided to simply introduce an effective vehicle fleet size adjustment factor (kn). This factor should be used to multiply vehicle fleet size everywhere that it appears in calculating WT (including the estimation of λ and subsequently V_{eff}). Based on the simulation experiments conducted at M.I.T., a reasonable range for this factor would be .7 - 1.0. For the Rochester test discussed earlier in this Appendix, a value of .85 was used.

The second adjustment was a much simpler one mentioned here only to avoid confusion. In a DRT system, the number of passengers in a group travelling together (i.e., a group of 1, 2, 3, or 4 passengers) does not impact the level of service. Thus in using the model, the desired demand input is the number of <u>trips</u>, rather than the number of passengers. Since the output of the demand model is passenger trips, a group size adjustment factor (kg) has been incorporated in the model.

The final supply model is:

$$WT = (1 + \alpha + \beta) \frac{f_a}{2 V_{eff}} \sqrt{\frac{A}{kn \times N}} \exp \left(k_1 \sqrt{\frac{A + 4}{kn \times N + 12}} \lambda^{k_2}\right)$$

$$RT = \frac{f_a L}{V_{eff}} \exp k_3 \left(\frac{A}{N} \lambda\right)^{k_4} - \frac{L}{\bar{L}} \beta WT_{\mu}$$

where:

$$WT_{\mu} = \frac{f_a}{2 V_{eff}} \sqrt{\frac{A}{kn \times N}} \exp \left(k_1 \sqrt{\frac{A + 4}{kn \times N + 12}} \lambda^{k_2}\right)$$

$$\lambda = \frac{D/kg}{N}$$

It should be pointed out that these models, which are incorporated in the software package, can also be used on their own as a preliminary design or sketch planning tool.

IDENTIFICATION

TITLE: DRT DEMAND FORCASTING PROGRAM (FORCAST)

WRITTEN BY: RICHARD E. NESTLE, C.S.I.,

SPONSOR: UMTA

INTRODUCTION

FORCAST IS A PROGRAM FOR THE PREDICTION OF PATRONAGE OF DEMAND RESPONSIVE TRANSIT (DRT) SYSTEMS IN URBAN AREAS OF 10 TO 20 SQUARE MILES IN SIZE. FORCAST AND THIS WRITEUP HAVE BEEN PREPARED SIMILARLY TO PROGRAMS AND WRITEUPS RELEASED BY UMTA AS PART OF THE UTPS SYSTEM OF TRANSPORTATION ANALYSIS PROGRAMS. THE USER WHO IS NOT FAMILIAR WITH THE STRUCTURE OF SUCH PROGRAMS AND WRITEUPS SHOULD BE PREPARED TO CONSULT THE 'UTPS REFERENCE MANUAL' (HEREAFTER REFERRED TO AS THE 'REFERENCE MANUAL') PREPARED BY:

U.S. DEPARTMENT OF TRANSPORATION
URBAN MASS TRANSPORTATION ADMINISTRATION
PLANNING METHODOLOGY AND TECHNICAL SUPPORT DIVISION
WASHINGTON, D.C. 20590

THE REFERENCE MANUAL IS AVAILABLE ON A COMPUTER TAPE FROM UMTA OR THROUGH THE NATIONAL TECHNICAL INFORMATION SERVICE IN SPRINGFIELD, VA. FOR $10.25 AS DOCUMENT NUMBER PB-231-8651/AS.

WITHIN BUDGET LIMITATIONS EVERY ATTEMPT HAS BEEN MADE TO MAKE THIS PROGRAM APPEAR TO THE USER LIKE A UTPS RELEASE. HOWEVER, THERE ARE SEVERAL WAYS IN WHICH FORCAST DIFFERS FROM WHAT ONE MIGHT EXPECT OF SUCH A UTPS RELEASE. THESE DIFFERENCES ARE DISCUSSED IN MORE DETAIL LATER IN THIS WRITEUP, BUT IN SUMMARY THEY ARE:

(1) THE CATALOGED PROCEDURE HAS A DUMMY DATASET DEFINED FOR THE UTPS LOG FILE.

(2) THE WRITEUP DOES NOT DESCRIBE ALL OF THE PROGRAM MESSAGES WHICH APPEAR. ONLY THE MOST SIGNIFICANT MESSAGES ARE COVERED.

(3) THE &EQUIV AND &PLOT CONTROL STATEMENTS ARE NOT USED. THE &PERIOD STATEMENT IS USED AND IT IS UNIQUE TO FORCAST.

(4) THE PROGRAM WAS NOT DEVELOPED IN CONFORMANCE WITH UMTA SOFTWARE DEVELOPMENT PROCESS STANDARDS. THEREFORE THE PROGRAM IS NOT DOCUMENTED TO THAT LEVEL OF DETAIL.

THE REMAINDER OF THIS SECTION IS DEVOTED TO A SUMMARY DESCRIPTION OF THE FORMAT OF THIS PROGRAM WRITEUP. THE USER WHO IS FAMILIAR WITH UTPS PROGRAM WRITEUPS CAN SKIP THIS DESCRIPTION AND BEGIN THE SUMMARY SECTION WHICH FOLLOWS.

REPORTS - THIS SECTION DESCRIBES THE OUTPUTS FROM FORCAST.

FILE TABLE - THIS SECTION DESCRIBES ALL THE FILES WHICH FORCAST USES. THE READER IS REFERRED TO CHAPTER IV, SECTION H OF THE REFERENCE MANUAL FOR HELP IN INTERPRETING THIS TABLE. THE ACTUAL STRUCTURE OF ANY UTPS MATRIX FORMAT FILES IS DESCRIBED IN CHAPTER VI, SECTION F OF THE REFERENCE MANUAL.

KEYWORD TABLE - THIS SECTION DESCRIBES THOSE KEYWORD EQUALITIES BY WHICH THE USER CAN CONTROL PROGRAM FUNCTIONS AND/OR SPECIFY INPUT PARAMETERS TO FORCAST. THESE KEYWORDS ARE INPUT IN THE CONTROL CARD FILE DESCRIBED IN CHAPTER III OF THE REFERENCE MANUAL. FORCAST USES THE &PARAM, &OPTION, AND &SELECT STATEMENTS DESCRIBED IN CHAPTER III, BUT DOES NOT USE THE &PLOT AND &EQUIV STATEMENTS. FORCAST ALSO HAS ONE ADDITIONAL STATEMENT, &PERIOD, WHICH IS UNIQUE TO FORCAST AND FOLLOWS ALL THE OTHERS. THE CONTROL STATEMENTS MUST ALL BE PRESENT AND IN THE FOLLOWING ORDER:

1 - &PARAM
2 - &OPTION
3 - &SELECT
4 - &PERIOD (FOLLOWED BY MORE IF DESIRED)

CORE REQUIREMENTS AND EXECUTION TIME - THIS SECTION DESCRIBES THE CORE REQUIREMENTS AND GIVES SOME EXAMPLE RUNNING TIMES FOR FORCAST.

