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Route-Level Demand Models:

A Review

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FOREWORD

All transit systems have a need for techniques which can accurately estimate the patronage impacts of service changes. To assist these systems UMTA's Office of Planning Assistance, through its Special Studies in Transportation Planning Program, has initiated prototype studies in Albuquerque, Cleveland, Los Angeles and Portland. The purpose of these studies is to develop patronage estimation techniques which can be used at a route level.

This document represents the first report from these studies. It summarizes the estimation techniques currently used by the transit industry. We believe that this report will be valuable to transit systems in their efforts to accurately estimate the patronage impact of proposed service changes.

Additional copies of this report are available from the National Technical Information Service (NTIS), Springfield, Virginia, 22161 at cost.

Information on the progress and findings of the prototype studies can be obtained from Brian McCollom, Office of Methods and Support (URT-41), (202) 426-9271.

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PREFACE

This report was prepared by Multisystems, Inc. The authors are Robert Menhard, Gary Ruprecht, and Imogene Burns. Technical and editorial input was received from John Attanucci of Multisystems and Richard Albright of the Transportation Systems Center. Draft and final documents were typed by Gail Bublis, Gail Pasquale, and Ranwa Ramadan.

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Finally, we would like to thank Brian McCollum of UMTA for his valuable comments and assistance throughout the project and in preparing this report.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

In this era of shrinking public resources and increasing scrutiny of the use of public funds, it is becoming increasingly important to operate public transportation efficiently. In order to assess the efficiency of existing operations, it is necessary to know the costs and revenue of specific services. This requires an effective program of data collection and a valid method of allocating costs to each route in the system. However, knowing the relative efficiencies of existing services is not sufficient. To improve efficiency of the operation, the cost, ridership, and revenue of options for improving services must be estimated.

Unfortunately, while a number of transit operators have reasonable models to estimate the cost implications of service changes, few have patronage models which are sensitive to route-level changes. Little is known about how to develop ridership models which are appropriately sensitive to changes in service variables (e.g., travel time, headway).

The Urban Mass Transportation Administration recognizes the need for improved route-level ridership prediction techniques and has recently initiated a series of prototype bus route planning studies. The objective of these studies is to develop route-level ridership prediction techniques which can be used by local transit operators. This working paper is a product of one of these studies which is being performed through the Transportation Systems Center.

A first step in developing improved ridership prediction techniques is to review the techniques that are currently being used by transit operators or that have been proposed by researchers. The major objectives of this review are:

- to assess the adequacy of current methods, and
- to identify promising directions for future development.

This report documents the results of a review of existing route-level ridership prediction techniques. To obtain information on current practices, discussions were held with 40 transit properties regarding their route-level ridership prediction procedures. This effort was complemented by a review of the recent literature on this topic.

Chapter 2 identifies the role of route-level ridership prediction techniques in the broader context of transit planning and management and describes criteria upon which route level ridership techniques can be evaluated. Building on this background material, Chapter 3 describes the techniques currently used by transit properties. Chapter 4 describes some recent advances reported in the literature but not yet regularly used.

An important trend in the local transit planning field is a move away from large-scale, capital intensive planning and toward low-cost operational planning. With most major transit and highway facilities in place, broader consideration is being given to making minor changes to improve the efficiency and increase the capacity of existing transit services.

Accompanying this emphasis on low-cost transit improvements, there has been a change in the anticipated impacts of transit improvements. Unlike large scale, capital intensive improvements, low-cost transit improvements have little impact on the diversion of automoble trips to transit. While new ridership may be generated, it will come from people making new trips. The resulting patronage may be significant but only in terms of transit ridership. It will have virtually no impact on highway level of service.

Traditional system planning models used in major urban areas are not effective in addressing the impact of low-cost improvements. There are a number of reasons for this:

- the margin of error associated with their use often significantly exceeds the likely change in transit ridership;
- key components of the modeling process such as trip generation and distribution models are frequently insensitive to transit service changes;
- the focus of transit patronage estimation is often limited to radial, peak work trips for which major facilities are designed;
- significant time and effort are required to obtain trip table volumes for input into these models; and
- the large size of the zones often makes transit route level analysis difficult (e.g., there is no easy, accurate way to assign ridership to specific routes).

2.1 Purpose and Function of Route level Models

In contrast to long-range, system-level demand models, the purpose of the route-level model is either to address the impacts (on ridership of the modified and related routes) of modifying an existing bus route (on its ridership and possibly on that of related routes) or to estimate ridership resulting from the implementation of a proposed new route. In addition, such techniques could be used to project loading characteristics along the route in order to assure that adequate service capacity is provided.

The transit manager needs to predict these ridership impacts of proposed service changes for a variety of reasons. First, there are always competing demands for new services or, in the case of budget reductions, competing demands that existing services be maintained. The transit planner or manager needs to have some basis on which to allocate vehicle and manpower resources. For example, decisions might be based on some measure of projected overall cost-effectiveness, such as "cost per new passenger" for service improvements or "savings per passenger lost" for service reduction. A second reason is to prepare budget requests for proposed service plans to the transit agency board or a local funding authority. In this case, revenue projections must be reasonably accurate to stay within the overall operating budget. Finally, ridership projections can be important inputs into the detailed route planning and scheduling tasks which must accompany new service plans. For example, route segment ridership predictions might be needed for a route restructuring effort in a heavily served area in order to schedule sufficient capacity on street segments and to identify appropriate short-turn points (at which a portion of the routes are ended).

To perform these tasks adequately, any such model should be able to estimate the impact of a wide variety of potential types of service modifications. A route-level patronage model must be sensitive to service characteristics, such as:

- frequency,
- coverage (e.g., route alignment),
- travel time,
- transfer opportunities, and
- accessibility (e.g., bus stops, park-and-ride locations),

as well as the more traditional socioeconomic characteristics of the area through which the route passes. These service quality measures are the ones most often affected by route level service modifications made by most transit properties: headway adjustment, route extension and contraction, limited and express service, shortlining, branching, through routing, creating transfer opportunities, fare adjustments, and new hours of service.

2.2 Types of Techniques

The specific uses, the inputs and the outputs desired by a property, together with the mathematics required, provide a framework in which to categorize any technique. Route level patronage prediction techniques are characterized in this study according to the following characteristics:

1. Service type restrictions - Each route-level demand model may be applicable to only a subset of all possible types of service. For example, express bus and local bus services might very well require different models. The type of environment in which the service exists — rural, suburban, CBD etc. -- might also be a restriction on the usefulness of the model.

2. Level of aggregation - The units of the forecast variable partially determine the model's level of aggregation. Is it the total number of riders in one day for a single route? One hour? One week? One run? The model may also produce predictions stratified by market segment. For example, demand by fare class or pedestrian age could be predicted. Also, boardings by stop could be estimated -- even an entire origin/destination table could be produced. The number and variety of possible stratifications are unlimited.

3. Forecast variable - Most route-level demand models produce estimates for total boardings in some time period (determined by the model's level of aggregation), but other volume statistics are available. For example, route-level demand models that predict peak load point volumes could be constructed, as could ones predicting cumulative passenger-miles.

4. Model form - The mathematical formulation which is used in developing the estimates. In many cases, the form can only be illustrated by example; however, the functional form can be described in terms of commonly used terms such as "linear" or "logit-form."

5. Model inputs - A variety of potential measures of service quality and socioeconomic inputs are used. Historical ridership data may be used as a basis for predictions. The input requirements not only indicate the cost of using a model, but also point out the factors to which it will be sensitive.

2.3 Technique Evaluation

In addition to classifying and describing various techniques, it is important to judge the value of the tool. One obvious criterion is the accuracy of the predictions made, but this is clearly not the only one. Even if a model is accurate in estimating the impacts for which it was designed, the value of these good predictions are minimized if the model is very restricted in its application, difficult to apply, expensive to operate, or requires extensive data collection. For example, if it is more expensive to apply a model than to run the service for a year, the value of the model would indeed be dubious.

The route level patronage prediction techniques discussed in the remainder of this working paper are evaluated in terms of the following criteria:

1. Accuracy - does the model have the ability to predict ridership accurately? Best measurement is done by predicting impacts of a modification before it is made and measuring the results afterwards. Most often, the analyst is most interested in either the change in ridership or the resultant ridership at the route level.[1]

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[1] In many cases, before-after experiments are not available, or do not cover a sufficient range of a model's applications, to allow its accuracy to be assessed. In such cases, it is necessary to base such evaluations on theoretical expectations of the quality of the model's predictions. For example, a model in which the estimate of route-level demand is based primarily on the number of seats on each bus could be judged to lack accuracy without any direct data to support the evaluation.

2. Sensitivity to decision variables - can the model predict changes resulting from key modifications made by the system operator (e.g., headway, fare, route orientation, transfers, etc.)?

3. Range of application - are there restrictions to specific modes of operation or to certain parts of the urban area? Does the model apply only to express routes; only to radial or crosstown routes?

4. Analyst dependence - will all analysts get the same results by applying the model or will the predicted ridership depend on who is making the prediction?

5. Cost of application - what are the manpower, data collection and/or computer expenses required to make an application?

6. Technical sophistication - does the user need significant technical expertise to apply the model; to develop the model?

7. Transferability - can a calibrated model be transferred from one geographical area to another? Is recalibration of the model necessary?

Whenever possible, examples are provided to explain the judgments made regarding the techniques and models. Unfortunately, the very nature of these criteria combined with a lack of data on individual techniques, uses and accuracy make all such evaluations somewhat subjective.

CHAPTER 3: THE PRACTICE

The current practice of the transit industry provides an important insight into the state-of-the-art of route level patronage prediction and into the desired direction for future modeling efforts. To determine what methods transit operators are using to generate route level ridership projections in transit properties' planning processes, a two step investigation was performed.

The first stage of the effort involved a review of the transit planning literature. This review yielded some specific models which have been used by operators (or by contracted consultants). The second stage of the review of current practices involved contacting a sample of properties in the United States and Canada. In-depth discussions were held with the planning staffs of 40 properties (see Table 3-1). These discussions focused on the use patronage prediction methods, either formal or informal, in the design and modification of fixed route bus service. For those properties that used route-level forecasts, an attempt was made to identify what types of service changes could be analyzed using the method, what applications were performed, the form of any formal models, and how the results were used in the planning process. Documentation on specific planning applications was requested, where available. The appendix presents a summary of techniques used by the properties contacted.

3.1 Overview of Current Practices

Eight types of service changes were identified for which ridership prediction techniques are used. These changes include:

- new routes,
- route extensions,
- route cutbacks or eliminations,
- changes in service hours,
- changes in route alignments,
- minor headway changes (five minutes or less),
- major headway changes (over five minutes), and
- fare changes.