DATA CARD FORMATS - THIS SECTION DESCRIBES THE FORMAT OF THE ZONAL DATA THAT FORCAST REQUIRES.

PROGRAM FLOW - THIS SECTION DESCRIBES THE FLOW OF CONTROL IN FORCAST. IT IS PRESENTED IN UMTA SPECIFICATION LANGUAGE FORMAT AND ILLUSTRATES THE WAY IN WHICH THE MODELS RELATE TO EACH OTHER AND THE USER'S INPUTS.

SAMPLE PRODUCTION RUN SETUPS - THIS SECTION PRESENTS SOME EXAMPLE CONTROL CARD FILES AND JCL WHICH ILLUSTRATE HOW VARIOUS TYPES OF FORCAST RUNS MIGHT BE MADE.

CATALOGED PROCEDURE - THIS SECTION PRESENTS A CATALOGED PROCEDURE THAT WOULD BE USEFUL IN RUNNING FORCAST. IT IS MODELLED AFTER THAT SUPPLIED FOR PROGRAM UMODEL IN THE UTPS SYSTEM.

NOTES - THIS SECTION PRESENTS MORE INFORMATION ON THE KEYWORD EQUALITIES. OTHER INFORMATION THAT RELATES TO REFERENCES IN THE DOCUMENTATION IS PRESENTED.

SUMMARY

FORCAST IS AN INTEGRATED SYSTEM OF MODELS WHICH ALLOWS THE USER TO PREDICT THE PATRONAGE OF A DEMAND RESPONSIVE TRANSIT (DRT) SYSTEM OVER THE COURSE OF A DAY. FORCAST HAS TWO PRINCIPAL FEATURES. FIRST, FORCAST INCORPORATES AN EQUILIBRIUM ALGORITHM TO RECONCILE THE SUPPLY AND DEMAND SIDES OF THE MODELLING PROBLEM. THE USER CAN CONTROL THIS PROCESS BY SETTING THE MAXIMUM NUMBER OF ITERATIONS TO BE PERFORMED AS WELL AS AN ERROR LIMIT CRITERIA BY WHICH THE ITERATIONS CAN BE TERMINATED BEFORE THE MAXIMUM SPECIFIED. SECOND, FORCAST CAN BE EXERCISED OVER VARYING CONDITIONS THROUGHOUT A DAY IN THE THE COURSE OF A SINGLE RUN. THE USER CONTROLS THIS FEATURE BY PROVIDING A SEPARATE &PERIOD STATEMENT FOR EACH TIME PERIOD THAT HE WISHES TO ANALYZE. ON THIS STATEMENT HE CAN SPECIFY PARAMETERS WHICH HAVE CHANGED FROM THE PREVIOUS PERIOD. HE DOES NOT HAVE TO SPECIFY ANY THAT REMAIN THE SAME.

FORCAST PROVIDES INFORMATION ON THE FOLLOWING DURING EACH PERIOD THAT THE USER SPECIFIES:

(1) VEHICLE PRODUCTIVITY

(2) AVERAGE DRT RIDE AND WAIT TIMES

(3) MODAL VOLUMES AND MODE SPLITS IN PERCENTS

THERE ARE SEVEN PRINCIPAL MODELS IN FORCAST. THEY ARE:

SUPPLY:
- (1) DRT WAIT TIME
- (2) DRT RIDE TIME

DEMAND:
- (3) WORK MODE CHOICE
- (4) NON WORK TRIP FREQUENCY
- (5) HOME BASED, NON WORK MODE AND DESTINATION CHOICE
- (6) NON HOME BASED, NON WORK MODE AND DESTINATION CHOICE

DEMOGRAPHIC:
- (7) MARKET SEGMENTATION

THE USER CAN SUPPLY INPUTS TO ALL OF THE MODELS, BUT IN MOST CASES THE DEFAULTS SUPPLIED WILL BE SUFFICIENT FOR HIS PURPOSES. THIS ALLOWS THE USER TO CONCENTRATE ON THOSE VARIABLES WHICH ARE MOST INTERESTING FROM A POLICY POINT OF VIEW. THUS, AT THE SIMPLEST LEVEL OF DETAIL THE USER NEED BE CONCERNED ONLY WITH SUPPLYING SERVICE AREA CHARACTERISTICS AND MODEL PARAMETERS SUCH AS:

(1) ZONAL DATA INCLUDING:
- COORDINATES
- AREAS
- EMPLOYMENT
- POPULATION

(2) A DAILY WORK TRIP TABLE

(3) THE NUMBER OF NON-WORKERS OVER THE AGE OF 16 IN THE SERVICE AREA

(4) LEVEL OF SERVICE FOR NON-DRT MODES WHICH ARE AVAILABLE INCLUDING:
- IN VEHICLE TIMES ON AN O-D BASIS
- OUT OF VEHICLE TIMES ON AN O-D BASIS
- FARES ON AN O-D BASIS OR AS AN AVERAGE SYSTEM FARE

(5) COST INFORMATION FOR DRT EITHER IN O-D FORM OR AS A SINGLE SYSTEM AVERAGE

(6) NUMBER OF VEHICLES IN SERVICE AND THEIR CAPACITY

(7) NUMBER OF ANALYSIS ZONES SERVED DIRECTLY BY DRT AND THE NUMBER OF ZONES AVAILABLE THROUGH A FEEDER CONNECTION

(8) BEGINNING AND ENDING OF EACH ANALYSIS PERIOD

(9) INITIAL ESTIMATE OF DRT PATRONAGE

(10) PRECISION OF THE NON-WORK MODEL RESULTS

AT A SLIGHTLY MORE COMPLICATED LEVEL, THE USER MIGHT CONSIDER OVERRIDING THE DEFAULT VALUES USED FOR OTHER VARIABLES SUCH AS:

(1) PERCENT OF TOTAL POPULATION OVER THE AGE OF 64

(2) AUTO OCCUPANCY OF SHARED RIDE TRIPS

(3) WORK TRIP DISTRIBUTIONS BY TIME OF DAY

(4) AVERAGE NUMBER OF PEOPLE RIDING TOGETHER IN GROUPS ON THE DRT SYSTEM

(5) EFFECTIVE VEHICLE FLEET SIZE ADJUSTMENT FACTOR

(6) VEHICLE SPEEDS FOR DRT AND AUTO MODES

(7) LOAD AND UNLOAD DELAYS FOR DRT

(8) DISPATCHING SYSTEM PARAMETERS

FINALLY, THERE IS A THIRD LEVEL AT WHICH THE USER CAN MAKE ADJUSTMENTS TO THE MODEL SYSTEM. THE VARIABLES AT THIS LEVEL ARE GENERALLY VERY DIFFICULT TO GENERATE, SO IT IS EXPECTED THAT MOST USERS WILL NEVER HAVE OCCAISION TO OVERRIDE THE DEFAULT VALUES FOR THE FOLLOWING:

(1) DISTRIBUTION OF POPULATION OVER HOUSEHOLD SIZE AND AUTO AVAILABILITY

(2) DISTRIBUTION OF DWELL TIMES AT HOME AND AWAY FROM HOME FOR PERSONS MAKING NON-WORK TRIPS

(3) PERCENTAGE OF RESIDENTS WHO DO MAKE NON-WORK TRIPS IN A GIVEN DAY

REPORTS

1. DYNAMICALLY ROUTED DEMAND MODEL ITERATION REPORT

THE USER OBTAINS THIS REPORT BY SPECIFYING TRACE(6)=T ON CONTROL STATEMENT &OPTION.

```
FORC6 3100 (TRACE) DYNAMICALLY ROUTED ITERATION REPORT

 PERIOD       1     CURRENT VALUE OF ERROR               0.4382
   BEGIN      530        CONVERGENCE LIMIT               0.0010
   END        730
 ITERATION    1     AVERAGE PERSON RIDE TIME            17.0403 MINUTES
                    AVERAGE PERSON RIDE DISTANCE         3.4561 MILES
```

MODE VOLUMES (PERSON TRIPS)
MODE SPLITS (PERCENTS)

BASIC	AUTO DRIVE ALONE	SHARED RIDE	DRT	BUS	TAXI	TOTAL
WORK MODEL	3705	6876	118	579	0	11278
	32.9	61.0	1.0	5.1	0.0	
NON-WORK MODEL	958	1457	1	0	0	2416
	39.7	60.3	0.0	0.0	0.0	
TOTAL	4663	8333	119	579	0	13694
	34.1	60.9	0.9	4.2	0.0	

```
  ADDITIONAL SIMULATION MODEL INFORMATION:
          NUMBER OF ENTITIES CONSIDERED:                48
          NUMBER OF PERSONS SIMULATED:         1757.376953
          NUMBER OF ENTITIES-TRIPS SIMULATED:           11
```

THIS REPORT PROVIDES A SUMMARY OF THE DEMAND MODEL RESULTS ON AN I BY ITERATION BASIS WITHIN EACH TIME PERIOD BEING ANALYZED. MODAL VOLUMES IN TRIPS AND MODAL SPLITS IN PERCENTS ARE REPORTED FOR ALL POSSIBLE MODES. THESE ARE BROKEN DOWN BETWEEN THE WORK AND NON-WORK DEMAND MODELS.

2. DYNAMICALLY ROUTED DEMAND MODEL PERIOD REPORT

THE USER CAN OBTAIN THIS REPORT BY SPECIFYING DUMP(6)=T ON CONTROL STATEMENT &OPTION. THIS REPORT IS IDENTICAL TO THE ITERATION REPORT EXCEPT THAT IT IS PRODUCED AT THE END OF EACH PERIOD. AN ACCOMPANYING MESSAGE INDICATES WETHER THE ITERATIVE PROCESS WAS TERMINATED BY THE MAXIMUM NUMBER OF ITERATIONS ALLOWED OR THE VALUE OF THE ERROR FUNCTION.

3. SUPPLY MODEL ITERATION REPORT

THE USER ALWAYS OBTAINS THIS REPORT.

FORC8 3900 (REPORT):

```
 UNCONSTRAINED PRODUCTIVITY                6.493   GROUPS PER VEH-HR

 CONSTRAINED AND SMOOTHED PRODUCTIVITY  6.493   GROUPS PER VEH-HR

 AVERAGE GROUP WAIT TIME      34.87     MINUTES

 AVERAGE GROUP RIDE TIME      13.42     MINUTES

 AVERAGE GROUP RIDE DISTANCE  2.721     MILES
```

THIS REPORT SUMMARIZES THE LEVEL OF SERVICE PERCEIVED BY DRT USERS ON AN ITERATION BY ITERATION BASIS WITHIN EACH PERIOD.

FILE TABLE

FILE NAME	DDNAME	CONTENTS OR FUNCTION
SYSIN	FT05F001	1. PROGRAM CONTROL CARDS 2.ZONAL DATA CARDS
J1- J9	FT11F001 -FT19F001	OPTIONAL MATRIX FILES
SYSOUT	FT06F001	PROGRAM REPORTS AND MESSAGES
	FT20F001	PROGRAM CONTROL CARD IMAGES
	FT21F001	LOG FILE

KEYWORD TABLE

NAMELIST - &PARAM

THESE NAMELIST VARIABLES ARE STORED IN COMMON <PAR>.

KEYWORD	TYPE	DEFAULT	MAX	VALUE OR PURPOSE
INZONS	I*4	20	100	NUMBER OF ZONES SERVED BY DEMAND RESPONSIVE TRANSIT <1.3>
EXZONS	I*4	0	100	NUMBER OF ZONES NOT SERVED BY DRT <1.1>,<1.3>
TRPTAB	I*4	101		UTPS TABLE NUMBER FOR WORK TRIP TABLE <1.4>
AMWORK	R*4 (12)	7*0, 5*20.		PERCENT OF WORK TRIPS BEING MADE IN HOME TO WORK DIRECTION DURING EACH OF THE HOURS FROM MIDNIGHT TO NOON <1.5>
PMWORK	R*4 (12)	5*20, 7*0		SAME AS <AMWORK> ONLY FOR WORK TO HOME TRIPS FROM NOON TO MIDNIGHT <1.5>
ADA	L*4	T		IF =T THEN AUTO DRIVE ALONE IS ALLOWED DURING AT LEAST ONE PERIOD <1.1>
SHR	L*4	T		SAME AS <ADA> FOR SHARED RIDE <1.1>
DRT	L*4	T		SAME AS <ADA> FOR DRT <1.1>
BUS	L*4	T		SAME AS <ADA> FOR BUS SERVICE <1.1>
TAX	L*4	T		<NOT USED>
SIMUL	I*4	100		NUMBER OF ENTITIES TO BE SIMULATED ON THE NON-WORK MODELS <1.2>
AUTOS	R*4 (5)			DISTRIBUTION OF THE PERCENT OF THE POPULATION FALLING INTO EACH OF 5 LEVELS OF AUTO OWNERSHIP. THE LEVELS ARE 0,1,2,3, AND 4 OR MORE. <1.6>
HHOLDS	R*4			SAME AS FOR <AUTOS> BUT FOR