Most properties that make ridership predictions use them primarily to identify, choose among, or justify major changes in their systems. The latter most often involve new routes and somewhat less often pertain to major changes in route length or configuration (e.g., through-routing or splitting routes in

Table 3-1

TRANSIT PROPERTIES CONTACTED

Peak Buses Used	Property	Location
<100	Greater Bridgeport Transit District	Bridgeport, CT
	CITRAN	Ft. Worth, TX
	Grand Rapids Area Transit Authority	Grand Rapids, MI
	Greater Peoria Mass Transit District	Peoria, IL
	Santa Cruz Metropolitan Transit District	Santa Cruz, CA
	South Bend Public Transportation Corp.	South Bend, IN
	Wichita Metropolitan Transit Authority	Wichita, KA
100-250	Capital District Transit Authority	Albany, NY
	Central Ohio Transit Authority	Columbus, OH
	Transit Authority of River City	Louisville, KY
	Madison Metro	Madison, WI
	Tidewater Regional Transit	Norfolk, VA
	North County Transit District	Oceanside, CA
	Phoenix Transit System	Phoenix, AZ
	Rhode Island Public Transit Authority	Providence, RI
	Sacramento Regional Transit District	Sacramento, CA
	San Diego Transit	San Diego, CA
	CNY Centro	Syracuse, NY
250-500	Calgary Transit	Calgary, Alberta
	Dallas Transit System	Dallas, TX
	Southeastern Michigan Transportation Authority	Detroit, MI
	City and County Bus Service	Honolulu, HI
	Metropolitan Transit Authority of Harris County	Houston, TX
	Utah Transit Authority	Salt Lake City, UT
	Santa Clara County Transit	San Jose, CA
	Winnipeg Transit System	Winnipeg, Manitoba
500-1000	Metropolitan Atlanta Rapid Transit Authority	Atlanta, GA
	Regional Transportation Authority	Chicago, IL
	Edmonton Transit	Edmonton, Alberta
	Milwaukee County Transit System	Milwaukee, WI
	AC Transit	Oakland, CA
	Ottawa-Carleton Regional Transit	Ottawa, Ontario
	Metropolitan Transit Commission	St. Paul, MN
	MUNI	San Francisco, CA
	Seattle Metro	Seattle, WA
>1000	Southern California Rapid Transit District	Los Angeles, CA
	Southeastern Pennsylvania Transportation Authority	Philadelphia, PA
	Toronto Transit Commission	Toronto, Ontario
	Washington Metropolitan Area Transit Authority	Washington, D.C.

half). These techniques are seldom used for route cut-backs or eliminations since most properties consider current ridership counts to be an adequate source of information. Few properties use modeling or forecasting techniques that can redistribute the riders from discontinued routes to alternative routes and modes; the tendency instead is to assume that ridership loss to the system will be equal to the total observed for the route or route segment in question.

Similarly, specific changes in service hours, headways or minor reroutings are seldom based on ridership predictions. Instead, they are typically made in response to observed overcrowding, insufficient loading complaints, or to comply with changes in policy. Many properties simply make such changes and evaluate them after they are implemented. The Capital District Transit Authority (Albany, New York) is one property which tried to model those small changes. They found that 70% of such applications resulted in predictions with no statistical difference between before and after ridership.

Not surprisingly, then, most properties use ridership predictions only to determine headways and service hours for new routes. In these instances, the predictions are used in conjunction with loading standards to determine what service levels will match the demand.

The impact of fare changes is usually evaluated at the system rather than route level. Some properties occasionally apply standard elasticity measures (see Section 3.5.1) from the literature to individual routes, but only to provide "ball-park" or "worst case" estimates. Five properties indicated that their use of fare elasticities has been complicated in the last year or two by secular trends in which ridership growth is related to gasoline price increases and shortages and to population growth. In particular, some properties (including those in Calgary and Ottawa) have reported sizable ridership increases in conjunction with fare increases.

The methods currently used to evaluate the above types of changes fall into four general categories:

- professional judgment,
- non-committal survey techniques,
- models based on cross-sectional data (between routes), and
- models based on time series data (varying over time for the route or routes).

Many properties use more than one technique to place bounds on the range of anticipated patronage. The approaches range from highly informal to highly complex.

Of the properties that do predict ridership, most (87%) use technically straightforward or otherwise simple methods because they require the least time, cost and technical sophistication. Many properties indicated that they are only interested in the potential performance of these routes in the most general terms. The precision of the ridership estimates often is less important to the property than simply <u>having</u> an assessment of the potential "success" of the new route or route change (as measured by the number of passengers it will carry or the amount of revenue it will generate). In some cases this is because routes are proposed for reasons other than ridership potential; in others, routes are systematically implemented on a trial basis and subsequently retained or dropped based on observed ridership. In these cases ridership predictions may assist in the choice among proposed routes or may be used to identify which routes have the potential to exceed a minimum productivity standard. Once the route is in place, however, direct observation typically replaces any sort of projection as a method of evaluation.

Properties using more sophisticated methods (see Sections 3.3, 3.4.3, 3.4.4) frequently have direct access to a computer or work closely with a regional planning organization. Survey methods are frequently used both by properties with and without computer support. The processing of more extensive surveys is clearly facilitated by computer support, but many surveys are quite limited (e.g. to a few employers in an unserved area or in the vicinity of a proposed route). Most properties using statistical techniques have easy if not direct access to a computer and the appropriate software packages, although a few properties use hand calculators to run simple statistical models. In general, the development of formal models requires a significant level of technical expertise and a relatively large amount of information. San Diego Transit, which currently maintains an extensive data base, indicated that the marginal cost of more complicated methods is actually quite low once the data is collected and coded. Others indicate that even if the data were not readily available, the cost is justified by the high cost of implementing an unsuccessful route, both from the point of view of operating cost and public relations.

Four properties contacted use several independent methods to develop a range within which potential ridership is expected to fall, and also to provide a check on the validity of the results of each method. These properties, along with those using the more sophisticated methods, seem to feel that the greater accuracy that may be obtained outweighs the additional expense.

Little documentation is available either in the literature or from properties themselves regarding the accuracy of ridership predictions made using the various techniques. The more informal methods tend to have been in use for longer periods of time, but due to their informality, also tend to be followed up more haphazardly. Those using professional judgment indicated that on balance the predictions are reasonably accurate, but that the actual results are not documented anywhere. Properties engaged in more formal methods frequently express more interest in the accuracy of the results than those using judgment or various rules of thumb, but in many cases routes either have yet to be implemented or were put in operation so recently that the evidence upon which to judge the models' accuracy is not available. Some properties also indicate that the lack of follow-up relates in part to the purpose of the ridership predictions. Often the predictions are used to justify routes prior to implementation, and once the routes are in place the <u>actual</u> performance becomes of primary importance. This is particularly true of stable systems making few changes, where the results of any formal follow-up may not be immediately applicable to other proposals.

As an alternative to ridership predictions, a number of properties have adopted non-forecasting procedures for route planning such as service warrants and requests for service. Service warrants typically include a series of indicators that identify when new or modified service is "warranted," or alternatively include standards that proposed new service or service changes must meet. For example, the criteria used for selecting route modifications used by Edmonton Transit are as follows:

- The proposed route will result in a ratio of six residents or more per vehicle route kilometer.
- Total access time of 30,000 person minutes or more has been reached.
- There is reason to belive that 20% of the route's operating costs can be met from farebox revenue.

The popularity of this approach appears to rest in its ease of use, a reliance on measures that can be directly observed, and a general mistrust of forecasting procedures. Furthermore, the data required are inexpensive to collect and process, and can be used for other purposes as well. One problem with some of these non-forecasting techniques is that, to some extent, they rely on subjective estimates of how a proposed new route will perform. In effect, such estimates (e.g., expected revenue to be generated by the route) represent direct judgmental demand models. Also, service warrants and requests for service do not provide the information necessary to choose among routes that meet the specified requirements, or to rank proposals according to incremental measures of their merit.

The following sections of this chapter present detailed descriptions of the methods employed to forecast route level patronage. Where possible, examples of transit property applications are presented to illustrate the uses of each approach.

3.2 Judgmental Methods

Seven of the forty properties contacted indicated that they estimate the impact of route changes on ridership based solely on the judgment of one or more of the property's operations analysts. Judgmental techniques rest on the premise that the individual's experience with the system and the community served provide sufficient insight into the problem that reasonably accurate predictions can be made. One aspect inherent in the definition of these judgmental techniques is that the mechanics and processes used by the service planner in making these predictions are not specified. As such, it is not possible to describe the type of concerns actually addressed by the analyst. In many cases, however, the description of service changes and associated data requirements specified by the planner give some idea of the issues addressed.

Model Form

Judgmental techniques do not exhibit a specific form. Some inferences may be drawn regarding the implicit form of the model from the observed results and the justifications for of the predictions outputs.

Forecast Variable

In general, a transit property may use judgmental techniques to predict whatever aspect of demand they feel is important. Ridership, for example, may be estimated at the system level, route level, by time of day, and even along short segments of the route. Most properties, however, are satisfied with the estimation of average daily ridership on a route level.

Model Inputs

As with all other aspects of judgmental methods, the input data used depends entirely on the application and the analyst.

Types of Analyses

There are virtually no restrictions on the types of analyses which can be performed using judgmental methods. Properties have used this technique to estimate ridership impacts of almost all types of service changes, including:

- the introduction of new routes,
- changes in service hours,
- route extensions or cutbacks,
- realignment of routes, and
- headway changes.

Application Process

There is no single procedure used for applying judgmental ridership prediction techniques. In most cases, estimates are made by individuals who have spent many years with a particular property (or at least in the transit profession) and, thus, feel they have the knowledge on which to base such estimates.

One aspect of judgmental approaches which is sometimes formalized is the format in which the planners' estimates are made. These formats are usually designed to control the interaction among individuals when each is requested to use his/her experience in the estimation process.

One method for using the judgment of more than one person is called the "delphi" approach. In this technique, a group of "experts" is asked to predict the impact of a change in service. Each member of the group is kept separate from the other members to eliminate one member's opinions from unduly influencing the opinions of others. Each estimate is submitted to a neutral individual governing the process. This individual tabulates the responses and determines the median and range of responses. The results are used as feedback to each member of the group. Each member is allowed to alter his/her forecast based on this information. This procedure continues for several rounds until the final median and range are established and results do not change significantly from one round to the next. This delphi technique is identified in the literature[1] and also was proposed and used to some extent by at least one property, the Southern California Rapid Transit District.

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[1] Jon E. Burkhardt, "Methods of Predicting Rural Transit Demand," Ecosometrics, Inc., prepared for PennDOT, 1976.

An alternative approach to the delphi process is the establishment of a review committee. This approach, used by two of the properties contacted (Regional Transportation Authority in Chicago and Philadelphia's Southeastern Pennsylvania Transportation Authority), allows interaction among individuals such that arguments justifying different positions can be made. This technique allows good arguments to be weighted more heavily and individual estimates to be "weighted" by the faith the individual has in them. The technique may also produce biases, however, since individuals who are strong-willed or influential may unduly affect the final estimates.

Accuracy of Results

During the course of this study, little information was found to document the degree of accuracy with which transit properties predict patronage using judgmental techniques. In general, there is little follow-up of these estimates to determine if the estimates were reasonable.

Application by Southern California Rapid Transit District (SCRTD)

SCRTD (Los Angeles) provided documentation on an application in which judgment was used to estimate the implications of a variety of changes to fourteen routes in one sector of the community. The specific route modifications included:

- splitting a U-shaped route to provide better service through the downtown area;
- shortening routes to eliminate some reliability problems and to fulfill previous interagency agreements regarding the provision of services;
- eliminating route segments which duplicate service on other routes
- connecting lines to provide non-transfer service along heavily traveled corridors; and
- changing headways as a result of other modifications.

In this application, the forecast variable was the expected change in daily ridership for each route modified and for each complementary or competitive route on which a secondary impact was anticipated.

Data from ridership counts taken during the previous two years were used for each of the lines of interest. These counts identified not only the route ridership but also boardings and alightings by stop. Field observations by the members of the planning staff involved in the demand prediction were also used.

The analysis was divided into a few distinct steps. The first step was an estimation of current ridership based on the previous ride counts. Growth factors were applied to those routes which were believed to have changed along with the systemwide ridership increase and because of specific operational changes which had occurred since data was collected. Once this adjusted base ridership was established, the staff estimated losses or gains to each route based on their expectations of user responses to the changes such as headways, required transfers, or new route alignment. They noted that the vast majority of riders lost from one route as a result of a cutback in service would shift to some other route in the system. Table 3-2 summarizes of the approach used and the results of this analysis.

The documentation provides no justification for the estimates of altered travel behavior. The following excerpts from the documentation indicate the type of judgments made:

- "Staff estimates realignment of service along 7th Street may change the boarding patterns of approximately 6,600 riders traveling into or out of the 8th Street segment on present Line 29. Line 47 is expected to absorb the majority of these riders as it provides service along 8th Street."

- "Approximately 3,300 passengers boarding present Line 47 service may be lost. Staff believes, however, the East 4th Street patronage loss may be more than offset by the extension of service along West 8th Street. Approximately 900 passengers using present Line 25 and 6,600 riders on existing Line 29 may be added to Line 47."

Most of the proposed route modifications were implemented; however, no data with which to validate these estimates have been collected to date.

Summary

Judgmental methods are attractive for a number of reasons. First, they are quick and inexpensive, expecially if only readily available data and resources are used. Second, they can be used to analyze virtually any change that a transit property might consider, as well as the impacts of exogenous factors. However, since this technique relies on the expertise of the analyst, the accuracy of any prediction is highly dependent on the knowledge and experience of the analyst. Even analysts with similar experience may predict significantly different results from the same information due to the informal manner in which this technique is applied. Also this informal manner of application, together with the technique's dependence on knowledge of the system under study and its service area, limit the transferability of any results.

The widespread use of judgmental methods by transit properties may indicate that this technique can provide the order-of-magnitude estimates and relative rankings needed by these properties to make decisions about the service they provide.

3.3 Noncommittal Survey Techniques

Another conceptually straightforward approach for the estimation of demand for transit services is the use of the noncommittal survey. In this method, potential riders are asked directly if they would use a proposed service. Their responses to the survey form the basis upon which the planner predicts anticipated patronage. The approach is called the "noncommittal survey technique" due to its reliance on the stated intentions of potential riders and not on their actual behavior.

Table 3-2

JUDGMENTAL RIDERSHIP ESTIMATES

Line No.	Check Date	Daily Riders (Nearest 100)	Estimated Growth Factor (%)	Riders Adjusted for Growth	Estimated Loss	Estimated Gain	Estimated Ridership Phase I
6	2-06-79	28,200	-	28,200	1,200	-	27,000
20	5-25-79	1,300	-	1,300	-	900	2,200
24	1-04-79	8,700	12%	9,700	-	-	9,700
16	11-30-79	9,600	10%	10,600	1,800	-	8,800
29	8-14-79	27,500	12%	30,800	6,600	-	24,200
35	6-13-79	13,000	-	13,000	-	1,000	14,000
-	10-79	10,800	-	10,800	3,300	7,500	15,000
81	1-03-79	8,900	15%	10,200	2,800	-	7,400
85(S210)	6-13-79	33,200	3%	34,200	9,700	-	24,500
142	1-02-79	900	7%	1,000	-	2,300	3,300
165	5-24-78	6,000	12%	6,700	900	-	5,800
305	7-30-79	2,000	-	2,000	2,000	-	Cancelled
359	3-23-79	1,000	7%	1,100	500	100	700
873(S232)	5-30-79	4,200	-	4,200	800	-	3,400
S212	-	-	-	-	-	12,000	12,000
TOTALS		155,300		163,800	29,600	26,400	160,600

Model Form

Once a noncommittal survey has been administered, ridership is estimated by extrapolating the survey responses to the population of potential users in the area to be served. This estimation involves a two step process. First, an unadjusted patronage estimate is calculated by multiplying the average trips per person (or household), as determined from the survey results, by the number of persons (households) in the service area. In many cases, this step involves segmenting the entire population into distinguishable groups which might be expected to have different travel patterns. For example, a separate estimation of trips for the elderly might be made by multiplying the average frequency of use from elderly respondents to the survey by the number of potential elderly users.

The second step is to adjust for a bias in responses resulting from the fact that individuals who will never use the proposed service often respond that they will use it. This "noncommittal bias" (multiplicative) factor is usually based on the judgement of the planner. Among the properties contacted this figure ranged between 5% and 50% (based primarily on previous experience with this technique).

In addition to these two steps, it is often necessary to further modify the results either in response to a factor that was not taken into consideration or when other data provides a benchmark indicating the reasonable range of results.

Forecast Variable

The basic information produced by this technique is an estimate of the average daily patronage on the specified route or on alternate routes. Usually the total ridership figure is sufficient, but some properties need to determine the riderships by time of day, for special market segments such as the elderly and handicapped, or along specific portions of the route.

Model Inputs

The basic inputs to this technique are the responses to a set of questions presented to the potential user. Noncommittal surveys contain two primary types of questions. One type is used to gather information with which the respondent can be classified into a category of interest to the planner. The other type elicits information on potential use of the proposed service(s).

The respondents are usually classified according to characteristics which appear to have a strong, direct bearing on the propensity to use the proposed service. Respondents may be classified as potential users or non-users based on information such as location and/or current travel patterns. The respondents are often divided according to trip purpose along the corridor of interest. The most common division is between commuters (work trip) and shoppers; groups such as students and persons who could use the service for both work and shopping are sometimes identified. Another breakdown is based on socioeconomic characteristics of the individual or household. A common question asked is the number of autos owned by the family.

Information on the propensity of an individual to use a proposed service is obtained using one of two basic questions. The simplest version of the question is whether the individual would or would not ride the bus. A more useful and informative question is how often the respondent is likely to use the service. In either of these cases, the questions must be prefaced with an adequate description of the proposed service. To be adequate, the description must include the route alignment, the frequency of operation, and the fare to be charged. Portions of the description may be unspecified in the general description and left for specification in individual questions. In this manner, the planner is able to judge the sensitivity of the patronage to specific variables.

Types of Analyses

Noncommittal surveys are used primarliy to estimate demand for a single well-defined service option or to choose among a small number of relatively specific alternatives. In most cases, this survey technique is preceded by an initial screening analysis which is used to identify the most needed new services and service modifications. Often this form of direct contact with users is applied to help planners decide on the detailed operational and service characteristics of a new or altered route. For example, noncommittal surveys are often used to evaluate alternative fare structures, frequency, hours of operation and routings.

Application Process

The primary concern regarding the application of this type of analysis is in the design and administration of the survey instrument. The specific survey instrument and format for asking these questions depends on the nature of the route modification proposed and of the sample desired. Home interview, telephone, mail-out/mail-back, and on-board surveys are commonly used. Each of these methods has advantages and disadvantages to be considered in survey design.[1]

An important aspect of the survey design is the sampling methodology. Two approaches are commonly used. One approach is to take a uniform sample of the population in the entire urban area. This technique is often chosen in smaller urban areas or when route changes are proposed throughout the urban area. An alternative to this uniform sampling strategy is to restrict the base population to a portion which is likely to use the proposed service. This selection may be based on several criteria. When a new route is to be introduced to a portion of the city, it is useful to sample from those residing in the area or residing within a certain distance of the proposed route. On the other hand, individuals with destinations along the transit corridor may be selected by choosing a sample of workers at employment centers along the route, of individuals parking at lots in the area, or of those shopping at stores served by the route. For modifications to existing routes, it may be desirable to select the sample from those riding on the affected routes.

Accuracy of the Results

The accuracy of this type of analysis depends to a great extent on the value chosen for on the noncommittal bias factor. When this is based on the judgement of the analyst, one might expect the results to be no more accurate than the use of a direct judgmental technique. Other studies have identifed more rigorous and formal methods upon which to establish the value of this factor. For example, a methodology to develop the noncommittal bias factor has been applied in New York State[2]. In this study ridership along a

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[1] The following sources provide a thorough discussion of survey techniques related to transportation planning: 1) Kenneth D. Bailey, Methods of Social Research, The Free Press, New York, 1978; 2) Nancy J. Hatfield, "Basic Market Research Techniques for Transit System," Texas Transportation Institute, USDOT Report # UMTA-TX-09-8003-79-2, June 1979. 3) UMTA, "Transit Marketing Management Handbook," Office of Transit Management, April 1976.

[2] D.T. Hartgen, "Forecasting Demand for Improved-Quality Transit Service with Small-Sample Surveys," Preliminary Research Report 51, New York State DOT, November 1973.

park-and-ride route was predicted using noncommittal survey results. The noncommittal bias factor for the route being analyzed was assumed to be the same as that for another local bus route for which a similar survey had been performed. A before and after study of these routes yielded a set of curves specifying this bias based on the travel time difference between transit and auto and the number of autos owned by the household. Based on a limited number of applications, this approach appears to produce reasonably accurate results. As shown in Table 3-3 the method was accurate to within 15% for high ridership routes and off by approximately 30% for lightly used routes.

Application by Grand Rapids

In an application provided by the Grand Rapids Transit Authority, a noncommittal survey was conducted in late 1979 to estimate ridership for a circumferential crosstown route. The proposed new service was well defined; the transit authority had identified the most appropriate areas to serve, the general route the bus would take and the fare structure. The property hoped to use the survey to determine the population and trip-making characteristics within the areas served by the route, the most appropriate fare structure, and to choose between two streets on which the route might operate.