	(5)		LEVELS OF HOUSEHOLD SIZE (COUNTING PEOPLE > 16 ONLY) THE LEVELS ARE 1,2,3,4, AND 5 OR MORE. <1.6>
OVR64	R*4		PERCENT OF THE TOTAL POPULATION >64 <1.6>
HHAVE	R*4	-1	(NOT USED)
NWPOP	R*4	2000	NUMBER OF NON-WORKERS OVER AGE 16 IN THE SERVICE AREA <1.4>
PTRIP	R*4 (5,2)	22.,38., 3*47.,38., 4*48.	PTRIP(N,M) IS THE PERCENT OF RESIDENTS WHO DO MAKE HOME BASED NON WORK TRIPS IN A GIVEN DAY BY AUTO AND AGE BREAKDOWN AS FOLLOWS: N=1-5 FOR AUTOS/HH =0-4+ M=1,2 FOR AGE<65, AGE>=65 <1.7>
HDWEL1	R*4 (48,6)		DISTRIBUTION OF PERCENT OF FIRST NON WORK TRIP DEPARTURES FROM HOME BY HALF HOUR INTERVALS STARTING AT MIDNIGHT FOR EACH OF 6 GROUPS OF PERSONS AS FOLLOWS: <1.7> (..,1): AUTOS PER HH =0, AGE <65 (..,2): AUTOS PER HH =1, AGE <65 (..,3): AUTOS PER HH =2+, AGE <65 (..,4): AUTOS PER HH =0, AGE >=65 (..,5): AUTOS PER HH =1, AGE >=65 (..,6): AUTOS PER HH =2+, AGE >=65
HDWEL2	R*4 (48,6)		DISTRIBUTION IN PERCENTS OF LENGTH OF STAY AT HOME BETWEEN NON WORK TRIPS IN HALF HOUR INTERVALS. BREAKDOWN AMONG PERSON TYPES IS THE SAME AS FOR <HDWEL1>. <1.7>
NHDWEL	R*4 (48,6)		SAME AS <HDWEL2> BUT FOR STAYS AWAY FROM HOME <1.7>

GRUPW	R*4	1.0	AVERAGE DRT GROUP SIZE FOR WORK TRIPS <1.9>
GRUPNW	R*4	1.2	AVERAGE DRT GROUP SIZE FOR NON-WORK TRIPS <1.9>

NAMELIST - &OPTION

THESE VARIABLES WILL BE READ INTO COMMON AREA <OPT>.

KEYWORD	TYPE	DEFAULT	MAX	VALUE OR PURPOSE
RDUTIL	I*4	F		IF =T THEN READ &UTILIT NAMELIST TO ALLOW THE USER TO INPUT SOME ADDITIONAL PARAMETERS OF HIS OWN.
TRACE	L*1 (100)	100*F		TRACE CONTROL SWITCHES
DUMP	L*1 (100)	100*F		DUMP CONTROL SWITCHES
GENT	I*4 (12)	12*0		THIS IS A VECTOR OF VALUES THAT THE USER CAN OPTIONALLY GENERATE INTO HIS INPUT MATRICES RATHER THAN READ THE MATIRICES FROM FILES. FOR I = 1 TO 10 <GENT(I)> WOULD BE LOADED INTO EVERY CELL OF THE MATRIX CONTROLLED BY <TABLES(I)> IN NAMELIST &PERIOD. <GENT(11)> WOULD BE LOADED INTO THE MATRIX CONTROLLED BY <TRPTAB>. <GENT(12)> IS NOT USED.

NAMELIST - &SELECT

THESE VARIABLES WILL BE READ INTO COMMON AREA <SEL>.

KEYWORD	TYPE	DEFAULT	MAX	VALUE OR PURPOSE
REPORT	L*1 (100)	100*F		REPORT SELECTION SWITCHES. <NOT USED>

NAMELIST - &PERIOD

THESE VARIABLES WILL BE READ INTO COMMON AREA <PER>.

KEYWORD	TYPE	DEFAULT	MAX	VALUE OR PURPOSE
BEGIN	I*4	600		BEGINNING OF ANALYSIS PERIOD IN MILITARY TIME. FIRST PERIOD SHOULD NOT BEGIN LATER THAN A SUBSTANTIAL PART OF THE WORK AND NON WORK DEPARTURE DISTRIBUTIONS OR THESE TRIPS WILL NOT BE CORRECTLY MODELLED. <4.1>
END	I*4	1800		END TIME OF ANALYSIS PERIOD IN MILITARY TIME. <4.1>
VEHS	I*4	10		NUMBER OF DYNAMICALLY ROUTED VEHICLES IN SERVICE <4.3>
VEHCAP	I*4	20		PASSENGER CAPACITY OF VEHICLES <4.4>
CARCOS	R*4 (10)	24,2,4, 7*0		PARAMETERS TO BE USED IN AUTO RELATED CALCULATIONS: <4.5> (1): AVERAGE AUTO SPEED IN MPH (USED FOR PER MILE COST CALCULATIONS) (2): PENALTY FOR SHARED RIDE IN VEHICLE TRAVEL TIME RELATIVE TO DRIVE ALONE TIME (MINUTES) (3): PENALTY FOR SHARED RIDE OUT OF VEHICLE TRAVEL TIME RELATIVE TO DRIVE ALONE TIME (MINUTES) (4)-(10): NOT USED

TAXFAR	R*4 (2)	'MATRIX'	FARE STRUCTURE FOR TAXI MODE: <NOT USED> 'MATRIX' - READ FARE MATRIX FROM TABLE GIVEN BY <TABLES(8)> 'COMPUTE' - FIGURE FARE USING <TAXCOS> 'OLD' - USE FARE FROM PREVIOUS PERIOD
BUSFAR	R*4 (2)	'MATRIX'	FARE STRUCTURE FOR BUS MODE: <4.6> 'MATRIX' - READ FARE FROM TABLE GIVEN BY <TABLES(7)> 'FIXED' - USE <BUSCOS> 'OLD' - USE FARE FROM PREVIOUS PERIOD
DRTFAR	R*4 (2)	'MATRIX'	LIKE <BUSFAR> BUT FOR DRT AND USES TABLE GIVEN IN <TABLES(9)> <4.6>
TAXCOS	R*4 (10)	50,70, 8*0	PARAMETERS FOR TAXI FARE CALCULATION IF <TAXFAR> ='COMPUTE': <NOT USED> (1) - CONSTANT IN CENTS (2) - MILEAGE CHARGE IN CENTS/MILE (3)-(10) - NOT USED
BUSCOS	R*4	50	BUS FARE IN CENTS IF <BUSFAR> ='FIXED' <4.6>
DRTCOS	R*4	100	DRT FARE IN CENTS IF <DRTFAR> ='FIXED' <4.6>
SHROCC	R*4	2.5	SHARED RIDE AUTO OCCUPANCY
LIMIT	R*4	.25	CONVERGENCE LIMIT CRITERIA <4.2>
MAXITR	I*4	3	MAXIMUM NUMBER OF ITERATIONS TO BE PERFORMED EACH PERIOD EVEN IF THE CONVERGENCE LIMIT IS NOT REACHED. <4.2>
ISHARE	R*4	5	NOT USED