Surveys were administered by telephone to approximately four percent of the households in the route corridor service area (one-half mile on either side of the route). This sample was identified using the telephone directory. Survey results were adjusted to reflect households with unlisted telephone numbers or without a telephone -- the total population estimate derived from the survey was in sufficient agreement with estimates from other sources to judge the sample valid, according to the property.

The basic information collected from each respondent was:

- residence and current travel habits,
- spouse's current travel habits,
- attitude toward the proposed service, and
- spouse's attitude towards the proposed service.

The first portion of the survey identified the respondent's residence based on a set of six zones bounded by three major streets. Location of the work place was identified in general terms (e.g., the southeast portion, downtown, specified surburban communities, or outside the county). Also requested were the usual mode of travel to work (auto, bus, carpool, etc.), the location of the most common non-grocery shopping destination, and frequency of non-grocery shopping travel. The respondent also was asked the same questions about his or her spouse's travel patterns.

Once these basic questions had been answered, the interviewer described the route of the proposed new service. It was mentioned that the service would operate on a schedule "similar to that of other routes" in the system on Monday through Saturday, but would not operate on Sunday. No information was provided on the fare to be charged. It should be noted that this description, in effect, uses the respondent's perception of the service quality on other routes as an input to choice decisions. Those with either no knowledge or a poor idea of bus service had little upon which to base their responses.

Table 3-3

ACCURACY OF SURVEY APPROACHES

Application	Predicted Ridership	Actual Ridership	Percent Difference
Grand Rapids	324	292	-9.9%
New York State	35	25	-28.6%
New York State	123	140	+13.8%

Following this description of the proposed route, the respondent was asked if he would have occasion to use the service. If the answer was yes, a series of questions were asked to determine the purpose, frequency of use, and portion of the route which would be used. Frequency of use was divided into five categories ranging from "less than once per week" to "more than five times per week." The frequency was stated in terms of round trips. Additional questions addressed the issue of using the route to transfer to other routes in the system. The final two questions in this group were used to determine the sensitivity of ridership to fare. Two different fare structures were specified. For each, the respondent was asked if he would be willing to pay the specified fare. The questions were then repeated allowing the respondent to express the likely attitude of his spouse toward the service.

The next step involved developing an average number of trips per week for each category from the survey data and applying this to the potential number of users. Since no such data were collected for school trips, an assumption was made that each student user would ride twice per day on each of the 180 school days per year.

In the final step, the number of trips per week was factored down to account for the respondents' tendencies to overestimate their potential usage. In this case, the property estimated that respondents would make only 5% of the trips they indicated that they were likely to take. This level of ridership was not anticipated to be realized until two years after implementation of the service; the ridership after one year was projected to be 37% of the two year estimate.

Summary

Noncommittal survey methods offer an advantage over judgmental methods in that they can provide information about an area or service change with which the analyst has no experience. With this increased information, of course, comes increased cost. The survey also presents the opportunity to formalize the manner in which the data is analyzed, thus enabling one service planner to replicate the work of another more easily. As with judgmental methods, the "what if" nature of the surveys used in this technique permits the planner to explore the impacts of a wide range of service-related changes. However, he is limited with this technique because he must be able to clearly define the changes of interest. Also, the level of technical sophistication required of the analyst may be higher, especially when a large number of surveys and more complex types of analyses are involved.

This technique offers a higher degree of transferability to other sites than judgmental methods when service and population characteristics are obtained through the surveys. Because this technique relies on individual's stated intentions, the accuracy of this technique is dependent on the analyst's ability to estimate the likelihood that individuals will act accordingly. As noted above, these estimates vary considerably and, thus, the accuracy of the results is to a large extent subject to the same uncertainties as the results of judgmental methods.

3.4 Direct Demand Based on Cross-Sectional Data

Many properties find it useful to formalize the prediction of patronage changes by developing mathematical formulas based on characteristics of the route and the type of change being made. These are called "cross-sectional" models because they examine the relationship between transit use and a range of characteristics of the service and populations and areas served, rather than the effects of changes in a single route over time. These models range from basing ridership predictions for a proposed route on a single "similar" route to sophisticated formal statistical methods.

3.4.1 "Similar Routes" Method

Nine of the 40 properties contacted perform some route level patronage analysis using a "similar routes" approach. The application of this form of model involves determining which route in a system is most like a proposed new or modified route and then basing the anticipated ridership for the new route on the patronage characteristics of that similar route. This approach tends to be employed on an informal basis and no documentation on a specific application could be obtained. While it was determined that the specific type of analysis performed and the methodology followed vary widely, some aspects of "similar route" methods are common to many of the properties.

Model Form

The form of mathematical equation used in estimating ridership using similar routes is generally direct and simple. In some cases, the estimate is developed by setting projected ridership equal to that on the similar route. Other forms use a trip rate taken from the similar route. Some of the trip rates mentioned by properties include:

- passengers per bus-mile,
- passengers per bus-trip,
- passengers per bus-hour,
- passengers per housing unit, and
- passengers per capita.

Several properties noted that the estimates resulting from these rates are subject to adjustment according to any differences which exist between the proposed and similar routes. None presented specific methods to perform the adjustment.

The classification scheme employed to determine which routes are similar is commonly informal. No properties could provide a detailed description of the classifications they deemed important nor did any have a classification of all routes in their system.

Forecast Variable

The primary output of this approach is an estimation of the daily ridership at the route level. Some estimation procedures separated the ridership predictions by time of day (e.g., a.m. peak, midday, and p.m. peak), but no example was found in which projected ridership was stratified further. The technique is sometimes applied only to a portion of a route, such as a route extension, in order to estimate ridership that may be generated in the new area.

Model Inputs

The inputs to the similar routes method include the socioeconomic, geographical and level of service characteristics of existing transit routes and those of the proposed new route. The factors most frequently identified as relevant to the choice of a similar route include:

- route type (express or local),
- population density of the area,
- income level of the residents of the area,
- total employment in the area,
- "directness" of route, and
- route frequency.

Once a similar route is chosen, various characteristics of the service it provides may be inputs with respect to that route, including passengers, hours of service, bus miles, bus trips, and bus hours of operation. These are the most commonly used factors, but other factors may prove appropriate in special situations. For example, the size of a park and ride lot may be relevant for express service between downtown and fringe area parking facilities.

Types of Applications

Similar route methods are most commonly used to estimate ridership for new routes or the change in ridership resulting from the extension of routes into new areas, expansion of service hours for a route, and realignment of the route to serve a different area.

Application Process

This method is applied in three basic steps. First, the characteristics of the proposed route or modification are compared to other routes in the system and one existing route is chosen as most similar. Next, the ridership and (usually) level of service characteristics of the similar route are used to estimate ridership or a trip rate. If a trip rate is used it is applied to a selected characteristic of the route to develop the ridership estimate. Finally, the analyst uses his judgment to adjust the results based on any differences between the similar route and proposed service.

Accuracy of Results

In spite of its common usage, no examples from which to judge the accuracy of this method could be obtained. This is largely a result of the informal manner by which it is applied.

Summary

The similar route method is a convenient way for a transit property to estimate ridership based on its past experience. The range of applications and decision variables that can be analyzed is limited only by the range of services the property currently provides and the availability of data on decision variables of interest. The cost of this method can be quite low for properties that regularly maintain the data needed to classify routes and service areas. Also, this technique can be replicated without significant difficulty when precise criteria are established for selecting similar routes. The accuracy of the technique is dependent on the service planner's ability to correctly identify a similar route and the major determinants of transit ridership on that route, and to correct for any differences that might exist.

3.4.2 Simple Rules of Thumb

A more formal approach used by a number of transit properties involves estimating expected ridership on a "rule of thumb." A "rule of thumb" is a method or procedure of analysis, based upon experience and common sense, intended to give approximately correct results. These rules can be developed from a variety of sources, including the analyst's familiarity with the system, results from repeated use of one or more other techniques, or a study done outside of the property. The information on which these rules are based may range from intuition to the results of scientifically performed studies.

Model Form

Rules of thumb generally use a model form in which the forecast variable is directly proportional to the single model input. For example, daily route ridership might be estimated at one hundredth of the population living within one quarter mile of the bus route.

Forecast Variable

The most frequently forecast variable is the average daily ridership on the route.

Model Inputs

Inputs differ among models. Of the three examples provided by the transit properties, model inputs included the number of dwelling units within 1/4 mile of the route, the number of bus miles operated, and the number of parking spaces in the fringe area park-and-ride lot.

Types of Analyses

Rules of thumb are appropriate for analyzing new or modified routes which serve new markets. The list of applications is similar to that of the similar route method. Specific models provided by contacted properties include the prediction of patronage for both new local and express (park-and-ride) bus routes. Rules of thumb are also sometimes used to estimate the change in ridership resulting from a change in a single service characteristic.

Application Process

The application process for these models can be divided into two steps: development of the rule and its use for prediction. The development of rules of thumb, as practiced by most transit properties, is an informal technique in which the analyst gathers data on the ridership and explanatory variable and then directly calculates the appropriate parameter. For example, the service planner may obtain the average daily ridership on a large number of the routes within the system and determine the population living near each route. The relationship between these two variables can then be evaluated either 1) by dividing the ridership on all routes by the total population living near these routes or 2) by averaging the ratios of ridership to neighboring population for each route. Both forms should give reasonably similar results, but are based on different assumptions regarding the relationships between ridership and population. The estimation of rule of thumb parameters usually takes only a short time and can be performed without the aid of a computer or calculator.

In many cases, the use of a rule of thumb does not involve the estimation of any parameters. The analyst simply uses a model for which the factors have already been established (from previous work performed either by that property or some other property). If the model does not need to be calibrated the analyst simply quantifies the one aspect of service used in the demand model and applies the specified trip rate.

Accuracy of Results

No data was provided on the accuracy of these techniques, but the properties who use them indicated they find the quality of results sufficient for preliminary analysis of a proposed service's feasibility.

Applications By Several Properties

Three of the fourteen properties contacted which use simple rules of thumb were able to provide explicit examples of how they are used in short-range transit patronage forecasting. The Milwaukee County Transit System uses the following formula in which daily route ridership is proportional to population served by the route.

$$\text{Daily route ridership} = (\text{TR}) \times (\text{\# of residents within 1/4 mile of the route}) \qquad (1)$$

where TR ranges between 0.1 and 0.45 depending on the type of route and its location in the community

In Oakland, California, AC Transit accounts for service quality in its rule of thumb by including the number of bus miles. The form of this model is as follows:

$$\text{Daily route ridership per bus-mile} = (0.03) \times (\text{population living within one quarter mile of a bus stop}) \quad (2)$$

In some cases, the population living near the route is not the relevant factor. For example, Seattle Metro uses a rule of thumb in which the number of stalls at a park-and-ride lot is used to estimate daily route ridership on park and ride routes:

$$\text{Daily route ridership} = (1.2) \times (\text{parking spaces at fringe area lot}) \quad (3)$$

Summary

Rules of thumb provide the transit planner with a simple and inexpensive method to predict ridership along new routes or on new sections of routes. Data requirements are typically limited to readily available sources and many require only desired values of level of service parameters as inputs. They can be applied easily by even the most novice analyst at almost any site. Rules of thumb, however, do have significant drawbacks, specifically in terms of accuracy and sensitivity to decision variables. Because route level ridership predicted by a rule of thumb is generally proportional to a single attribute, such a model cannot be used to examine the impacts of complex route modifications in which several service attributes are modified. This lack of sensitivity to all but one factor also implies that rules of thumb are probably not accurate over a wide range of changes. For example, a model based on population living near a route which produces accurate predictions for new routes in "average" areas is likely to underpredict ridership for new routes in areas with many captive transit riders.

3.4.3 Multiple Factor Trip Rate Models

A more sophisticated form of the simple rule of thumb involves the modification of a basic trip rate by several factors which account for a variety of characteristics of the route.

Model Form

The form of these two models are virtually indentical. Mathematically, they are stated as follows:

$$R = T(POP)\ F_1(LOS_1) * \ldots * F_j(LOS_j) \quad (4)$$

where:

R = ridership,
$T(POP)$ = base trips generated per day based on the population, and
$F_j(LOS_j)$ = a factor based on the value of service quality measure j.

Forecast Variable

The basic forecast variable is generally the ridership per day on the route. No model was encountered which attempts to disaggregate this figure by time of day, market segment, or other potentially useful categories.

Model Inputs

The primary inputs to these models include a description of the area served by the route and the quality of service provided.

Types of Analyses

As with the rules of thumb, these models are most frequently used in the estimation of patronage for proposed new routes. Since they include factors which directly relate demand to such service quality characteristics as fare, headway, and hours of operation, they may also be used to determine the impact of changes in level of service.

Application Process

Once the necessary data have been collected, the application process is a straightforward manual procedure. First, the base trip generation figure and multiplicative factors are derived from the appropriate nomograph or rule of thumb. Most often, the base trip generation figures and service quality factors are defined using nomographs. In general, both the nomographs and subjective rules of thumb describe non-linear relations between the input variable and the trip rate or modifying factor. The calibration of the curves, nomographs and factors used in these models involves the comparison of available ridership figures with the service characteristics of interest. These figures are then multiplied together to develop the final patronage prediction.

Sample Applications

Two models of this type are well documented and exemplify their general use. One employs information about the population near the bus route, classifying the population by auto ownership levels and quality of service in the area as follows:[1]

- fare,
- walking distance to the bus stop,
- distance from CBD, and
- route speed.

This model was applied to the existing transit service in the Fitchburg/ Leominister (Massachusetts) area yielding good comparisions with observed zonal trip production. It should be noted that this "validation" was not on a before/after basis, but was performed on the same data on which the model was

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[1] Marvin Golenberg and Steve Pernaw, "A Demand Estimating Model for Transit Route and System Planning in Small Urban Areas," presented at the 58th Annual Meeting of the Transportation Research Board, January 1979.

calibrated. These results, however, do not assure that the same level of validity can be extended to other applications. This model has also been applied in two additional locations, but to date, no data are available on the ridership generated.

The "Small Urban Communities"[1] model uses two population characteristics to describe the area served by the route: elderly and non-elderly populations living within 1/4 mile of the bus stops along the route. Service quality inputs for this model include:

- number of stops on one-way loops,[2]
- peak headways,
- off-peak headways,
- days of operation, and
- transfer coordination with other routes.

No documentation is provided on which to judge the accuracy of patronage projections produced by the model.

For the two examples, the relationships applied appear to have been established in part by the expectations of the analyst and/or by trial and error. The documentation does not indicate that the models were calibrated using a formal statistical technique such as ordinary least squares regression. As a result, there probably exist other coefficients to the models which can more accurately replicate the anticipated route ridership.

Summary

Multiple factor trip rate models take more factors into account than do simple rules of thumb. Thus, they have a wider range of applicability and might be expected to produce more accurate results. Since the data required for calibration can be derived from nomographs and transit data that, typically, are regularly maintained, the cost of obtaining the necessary data and applying the model should not be much greater than for rules of thumb. On the other hand, a higher degree of technical sophistication may be required of the user. As with the rules of thumb, the applications and variables considered are limited to those covered by the model. Also, the basic models are generally transferable from one property to another, although the base ridership and service quality factors may be different among properties. If models calibrated at other sites are to be used, it is necessary to validate the predictions on existing local routes prior to using the model for prediction.

3.4.4 Aggregate Route Regression Models

The most common application of formal statistical techniques in the development of transit route patronage models involves the use of regression.

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1 Peat, Marwick, Mitchell and Co. and D.H. James, "Analyzing Transit Options for Small Urban Communities," Volume II, U.S. DOT Report IT-06-9020-78, January 1978.

2 This factor accounts for the circuity of travel and higher perceived headways for individuals who wish to board or alight at a bus stop where the bus only travels in one direction.

Three properties contacted currently use these methods, several others anticipate the development of some form, and the literature presents several additional examples.

Model Forms

The linear model is the form most commonly used. Linear regression techniques are used to determine the best mathematical fit between a dependent variable (one which the analyst wishes to predict) and one or more independent variables. This form of regression assumes a relationship between the dependent and independent variables as follows:

$$Y = B_0 + X_1B_1 + X_2B_2 + \ldots X_NB_N \tag{5}$$

where:

Y = dependent variable,
X_i = an independent variable, and
B_i = a factor (coefficient) which specifies the rate at which the corresponding independent variable induces change in the dependent variable.

In a route patronage prediction model, Y in this equation might represent route ridership, and the X variables might represent characteristics of the route (such as population served, headway, employment centers served, and fare charged) which explain the variation in ridership among routes. Figure 3-1 illustrates such a regression model which might be applicable to predict transit ridership.

When developing a demand model using statistical techniques, it is necessary to select independent variables (X's in equation 5) whose values actually affect the value of the dependent variable (Y in equation 5). The use of dependent variables which are merely correlated with the dependent variable (that is, they change when the dependent variable changes but do not cause the dependent variable to change) will produce a model which may generate erroneous predictions. The following example illustrates the potential difficulty which can occur. Figure 3-2 presents two sets of curves. Those marked "D" illustrate a hypothetical relationship of how the ridership on a transit route actually responds to changes in frequency on the route. Each "D" curve is for a different transit route. The curve denoted by an "S" represents the rule the transit property uses to decide how many buses are required on a route given the number of passengers riding. In this case, if the scheduler is doing a good job, the actual ridership on each route should be close to the point at which the "D" (demand) curve and "S" (schedule's rule) curve intersect. As a result, if an equation were calibrated based on this ridership and service frequency data, it would yield a line very close to that of "S." Note, however, that such an equation would indicate the demand for service is much more responsive to change in headway than it actually is.

A few properties have also experimented with transformations of the common linear form, representing the next level of complexity. One model of this type encountered in the literature[1] is a logarithmic transformation in which

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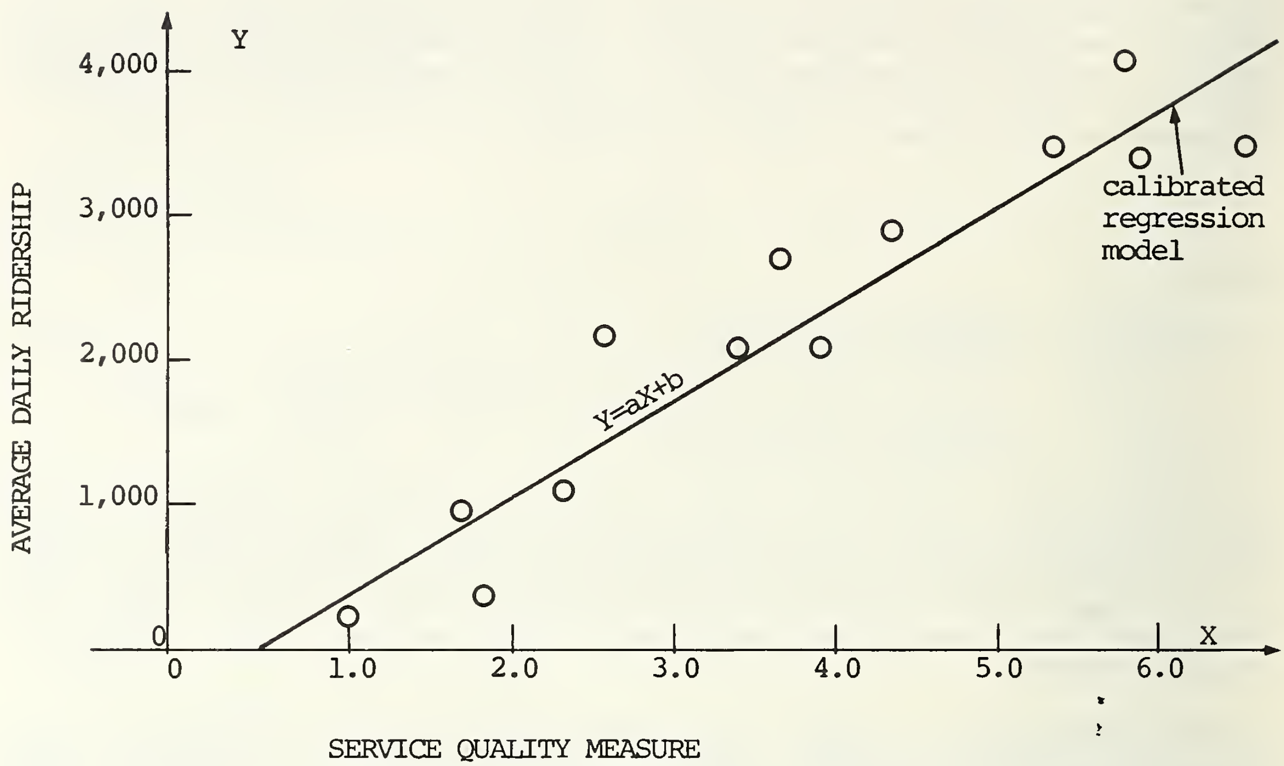
1 Ecosometrics, Inc., Methods of Predicting Rural Transit Demand, prepared for Pennsylvania Department of Transportation, 1976.