PATRON	R*4	300	INITIAL ESTIMATE OF PATRONAGE FOR THE PERIOD (WILL BE SPREAD EVENLY OVER ALL O-D PAIRS) <4.7>
NEWZON	L*4	T	IF =T ZONAL DATA CARDS ARE READ IN THIS PERIOD. ALL ZONAL DATA WILL BE REREAD.
TABLES	I*4 (10)	101,102, ...,110	LIST OF UTPS TABLE NUMBERS FOR MATRICES TO BE READ. THE INDICES IN <TABLES> CORRESPOND TO THE FOLLOWING MATRICES: <4.8>,<4.9> 1 - UNUSED 2 - IVTT FOR ADA,SHR 3 - IVTT FOR BUS 4 - IVTT FOR FEEDER LINEHAUL 5 - OVTT FOR BUS 6 - OVTT FOR FEEDER LINEHAUL 7 - FARE FOR BUS 8 - UNUSED 9 - FARE FOR DRT 10 - FARE FOR FEEDER LH (IVTT = IN VEHICLE TRAVEL TIME, AND OVTT = OUT OF VEHICLE TRAVEL TIME). ALL TIMES ARE IN MINUTES. IF THE VALUES FOR THE ENTRIES IN <TABLES> DO NOT CHANGE FROM PERIOD TO PERIOD A NEW TABLE IS NOT READ

NAMELIST - &UTILIT

THESE VARIABLES ARE STORED IN COMMON AREA <UTIL>. ONLY THE VARIABLES PRECEEDED BY AN ASTERISK ARE IN THE NAMELIST.

KEYWORD	TYPE	DEFAULT	MAX	VALUE OR PURPOSE
ZONES	I*4	20		TOTAL NUMBER OF ZONES (=INZONS+EXZONS)
MODES	I*4	10		MAXIMUM NUMBER OF MODES IN THE MODEL SYSTEM.
*NMXS	I*4	31		NUMBER OF O-D MATRICES STORED INTERNALLY
NMXI4	I*4	11		NUMBER OF INTEGER*4 MATRICES
NMXR4	I*4	7		NUMBER OF REAL*4 MATRICES
DYNA	L*4	T		IF =T THEN DRT IS BEING MODELLED IN THE CURRENT PERIOD
NPER	I*4	0		CURRENT ANALYSIS PERIOD NUMBER
*ZONFIL	I*4	5		FORTRAN FILE NUMBER FOR ZONAL DATA
*ZONDAT	I*4	7		NUMBER OF ZONAL DATA ITEMS TO BE READ FROM THE ZONE DATA CARDS.
ZPLUS1	I*4	21		USED FOR DIMENSIONING PURPOSES, (= ZONES + 1)
*FA	R*4	1.3		FACTOR FOR CONVERTING STRAIGHT LINE DISTANCE TO TRAVEL DISTANCE ON THE GROUND <1.8>
NEED	L*4 (10)	10*F		USED TO DETERMINE WHETHER THE TABLES CONTROLLED BY <TABLES> NEED TO BE READ IN AT THE START OF A PERIOD

BKDOWN	R*4 (5,5,2)	MATRIX GIVING THE DEMOGRAPHIC BREAKDOWN OF THE POPULATION. IT IS COMPUTED FROM AUTOS, HHOLDS, AND OVR64. 1ST INDEX - AUTO LEVEL INDEX (0,1,2,3,4+) 2ND INDEX - HOUSEHOLD SIZE INDEX (1,2,3,4,5+) 3RD INDEX = 1 IS FRACTION OF TOTAL POPULATION IN THIS COMBINATION OF AUTOS AND HOUSEHOLD SIZE 3RD INDEX = 2 IS FRACTION OF THIS CELL WHICH IS OVER 64
*COEFDE	R*4 (300)	COEFFICIENTS FOR DEMAND MODELS: 1-100 WORK MODEL 101-200 HOME BASED NON WORK MODEL 201-300 NON HOME BASED NON WORK MODEL WITHIN EACH BLOCK OF 100, 1-50 ARE DIRECT MODES AND 51-100 ARE ACCESS MODES. WITHIN EACH BLOCK OF 50 THEY ARE ORGANIZED IN GROUPS OF 10 FOR ADA, SHR, DRT, BUS, AND TAX IN THAT ORDER

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*COEFSU     R*4                       PARAMETERS FOR THE SUPPLY
            (100)                     MODEL &lt;1.9&gt;
                                      THE USER IS MOST INTERESTED
                                      IN THE FOLLOWING PARAMETERS:

                    .5,               (1)  - PAX LOAD DELAY IN
                                             MINUTES
                    .5,               (2)  - PAX UNLOAD DELAY IN
                                             MINUTES
                    15.,....          (3)  - VEHICLE SPEED (MPH)
                    .85,              (12) - EFFECTIVE VEHICLE
                                             FLEET SIZE FACTOR
                    0.,               (13) - COMPUTER DISPATCH
                                             CONSTANT
                    0.,               (14) - WEIGHT ON RIDE TIME
                    .5,               (15) - FRACTION BY WHICH
                                             NEW PRODUCTIVITY IS
                                             WEIGHTED
                    10.,              (16) - PRODUCTIVITY MAXIMUM
                                             FOR THE START OF
                                             EACH PERIOD
                    2.,               (17) - PRODUCTIVITY MINIMUM
                                             FOR THE START OF EACH
                                             PERIOD
                    .1                (18) - MINIMUM EFFECTIVE
                                             VEHICLE SPEED IN
                                             MILES PER MINUTE
```

THE FOLLOWING VARIABLES WILL BE USED TO REFERENCE MATRICES INTERNALLY.

*SAVT	I*4	01	SCRATCH MATRIX FOR ERROR
*AIVT	I*4	02	IVTT FOR ADA,SHR,TAX
*BIVT	I*4	03	IVTT FOR BUS
*ZIVT	I*4	04	IVTT FOR FEEDER LINEHAUL
*BOVT	I*4	05	OVTT FOR BUS
*ZOVT	I*4	06	OVTT FOR FEEDER LINEHAUL
*BFAR	I*4	07	FARE FOR BUS
*TFAR	I*4	08	FARE FOR TAX
*DFAR	I*4	09	FARE FOR DRT
*ZFAR	I*4	10	FARE FOR LINE HAUL
*DLYT	I*4	11	DAILY WORK TRIP TABLE
*ADAT	I*4	12	MODAL TRIP MATRIX FOR ADA
*SHRT	I*4	13	MODAL TRIP MATRIX FOR SHR
*DRTT	I*4	14	MODAL TRIP MATRIX FOR DRT
*BUST	I*4	15	MODAL TRIP MATRIX FOR BUS
*TAXT	I*4	16	MODAL TRIP MATRIX FOR TAX
*DIVT	I*4	17	IVTT FOR DRT
*DOVT	I*4	18	OVTT FOR DRT
*AAIVT	I*4	19	IVTT FOR AUTO + LINE HAUL
*AAOVT	I*4	20	OVTT FOR ADA + LINE HAUL
*AAFAR	I*4	21	FARE FOR ADA + LINE HAUL
*ASOVT	I*4	22	OVTT FOR SHR + LINE HAUL
*ASFAR	I*4	23	FARE FOR SHR + LINE HAUL
*ATOVT	I*4	24	OVTT FOR TAX + LINE HAUL
*ATFAR	I*4	25	FARE FOR TAX + LINE HAUL

*ABIVT	I*4	26	IVTT FOR BUS + LINE HAUL
*ABOVT	I*4	27	OVTT FOR BUS + LINE HAUL
*ABFAR	I*4	28	FARE FOR BUS + LINE HAUL
*ADIVT	I*4	29	IVTT FOR DRT + LINE HAUL
*ADOVT	I*4	30	OVTT FOR DRT + LINE HAUL
*ADFAR	I*4	31	FARE FOR DRT + LINE HAUL

THE FOLLOWING VARIABLES WILL BE USED TO REFERENCE ZONAL DATA ITEMS INTERNALLY.

*NZ	I*4	01	ZONE NUMBER INDEX
*NA	I*4	02	ZONAL AREA
*NX	I*4	03	X COORDINATE INDEX
*NY	I*4	04	Y COORDINATE INDEX
*NE	I*4	05	EMPLOYMENT
*NP	I*4	06	POPULATION
*NT	I*4	07	TAXI WAIT TIME <NOT USED>

CORE REQUIREMENTS AND EXECUTION TIME

FORCAST REQUIRES 117K BYTES FOR BASIC PROGRAM STORAGE WHEN THE OVERLAY STRUCTURE IS USED. ADDITIONAL STORAGE IS REQUIRED AS A FUNCTION OF: BUFFER SIZES, NUMBER OF ZONES, AND NUMBER OF SIMULATED ENTITIES. THE NUMBER OF ZONES IS BY FAR THE MOST CRITICAL ELEMENT.

FORCAST'S RUNNING TIME IS DETERMINED BY THE SAME ELEMENTS AS CORE PLUS THE NUMBER OF PERIODS REQUESTED AND THE NUMBER OF ITERATIONS PER PERIOD.

THE FOLLOWING EXAMPLES RELATE TO EXPERIENCE ON A IBM 370/158 WITH VS2:

ZONES	SIMUL	# OF PERIODS	ITERATIONS PER PERIOD	CORE (K)	CPU MIN
5	100	1	1	136	.07
5	500	3	5	140	1.73
5	500	3	2	140	.67
9	500	3	5	152	5.00
16	1000	4	5	-	28.62
14	100	4	2	-	1.67
23	250	4	1	-	3.53

DATA CARD FORMATS

ZONAL DATA CARDS:

THESE CARDS FOLLOW THE &DATA INPUT CONTROL CARD. THERE IS ONE SET OF ZONES+1 CARDS FOR EACH TIME NEWZON=T IS SPECIFIED ON AN &PERIOD CONTROL CARD. THE CARDS CONSIST OF ONE HEADER CARD AND 'ZONES' DATA CARDS. THE 'ZONES' DATA CARDS MUST BE IN ORDER BY ZONE NUMBER.

ZONAL DATA HEADER CARD FORMAT

COLUMNS	FORMAT	CONTENTS
1-10	I10	PERIOD IN WHICH THIS SET IS TO BE READ

ZONAL DATA CARD FORMAT

1-10	I10	ZONE NUMBER
11-20	F10.0	ZONAL AREA IN SQUARE MILES
21-30	F10.0	ZONE X COORDINATE (IN UNITS OF MILES)
31-40	F10.0	ZONE Y COORDINATE (IN UNITS OF MILES)
41-50	F10.0	TOTAL EMPLOYMENT
51-60	F10.0	TOTAL POPULATION
61-80	F10.0	NOT USED

PROGRAM FLOW

```
PROCEDURE FCAST (FORCAST)
   SIGNON
   INITIALIZE AREA NAMELIST DATA
   READ AREA NAMELISTS
   CHECK AREA NAMELIST DATA
   READ AREA DATA MATRICES
   INITIALIZE PERIOD NAMELIST DATA (FORC3A)
   WHILE OPERATING PERIOD DATA EXISTS
      INPUT OPERATING PERIOD DATA (FORC3B)
      INITIALIZE OPERATING PERIOD RESULTS (FORC3C)
      MODEL DYNAMICALLY ROUTED SERVICE (FORC6)

PROCEDURE INPUT OPERATING PERIOD DATA (FORC3B)
   READ PERIOD NAMELISTS
   CHECK PERIOD NAMELIST DATA
   READ PERIOD DATA MATRICES
   READ PERIOD DATA VECTORS
   PRINT OPERATING PERIOD DESCRIPTION REPORT
PROCEDURE MODEL DYNAMICALLY ROUTED SERIVCE (FORC6)
INITIALIZE DRT TRIP MATRIX
SAVE DRT TRIP MATRIX (FOR47A)
   ERROR:=CONVERGENCE LIMIT +1
   NITER:=1
   WHILE ERROR>=CONVERGENCE LIMIT AND NITER<=MAXITR DO
      FIND DYNAMICALLY ROUTED SUPPLY (FORC8)
      INITIALIZE ALL MODAL MATRICES TO ZERO (FORC46)
      IF WORK TRIP FRACTION > 0 THEN
         FIND WORK DEMAND (FORC9)
      IF NUMBER OF SIMULATED ENTITIES > 1 THEN
         FIND NONWORK DEMAND (FORC10)
      CREATE ERROR MEASURE (FOR47B)
      SAVE DRT TRIP MATRIX (FOR47A)
      NITER:=NITER+1
      IF REQUESTED PRINT DYNAMICALLY ROUTED ITERATION REPORT
   RESET PERSON FILE INDICES (FOR50C)
   PRINT NONWORK DYNAMICALLY ROUTED PERIOD REPORT (FORC57)
```

```
PROCEDURE FIND WORK DEMAND (FORC9)
   INITIALIZE ALL MODAL MATRICES TO ZERO
   FOR EACH LEVEL OF AUTO AVAILABILITY DO
      FOR EACH LEVEL OF HOUSEHOLD SIZE DO
         CALCULATE POPULATION IN CURRENT MARKET SEGMENT
         IF POPULATION > 0 THEN
            FOR EACH HOME ZONE DO
               FOR EACH WORK ZONE DO
                  COMPUTE NUMBER OF WORK TRIPS
                  IF NUMBER OF WORK TRIPS>0 THEN
                     IF EITHER WORK ZONE OR HOME ZONE IS AN
                     EXTERNAL ZONE THEN
                        INVOKE FEEDER OPTION
                        ACCUMULATE MODE SPLITS
                     ELSE
                        LOAD VARIABLES INTO BUFFER
                        EVALUATE LOGIT MODEL
                        ACCUMULATE MODE SPLITS
   SUMMARIZE WORK DEMAND
```