FIGURE 3-1 SAMPLE REGRESSION MODEL



O -observations

FIGURE 3-2 TRANSIT DEMAND CURVES AND SCHEDULER'S RULE

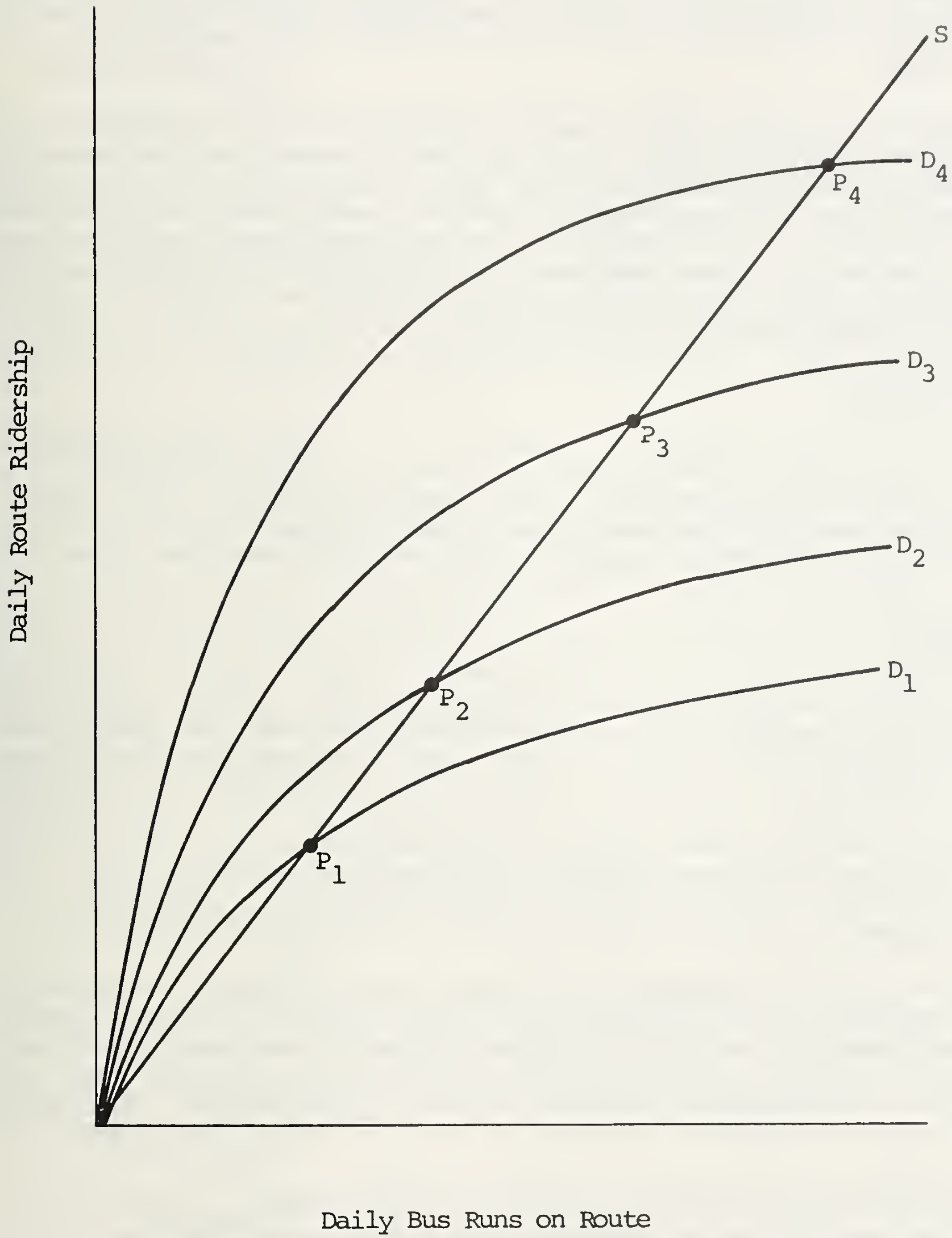


Figure taken from:
Gonzales, L.S.Q., "Short Range Bus Transit Planning: Demand Prediction at the Route Level", Master's Thesis, Civil Engineering Department, Massachusetts Institute of Technology, Cambridge, MA, 1980

the log of ridership is a function of the log of a series of independent variables. As in the previous regression models, the independent variables are again selected from various level of service and socioeconomic or demographic variables. The difference, however, is in the underlying assumptions that are made regarding the way in which the independent variables interact and explain ridership. Non-linear transformations allow the planner to specify equations which can be "better behaved" (e.g., they cannot predict negative ridership) and which may have more justifiable relationships than the simple linear form.

Calibration of a regression model cannot normally be done by hand. For relatively simple formulations with few explanatory variables, the service planner can use a hand calculator. On the other hand, the development of regression models based on cross-sectional data with more than one parameter is simplified with the use of a computer and software designed to estimate the parameters of the model. (Those interested in developing regression models and using available software are directed to the variety of statistics texts and statistical package manuals which are readily available.)

Forecast Variable

The primary forecast variable is usually the average daily ridership expected on a route, but regression models may also be used to project more detailed characteristics of ridership. For example, equations to estimate route ridership by direction and time period between selected zones have been discussed, although no successful applications of this form were identified in this study.

Model Inputs

The input data typically used are ridership counts from a number of different routes in a system, combined with information on service levels and socioeconomic attributes of the route corridor. In these models the variables are intended to measure:

- the general quality of the transit service available,
- the socioeconomic characteristics of area residents, and
- characteristics of the area, such as trip attractors or generators along the route.

The level of service variables typically include headway or daily round trip frequency of service,[1] round trip distance in miles, hours of service, and/or fares. The socioeconomic variables include average income per zone, age variables such as the number of senior citizens or school age children, or auto ownership. The demographic variables include population or employment density, the number of households or dwelling units per zone, the number of

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[1] The use of headway and/or frequency in route aggregate models has been shown to produce poor predictions of ridership because models with this input tend to replicate the scheduler's decision rule (how many buses are needed given a specific demand level) rather than how ridership actually responds to increased service. Such models often prove to be overly sensitive to frequency of service.

workers residing in a zone, and so forth. Finally, although few route ridership regression equations directly account for the presence of competing modes, the South Eastern Michigan Transportation Authority in Detroit found the presence of a railroad station on a route was often a significant variable. (Household income and auto ownership variables are related to the availability of travel options and can be used to implicitly capture the effects of the alternate modes.)

Types of Analyses

The sophistication of the regression models used by various transit properties varies widely. The simplest models are bivariate linear regressions in which route ridership is a function of a single independent variable such as population or employment density in the immediate vicinity of a route. Often these models represent a formalization of a rule of thumb, and can easily be calibrated using a hand calculator.

The next most prevalent model form is the multivariate linear regression in which route ridership is a function of two or more levels of service and socioeconomic or demographic variables.

Application Process

The process for employing these models, once calibrated, can range from relatively straightforward to fairly complicated and tedious. The first step is to gather the necessary input data for each model. Many inputs will be easy to obtain; others, such as "population at the main destination along the route" and factors which depend on origin to destination characteristics of service, may be difficult to specify. Models which use simple variable inputs and produce only route level ridership may also be processed quickly by hand. Those which estimate ridership by origin and destination may require a significantly greater level of effort. If the level of ridership estimation is sufficiently disaggregated, such as from census tract to census tract, a computer may be required to handle data storage and processing functions. Furthermore, if the functional form of the models contains mathematical functions such as logarithms, exponentials, and square roots, the assistance of at least a scientific calculator is desirable.

Application by Southeastern Michigan Transit Authority (SEMTA)

SEMTA used regression techniques to estimate two models that were specified in a form similar to the Cobb-Douglas production function.[1] Separate models were developed for CBD and non-CBD routes by testing a number of alternative forms using a variety of socioeconomic variables. The models judged to be the best were:

(1) The non-CBD model:

$$R = 104\ K^{-.467} P^{(.021E\ +\ .00002D)} \tag{6}$$

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[1] In the economic literature, the Cobb-Douglas production function takes the general form: $P = L^{B} K^{(1-B)}$ in which P = goods produced, L = labor and K = capital.

where: R = average daily ridership,
K = peak period headway (minutes),
P = population of the service area, defined as ¼ mile on either side of the route,
E = percent population over 65, and
D = population density (per sq. mi.).

(2) The CBD Model:

$$R = 665\, P^{.076}\, E^{.577}\, e^{(-.06K - .014F)} \qquad (7)$$

where: F = off-peak headway (minutes), and
R,K,P,E are defined as above.

<u>Application by Pennsylvania Department of Transportation (PennDOT)</u>

One of the few studies in the literature that presents alternative specifications of route-specific demand models is a study by Ecosometrics, Inc. for PennDOT.[1] This study used existing data on a number of rural routes operated by different transit operators in Pennsylvania, experimenting first with linear formulations and then with logarithmic transformations. The authors found that the logarithmic transformations outperformed the linear forms, both in terms of fit and the statistical significance of the regression coefficients. Most of the coefficients calibrated in the study related ridership to either the population served or to trip rates in the area. The independent variables considered include:

- the origin population,
- the population at the main destination along a route,
- the round trip distance,
- round trip travel time,
- frequency of service,
- fares charged,
- county population divided by the number of taxis in counties served by a route, and
- the ratio of fixed route bus miles to demand responsive bus miles.

In addition, three definitions of population served were tried:

- population residing within one-half mile of the route,
- borough population, and
- borough plus township population.

After calibrating a number of equations, the two preferred equations were the following:

$$\log PASS = 1.461 + 0.068 \frac{POP_o \times POP_d}{D^{3.423}} + 0.728 \log(FRQ) - 0.129 \log \frac{(1000)(FARE)}{MILES} \qquad (8)$$

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[1] Ecosometrics, Inc., <u>Methods of Predicting Rural Transit Demand</u>, prepared for Pennsylvania Department of Transportation, 1976.

and

$$\log \frac{PASS}{(POP_o)(POP_d)} = -3.656 + 2.547 \log (D) + 0.697 \log (FRQ) \qquad (9)$$

where: PASS = average one-way daily passengers on a given route,
POP_o = origin population served computed either as borough population, or borough plus township population, or population residing within one-half mile of the route,
POP_d = population at main destination along the route,
D = round trip distance in miles between the farthest origin place served and the main destination,
FRQ = number of round trips per day,
FARE = round trip fare in cents, and
MILES = round trip miles.

It must be reiterated that these equations were developed specifically for transit services in rural areas.

In general the PennDOT models appear fairly promising when evaluated according to standard statistical criteria such as the amount of variation in the dependent variable explained by the independent variables, whether each coefficient has the appropriate sign, whether the elasticities are reasonable, and whether the value for the coefficient is higher than the standard error. On the other hand, the strong reliance on the fit to the current data does not necessarily assure the models' predictive ability. Unfortunately, these models have not yet been applied to routes other than those used to calibrate them. In addition, the models may not be transferable to areas with higher population or service densities, since the routes modeled had daily frequencies as low as two trips per day and were located in areas with little or no competing service.

Summary

Aggregate route regression models may provide the transit planner with a very effective tool for forecasting route-level ridership. Models of this sort can be developed to account for a wide variety of decision variables (representing choices open to the service planner) and exogenous factors (e.g., population, gasoline prices, employment, land use, etc.) which directly affect transit patronage. The fact that many exogenous factors and service variables may be included indicates that such models may be applicable over a wide range of situations and potentially may be more transferable than other models. Furthermore, applications of these models to date indicate that a high degree of accuracy can be achieved between the data upon which models were calibrated and the predictions of the model.

Unfortunately, little data exists upon which to judge the accuracy of these models with respect to routing modifications. Based on theoretical arguments, it appears that the specifications of the existing models leave much to be desired. Lack of a clear causality between independent and dependent variables and the potential for estimating the scheduler's decision rule, rather than the response of potential riders to service quality changes, are shortcomings found in those models used by properties. Although further research may prove aggregate route regression models to contain inherent problems, the potential for this approach seems to exist since the statistical technique at least assures that the best coefficients are chosen for the model given the variables included and the mathematical form chosen.

From an operational viewpoint, aggregate regression models tend to be more difficult to apply and require a greater level of technical sophistication. To calibrate a regression model, a large data set must be generated which contains a variety of information on routes and the socio-economic characteristics of the potential users. In addition, the planner or analyst who calibrates a model must have a good understanding of regression techniques to insure that the calibrated coefficients are reliable and that the form of the model is acceptable. Once calibrated, a model may require substantial amounts of data to apply, thereby increasing the cost and time required to apply the model.

3.5 Methods Based on Time Series Data

Another approach to developing models of route level demand is to estimate the impacts of changes based on what happens to ridership on a single route (or group of routes) as service changes over time. These techniques are considered to be based on "time series" data. An example of such a model is encompassed in what is commonly called the "Curtin Rule" for the impact of fare changes.[1] This model was developed by comparing before and after ridership statistics on a variety of transit systems when a fare change was implemented. This study led to the model that for each percent increase (decrease) in the average fare charged, patronage would decrease (increase) by 0.3%. This section presents several models of this type plus a patronage estimation technique based entirely on the historical trend of ridership on a route.

3.5.1 Elasticity Methods

Elasticity methods are a relatively simple form of analysis which can provide quick estimates of the change in ridership which will result from a specified change in the level of service provided along a route.

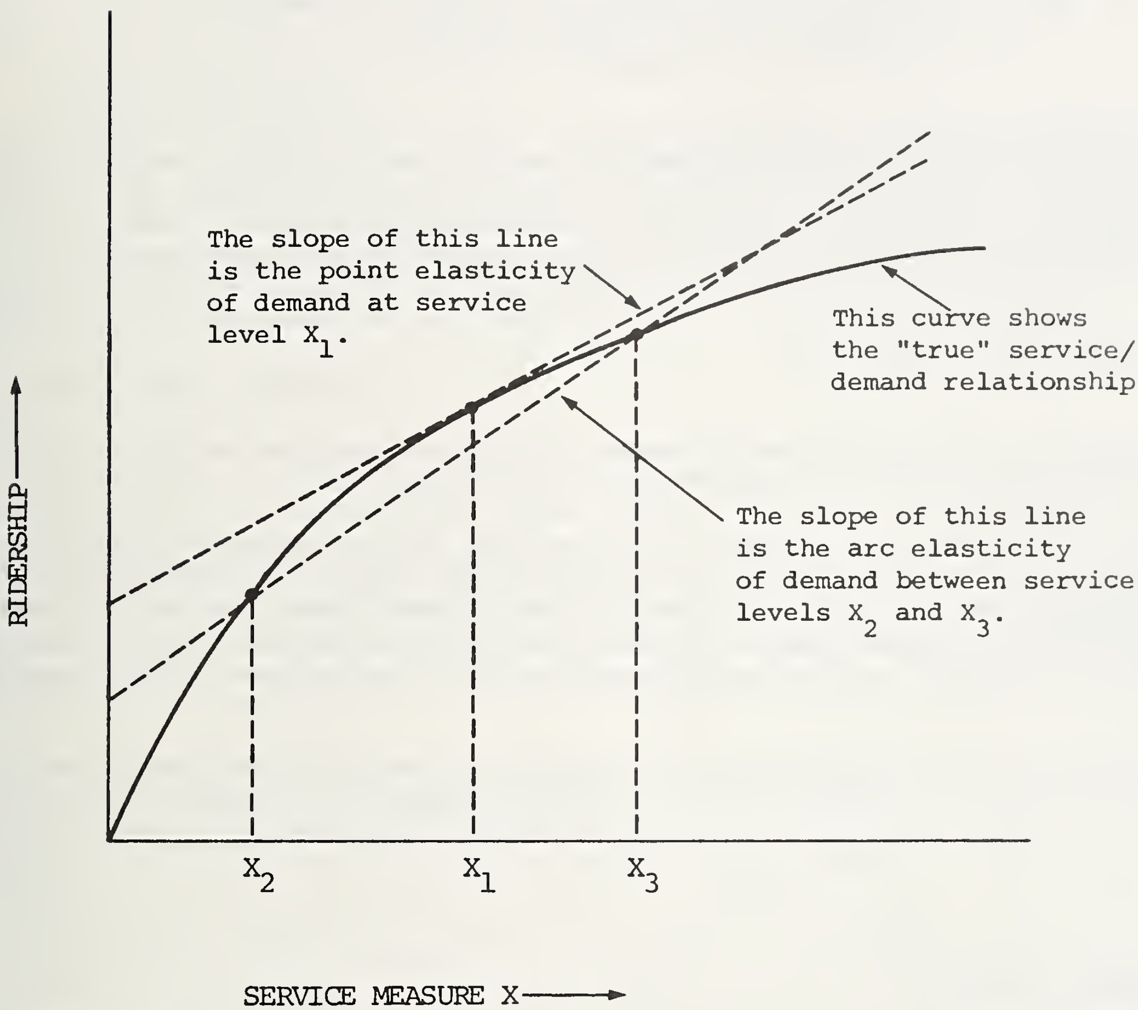
Model Form

There are two forms of elasticity models noted in the literature and used by transit properties: point and arc. Point or "true" elasticities measure the responsiveness of ridership to a minute change in service quality. (See Figure 3-3) The formula for calculating a point elasticity is as follows:

$$E_x = \frac{X}{V} * \frac{dv}{dx} \qquad (10)$$

[1] Although originally developed by John Curtin in 1947 from the results of a survey of fare increases on 91 U.S. transit properties, the most common reference is: John F. Curtin, "Effects of Fares on Transit Riding", Highway Research Record 213, Highway Research Board, Washington, D.C., 1968.

FIGURE 3-3 "POINT" AND "ARC" ELASTICITIES



where: E_X = the elasticity of ridership with respect to level of service variable X,

V = ridership,

X = level of service variable, and

$\frac{dv}{dx}$ = a mathematical function which specifies the rate at which ridership changes with changes in the level of service variable (i.e., the derivative of the demand function).

Practically speaking, computation of a point elasticity is impractical since it requires knowledge of the true functional form of the service/demand relationship. Instead, "arc" elasticities are computed where the arc is the segment of the demand curve lying between the before and after data points. (See Figure 3-3.) The expression for an arc elasticity can be written as:

$$E_x = \frac{X^b}{V^b} * \frac{(V^a - V^b)}{(X^a - X^b)} \tag{11}$$

where: E, V, and X are defined as above and the superscripts "b" and "a" denote "before" and "after" measurements.

The arc elasticity is a single value for the entire arc; therefore, the larger the change being measured, the less precise the arc elasticity is.[1] It is important to note that an elasticity calculated in this manner is only applicable when a single level of service variable is affected by the change in service. If other service quality measures are also altered, an incorrect estimate of the elasticity may result.

Equation 11 can be rearranged to provide a ridership prediction model. The general form of a route-specific elasticity model is as follows:

$$V^a = V^b (1 - E_x (1 - X^a/X^b)) \tag{12}$$

Forecast Variable

The forecast variable in elasticity models is generally the change in average daily route ridership. The method, however, will also allow the investigation of ridership along specific segments of the route (for example, if a fare increase applies to only a portion of the riders), for certain times of day, by direction, and even for specific market segments (e.g., the elderly), if the appropriate data are available.

Model Inputs

Each elasticity model requires four data elements for calibration and three for application. Inputs to the model calibration procedure involve the identification of ridership levels before and after the service change

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[1] As (X^a-X^b) approaches zero, the arc elasticity approaches the point elasticity. If the demand curve is linear, then the slope is constant along its length and equal to V/X.

implemented and the value of the factor which measures the type of service change. For example, if the elasticity of ridership with respect to headway is being calibrated, ridership and headway measures are required with respect to the service before and after the headway change. This data should at least be collected on the route level and may be further disaggregated if desired. When applying elasticity models all but the after implementation ridership (which is being predicted) must be input to the estimation procedure.

Types of Applications

The types of applications for which these techniques are most commonly used involve the adjustment of fare or service frequency on an existing route. Elasticity methods cannot be used to estimate ridership on new routes, since they require a base ridership figure to project future ridership. They are most commonly applied when only one service factor is being modified, but can be applied sequentially to judge the impact of simultaneous change.

Application Process

The application of elasticity models begins with the choice of an appropriate value for the elasticity of interest. Two basic methods are used to estimate the elasticities for these models: 1) use of a combination (e.g., weighted average) of elasticity measures derived in prior studies and documented in the literature or by other properties; and 2) calculation of average elasticity measures using "before" and "after" data for routes of a given property. Both of these methods require separate sets of information to be gathered for each type of level-of-service change for which ridership predictions are desired.

The first method is limited by the nature and quality of the elasticity measurements previously calibrated and documented in the literature. It can only be used to estimate the impacts of changes in the most common level of service variables, such as fare, headway, and travel time.

The second method requires two or more observations (over time) of ridership levels for each level-of-service attribute. These observations must be made over a period in which transit routes become more or less attractive due to a change in fare, travel time, frequency of service, or other service attribute. For each type of change (i.e., modification in a level-of-service variable), a direct elasticity value can be calculated for each with before and after data for all routes combined. Once the elasticity for the service factor being altered has been determined, the estimation of the ridership change is a straightforward application of the model form described above.

Accuracy of Results

Although many properties indicated that they use elasticities to perform quick analysis of service changes, none could provide any documentation of an application or the accuracy of this technique.

Applications in the Literature

Two recent studies have consolidated a number of calibrated elasticities so that they can be used directly by a transit property. Barton-Aschman

Associates, Inc. investigated fare and service elasticity in 62 cities throughout the U.S., Canada, and Great Britain.[1] An Ecosometrics, Inc. study extracted elasticities from other published reports and calibrated some additional ones from its own data on travel behavior.[2] The Ecosometric study considered a greater number of service characteristics than the Barton-Aschman study but includes fewer observations.

As shown in Tables 3-4 and 3-5, these two studies suggest that there is a relatively large degree of variation in elasticities estimated in different areas. It is necessary for the planner to remember that the range of projected ridership for a specific application may be relatively large based on this data. Most of the entries to these tables were developed using time series data, specifically collected to measure the elasticities. On the other hand, some of the elasticities presented were either inferred from cross-sectional data or were taken from time-series demand studies that did not specifically focus on fare or service changes. These non-experimental elasticities were found by the authors to be larger and less reliable than those estimated directly from time-series data reflecting an actual change.