```
PROCEDURE FIND NONWORK DEMAND(FORC10)
   COMMENT - A SIMULATED ENTITY IS A RECORD CONSISTING OF:
      HOME ZONE
      ZONE NUMBER OF CURRENT LOCATION (=0 IF AT HOME)
      MARKET SEGMENT (AUTO AVAILABILITY AND HOUSEHOLD SIZE)
      DEPARTURE TIME FOR NEXT TRIP
   IF FIRST TIME THROUGH THEN
      SET PERSON FILE INDICES (FOR50A)
     CALCULATE TOTAL POPULATION IN SERVICE AREA
      FOR EACH HOME ZONE DO
         FOR EACH MARKET SEGMENT DO
            COMPUTE WEIGHT OF EACH SIMULATED ENTITY
            CALCULATE NUMBER OF SUCH ENTITIES
            FOR EACH ENTITY TO BE SIMULATED IN EACH MARKET
               SEGMENT AND HOME ZONE COMBINATION DO
                  DRAW RANDOM FIRST DEPARTURE TIME (FORC49)
                  CREATE PERSON
                  PUT PERSON (FOR50B)
      RESET PERSON FILE INDICES (FOR50C)
   RESET PERSON FILE COUNTERS (FOR50E)
   HOMEID:=0
   MARKETID:=0
   WHILE PERSONS EXIST FROM LAST PERIOD DO
      GET PERSON (FOR50D)
      IF PERSON(DEPARTURE TIME)<=END THEN
         IF PERSON(HOME ZONE)<>HOMEID OR PERSON(MARKET
         SEGMENT) <>MARKETID THEN
            MARKETID=PERSON(MARKET SEGMENT)
            HOMEID=PERSON(HOME ZONE)
            COMPUTE MATRICES OF CUMULATIVE PROBABILITIES (FORC51)
         PERFORM NONWORK DEMAND MODEL (FORC52)
      PUT PERSON (FOR50B)
```

<u>SAMPLE PRODUCTION RUN SETUP</u>

```
//    EXEC  FORCAST,TIME=(05),LIB='WYL.AR.CLW.AUG16',MEMB=FORCAST,
//    J1='DSN=WYL.AR.CLW.SKPLMXS1(WORKT10K)',
//    UNITJ1='2314,VOL=SER=WYL001',
//    J2='DSN=WYL.AR.CLW.SKPLMXS(AIVT16)',
//    UNITJ2='2314,VOL=SER=WYL001',
//    DISPJ1='(SHR,KEEP)',
//    DISPJ2='(SHR,KEEP)'
//FORCAST.SYSIN  DD  *
SAMPLE RUN:  AREA=6 MI  POP=10K  VEHS=3  DRT FARE=$.50  BUS=F

 PERIODS ARE 6-9, 9-3, 3-6; EACH HAS 2 ITERATIONS


 &PARAM INZONS=5,  EXZONS=0,  TRPTAB=101,
      TAX=F, BUS=F,  SIMUL=500,
      AUTOS=8., 48., 36., 8., 0.,
      HHOLDS=15., 55., 19., 8., 3.,
      OVR64=12.,  NWPOP=2800,
      AMWORK=0., 0., 0., 0., 5., 5., 40., 30., 10., 5., 5., 0.,
      PMWORK=0., 0., 0., 20., 30., 30., 20., 0., 0., 0., 0., 00.,
      &END
```

```
&OPTION  GENT=10*0,  GENT(8)=1,
     TRACE(6)=T,DUMP(6)=T,
     TRACE(8)=T, RDUTIL=T,
     TRACE(9)=F, DUMP(9)=F,
     TRACE(10)=F, DUMP(10)=F,
     TRACE(17)=T, DUMP(17)=T,
  &END
&SELECT REPORT=100*F &END
&UTILIT   COEFSU(1)=.5,.5,16.2, COEFSU(12)=.85,.4,.1,
     COEFDE(31)=2.,
 &END
&PERIOD BEGIN=600, END=900,
     VEHS=3,  LIMIT=.0001, PATRON=50,
     VEHCAP=12,
     TABLES(2)=201,
     MAXITR=2, NEWZON=T,
     DRTFAR='FIXED',   DRTCOS=50.,
&END
&PERIOD
     BEGIN=900, END=1500, PATRON=200, NEWZON=F,
&END
&PERIOD
     BEGIN=1500, END=1800, PATRON=110.,
&END
&DATA
        1  PERIOD WHEN THIS ZONAL DATA WILL BE READ
        1       .72     2.235     2.235        800       1000
        2      1.28     2.235     3.010        350       2250
        3      1.28     3.010     2.235        250       3000
        4      1.28     2.235     1.410        250       2000
        5      1.28     1.410     2.235        350       1750
/*
```

CATALOGED PROCEDURE

```
//*
//*   CATALOGED PROCEDURE NAMED  FORCAST (09DEC76)
//*
//FORCAST   PROC CLASS=A,CORE=128K,MEMB=DUMMY,
//             LIB='NULLFILE',UNITLIB=SYSDA,
//             LOG=DUMMY,UNITS1=SYSDA,
//             J1=DUMMY,UNITJ1=2400,DISPJ1='(OLD,KEEP)',
//             J2=DUMMY,UNITJ2=2400,DISPJ2='(OLD,KEEP)',
//             J3=DUMMY,UNITJ3=2400,DISPJ3='(OLD,KEEP)',
//             J4=DUMMY,UNITJ4=2400,DISPJ4='(OLD,KEEP)',
//             J5=DUMMY,UNITJ5=2400,DISPJ5='(OLD,KEEP)',
//             J6=DUMMY,UNITJ6=2400,DISPJ6='(OLD,KEEP)',
//             J7=DUMMY,UNITJ7=2400,DISPJ7='(OLD,KEEP)',
//             J8=DUMMY,UNITJ8=2400,DISPJ8='(OLD,KEEP)',
//             J9=DUMMY,UNITJ9=2400,DISPJ9='(OLD,KEEP)'
//FORCAST   EXEC PGM=&MEMB,REGION=&CORE
//STEPLIB  DD  DSN=&LIB,UNIT=&UNITLIB,DISP=(SHR,PASS)
//FT05F001 DD  DDNAME=SYSIN
//FT06F001 DD  SYSOUT=&CLASS
//FT11F001 DD  &J1,UNIT=&UNITJ1,DISP=&DISPJ1
//FT12F001 DD  &J2,UNIT=&UNITJ2,DISP=&DISPJ2
//FT13F001 DD  &J3,UNIT=&UNITJ3,DISP=&DISPJ3
//FT14F001 DD  &J4,UNIT=&UNITJ4,DISP=&DISPJ4
//FT15F001 DD  &J5,UNIT=&UNITJ5,DISP=&DISPJ5
//FT16F001 DD  &J6,UNIT=&UNITJ6,DISP=&DISPJ6
//FT17F001 DD  &J7,UNIT=&UNITJ7,DISP=&DISPJ7
//FT18F001 DD  &J8,UNIT=&UNITJ8,DISP=&DISPJ8
//FT19F001 DD  &J9,UNIT=&UNITJ9,DISP=&DISPJ9
//FT20F001 DD  UNIT=&UNITS1,SPACE=(TRK,(1,1),RLSE),
//             DCB=(RECFM=FB,LRECL=80,BLKSIZE=800)
//FT21F001 DD  &LOG,DISP=SHR,DCB=BLKSIZE=1024
//*   END OF CATALOGED PROCEDURE   FORCAST
```

NOTES

1.0 &PARAM

1.1 EXZONS, ADA, SHR, DRT, AND BUS ARE KEYWORDS THAT DETERMINE MODAL AVAILABLITY. SEE (1) IN SECTION 3.2 OF THE REPORT FOR MORE DETAILS.

1.2 SIMUL CONTROLS THE PRECISION OF THE NON-WORK MODELS. IF SET =1 IT TURNS OFF THE NON-WORK MODELS. SEE (2) IN SECTION 3.2 OF THE REPORT FOR MORE DETAILS.

1.3 INZONS AND EXZONS DESCRIBE THE EXTENT OF THE SERVICE AREA AND EXTERNAL ZONES. SEE (1) IN SECTION 3.3 OF THE REPORT FOR MORE DETAILS.

1.4 TRPTAB AND NWPOP DEFINE THE WORK TRIPS AND THE NON-WORK POPULATION TO BE MODELLED. SEE (2) IN SECTION 3.3 OF THE REPORT FOR MORE DETAILS.

1.5 AMWORK AND PMWORK DESCRIBE THE DISTRIBUTIONS OF WORK TRIPS OVER THE DAY. SEE (4) IN SECTION 3.3 OF THE REPORT FOR MORE DETAILS.

1.6 AUTOS, HHOLDS, AND OVR64 DESCRIBE THE SOCIOECONOMIC CHARACTERISTICS OF THE POPULATION BEING SERVED. SEE (5) IN SECTION 3.3 OF THE REPORT FOR MORE DETAILS.

1.7 PTRIP, HDWEL1, HDWEL2, AND NHDWEL ARE INTEGRAL PARTS OF THE NON-WORK MODELS. SEE (6) IN SECTION 3.3 OF THE REPORT FOR MORE DETAILS.

1.8 FA, THE STREET ADJUSTMENT FACTOR IS FURTHER DISCUSSED IN IN SECTION 3.4 OF THE REPORT.

1.9 THE SUPPLY MODEL PARAMETERS ARE FURTHER DISCUSSED IN SECTION 3.3 OF THE REPORT.

4.0 &PERIOD

4.1 BEGIN AND END DEFINE THE ANALYSIS PERIODS OF INTEREST. SEE (3) IN SECTION 3.2 OF THE REPORT FOR MORE DETAILS.

4.2 LIMIT AND MAXITR CONTROL THE PRECISION OF THE WORK AND NON-WORK MODELS TOGETHER. SEE (4) IN SECTION 3.2 OF THE REPORT FOR MORE DETAILS.

4.3 FOR FURTHER DETAILS ON VEHS SEE (1) IN SECTION 3.3 OF THE REPORT.

4.4 FOR FURTHER DETAILS ON VEHCAP SEE APPENDIX B OF THE REPORT.

4.5 CARCOS DESCRIBES AN AUTO COST INPUT AS WELL AS THE SHARED RIDE PENALTIES. SEE (4) IN SECTION 3.5 OF THE REPORT FOR MORE DETAILS.

4.6 BUSFAR, DRTFAR, BUSCON, AND DRTCOS DESCRIBE THE FARES ASSOCIATED WITH BUS AND DRT. SEE (3) IN SECTION 3.5 OF THE REPORT FOR MORE DETAILS.

4.7 PATRON IS USED TO PROVIDE AN INITIAL VOLUME IN THE DRT SYSTEM. IT IS SPREAD EVENLY OVER ALL INTERNAL TO INTERNAL O-D PAIRS AFTER BEING DIVIDED BY THE AVERAGE OF THE WORK AND NON-WORK GROUP SIZES.

4.8 FOR A FURTHER DISCUSSION OF THE REQUIRED MATRIX INPUTS SEE (2) IN SECTION 3.5 OF THE REPORT.

4.9 FOR A FURTHER DISCUSSION OF THE OPTIONAL MATRIX INPUTS SEE (3) IN SECTION 3.5 OF THE REPORT.

APPENDIX D

DESCRIPTION OF DELIVERY TAPE FORMAT

A source deck listing has not been included in this report because of the size of the programs. (A listing would be approximately 100 pages in length.) A computer tape can be obtained from TSC, however, with the following information:

Cataloged Procedure

Linkage Editor Control Cards

FORTRAN Source Deck

The format of the tape files is described on the following tape log. All the files are card image (EBCDIC) 80 byte logical records, blocked 10 per physical record, on standard IBM labeled files, on a 9 track tape 1200 feet long.

For further information about this tape, contact:

Dr. Howard Simkowitz
DOT/TSC
Kendall Square
Cambridge, Massachusetts 02142

Density 3200 fci   Length 1200 ft.   Track 9

Seq # 1   Name WYL.AR.CLW.FORCAST.PROC
LABEL SL JOB ____ DSORG PS RECFM FB LRECL 80 BLK SIZE 800
Description: See page D-1.

Format: EBCDIC

Seq # 2   Name WYL.AR.CLW.FORCAST.LKEDCARD
LABEL SL JOB ____ DSORG PS RECFM FB LRECL 80 BLK SIZE 800
Description: See page D-1.

Format: EBCDIC

Seq # 3   Name WYL.AR.CLW.FORCAST.SOURCE
LABEL SL JOB ____ DSORG PS RECFM FB LRECL 80 BLK SIZE 800
Description: See page D-1.

Format: EBCDIC

APPENDIX E

REPORT OF INVENTIONS

Although a diligent review of the work performed under this contract has revealed that no new innovation, discovery, or invention of a patentable nature was made, this report contains many advances to the state-of-the-art of patronage forecasting applied to demand responsive transit systems. The non-work trip model represents a significant methodological advance over prior models. It explicitly allows for variations over the day in the propensity of people to travel and also includes complex tours. The non-work model not only represents a traveller's choice of mode, but also the choice of destination. Thus, the model is capable of forecasting how DRT service will alter the pattern of non-work travel in an urban area.

The level of service, or supply, model is a set of equations which predict period by period DRT average systemwide wait time and ride time on an origin-destination basis. These equations were estimated using data generated with the MIT simulation model. These models can be used in the overall model system or as stand alone forecasting models.

Demand and level of service models are solved simultaneously to obtain the equilibrium travel pattern. The model system has been implemented in a computer software package and applied in a set of highly simplified prototypical cities representing a wide range of DRT systems. The resulting forecasts serve as a sketch planning tool which can be used by planners who lack the time or resources to use the detailed model system.

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