Summary

Elasticity models are a relatively simple and inexpensive way for the analyst to estimate changes in ridership using a limited number of variables and observations. The technique can be applied to a wide range of applications involving modifications to routes (assuming that the data are available) but not to predict ridership of new routes. When several elasticities are used sequentially, this approach can take into account many different factors. Since the calculations are straightforward, a high level of technical sophisticiation is not required of the service planner, and, given the same data, all analysts would obtain the same results. The accuracy of the results of this type of model is dependent on a number of factors including: 1) how the dependent (ridership) and independent variables are affected by other factors and 2) the nature of the demand for transit services (i.e., the shape of the demand curve) and the magnitude of the change in the independent variables. The transferability of calibrated models is probably limited; they may be useful to systems of similar size contemplating changes of similar magnitude.

3.5.2 Trend Analysis

Sometimes a long-term pattern of ridership change may occur due to population growth or to any number of other factors. Some transit properties find it useful to model this underlying trend using a bivariate regression. If the trend is significant, this model can serve as a ridership prediction tool. A model of this type also is useful in separating the ridership impacts of this underlying trend from impacts of, for example, service or fare changes.

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[1] Published in Short-Range Transit Plans: Final Technical Work Papers 1-7, Prepared for the Planning and Zoning Department of Springfield, Missouri by Barton-Aschman Associates, Inc., Washington, D.C., July 1980.

[2] Mayworm, Patrick, Armado M. Lago, J. Matthew McEnroe, "Patronage Impacts of Changes in Transit Fares and Services," Ecosemetrics, September 3, 1980.

Table 3-4

FARE AND SERVICE ELASTICITIES
FROM SELECTED TRANSIT PROPERTIES

	Fare Elasticity	Service Elasticity	Service Measure Used
Atlanta	-0.15 to -0.20	+0.30	vehicle miles
San Diego			
all routes	-0.51	+0.85	vehicle miles
established routes	-0.67	+0.65	vehicle miles
17 U.S. Transit operators	-0.48	+0.76	bus miles per capita
Montreal	-0.15	-0.54	waiting time
		-0.27	travel time
12 British bus operators	-0.31	+0.62	vehicle miles
30 British towns			
work trips	-0.19	+0.58	vehicle miles per capita
non-work trips	-0.49	+0.76	vehicle miles per capita

Source: Barton-Aschman Associates, "Patronage Effects of Transit Fare and Service Adjustments," May 20, 1980. Memorandum in Short-Range Transit Plan Draft Final Technical Work Papers 1-6, Prepared for Planning and Zoning Department, Springfield, Missouri, August 1980.

Model Form

The form of the model used in trend analysis is:

$$R = a * T + b \quad (13)$$

where: R is the ridership during the time period,
T is the number of the time periods, and
a and b are calibrated coefficients.

The time period chosen can be any regular interval such as day, month, or year. In this equation, the rate of growth or decline of the route ridership is represented by the calibrated coefficient "a".

Table 3-5

FARE AND LEVEL OF SERVICE ELASTICITIES
BUS ONLY (UNLESS OTHERWISE NOTED)

Characteristic	Elasticity mean/std.dev*	# of Cases
Fare	-0.35 ± 0.14	12
Fare by trip length (London):		
Less than one mile	-0.55	1
One to three miles	-0.29	1
Headway:		
Peak	-0.42 ± 0.18	4
Off-peak	-0.46 ± 0.26	9
All hours	-0.47 ± 0.14	5
Vehicle miles		
All hours	+0.63 ± 0.24	3
Peak**	+0.33 ± 0.18	3
Off-peak**	+0.63 ± 0.11	3
All hours**	+0.69 ± 0.31	17
Total Travel Time		
Peak	-1.03 ± 0.13	2
All hours	-0.92 ± 0.37	2
In-vehicle Time		
Peak	-0.29 ± 0.13	9
Off-peak	-0.83	1
Peak**	-0.68 ± 0.32	7
Off-peak**	-0.12	1
Out-of Vehicle Time		
All hours (bus and rapid rail)**	-0.59 ± 0.15	3
Walk time		
Peak**	-0.26	1
Off-peak**	-0.14	1
Wait time		
Peak (bus and rapid rail)**	-0.20 ± 0.07	4
Off-peak (bus and rapid rail)**	-0.21	1
Transfer time		
Peak (bus and rapid rail)**	-0.40 ± 0.18	3
Number of transfers		
Off-peak	-0.59	1

Source: Patrick Mayworm, Armado M. Lago, J. Matthew McEnroe, "Patronage Impacts of Changes in Transit Fares and Services," September 3, 1980.

* Where available.

** Starred elasticities are based on non-experimental data, e.g., data that do not reflect an actual fare or service change.

Forecast Variable

The forecast variable in trend analysis is the anticipated ridership at a specified time in the future. Ridership is predicted on the basis of a specific time period (e.g., day, month, or year). Most properties who indicated the use of this method use it to predict average monthly ridership.

Model Inputs

The only inputs required to calibrate this form of model one the ridership levels for a number of past periods. The number of data points and the extent to which they go back in time depend on the analyst's judgement of the consistency of a trend and data availability. Since this procedure is completely insensitive to the alternative programs and policies (such as a new fare structure, a different loading standard, different service frequencies or route configurations), the use of this method over periods when major service changes have been made is inappropriate. (Other more complex types of time series analysis, which could potentially account for these factors, along with many other techniques which have not yet been applied directly to route level patronage projection are discussed in the next chapter.)

Types of Applications

The primary application of trend analysis is to identify those routes which are losing or gaining ridership in a stable pattern.

Application Process

The application process is straightforward. It involves calibrating the model using existing data (as discussed above) and then inserting the number of the desired time period to be forecast into the equation.

Accuracy of Results

The accuracy of this approach can be expected to be reasonable over short periods of time; however, the result should not hold if any major service characteristic or other exogenous factor (such as gas prices) changes significantly.

Application by the Dallas Transit System

The Dallas Transit System (DTS) uses this technique to identify major areas of ridership growth or decline, and to provide a basis against which to assess changes in the route structure or level of service. The actual analysis of the change, however, is largely based on a judgment as to which routes can be expected to respond in a similar manner. To assess the impact of a route change, the property uses a "similar route" philosophy, in which the experience on a route that has already undergone a change is used to assess the probable impact on a similar route. In other words, the property simply replaces the rate of growth identified in one regression equation with another it feels will more accurately reflect the ridership response to a given type of change.

For new routes, DTS indicated that it again uses a bivariate regression, but in this case one in which ridership is a function of the number of dwelling units in a zone. Although not documented anywhere, they judge this to be a "fairly reasonable" approach for rapidly growing areas of the city.

To project into the future, projected densities are plugged into an equation calibrated on data from similar areas. Implicit in this model is the assumption that the level of service, socioeconomic and demographic variables that influence ridership will continue to change in exactly the same ways in the future as they did in the past. In addition, the model does not control for differences among the months, with the result that seasonal effects are ignored.

Summary

Trend analysis can be a useful tool for estimating ridership during period when service and exogenous factors are not changing or are changing in a consistent manner. The technique can be applied to any type of route for which the appropriate data are available, but it is totally insensitive to changes in other factors (e.g. service changes, fare changes, etc.). As such, it is not useful in most route planning contexts. The technique is inexpensive and relatively simple to use, requiring little more than a calculator with statistical capabilities. (In fact, an estimate could be obtained by plotting the data.)

3.6 Conclusion

Most transit properties recognize the need to predict transit patronage at the route level and have adopted one or more techniques to perform these analyses. Yet, despite the widespread use of route-level demand models, few properties can quantify the accuracy of their models or explain the value of the techniques to their planning processes. Most of these models are simplistic, easy to apply, rely on minimal data and, thus, yield only "ball-park" ridership estimates. On the other hand, some techniques attempt to reflect the processes underlying the generation of transit ridership. A number of researchers have developed formal statistical models which account for a variety of factors which may impact ridership and have incorporated the effects of a number of decision variables available to the bus service planner. Unfortunately, no existing model is totally adequate for the planning function; all have drawbacks and few have been shown to be accurate through before-after experimentation.

The value of any technique to the service planner should be based on the criteria identified in Chapter 2. Key among these is accuracy. This attribute is difficult to evaluate, however, because few empirical tests have been performed, in which estimates of ridership made before implementation of a route or route modification are compared with the actual resultant ridership. Data available for non-committal surveys indicate that this technique may be accurate to within 30%. The wide range of elasticities measured at different properties and routes indicates that the accuracy of predicted changes in ridership is probably no better than ± 40% for fare related changes and ± 45% for service related changes. Regression models generally predict route ridership well for those counts included in the calibration data set, but few have been tested on an experimental basis.

To some extent the accuracy of the techniques can be assessed without actual experimental data. While most properties that use relatively simple techniques, such as rules of thumb, say the results are "adequate" for their purposes, the lack of a strong theoretical basis indicates that one should not expect these models to be accurate for a wide range of applications. For example, models which do not take into account major determinants of travel demand (e.g., a rule of thumb which uses the population near the bus route as its only input) are not likely to yield accurate predictions if any of these excluded factors change significantly. Similarly, misspecification of a model can also result in inaccurate predictions. For example, the use of service frequency as an explanatory variable (as in the example in Section 3.4.2) is more likely to produce a model representing the schedulers' decision rule as to how many buses are needed to serve specific level of demand than the increased ridership generated by increasing the route's frequency.

A second evaluation criterion involves the sensitivity of the model to key decision variables. Generally speaking, the more complex the model form, the greater the number of decision variables to which it is sensitive. Those approaches which tend to be most sensitive to a variety of decision variables include judgmental methods and regression models. Judgment can be used to evaluate almost any action a planner might wish to take. Approaches providing a medium range of sensitivity include elasticities, trip rate models, non-committal surveys and similar route methods. These approaches tend to restrict the decision variables either based on how the specific application was set up (trip rate models), the user's ability to comprehend the impacts of a service change (surveys), the range of characteristics existing on other routes in the system (similar route technique) or the variety of models available to measure the impacts of service changes (elasticities). Finally, rules of thumb and trend line analyses used by properties tend to be responsive to few, if any, of the route characteristics which are controlled by the planner.

The range of applications of a specific technique is closely tied to the sensitivity of the model, but is slightly different. Judgmental techniques, regression models, multiple factor trip rate models and survey techniques tend to have the widest range of applicability. All can be used for both new routes or changes in existing routes and can be reasonably sensitive to a number of route characteristics set by the operations planner. The range of applications for which similar routes, rules of thumb, and elasticity techniques can be used is somewhat more restricted than for judgmental models but still is relatively broad. The first two of these are usually used only for studying new routes while the final one is used primarily for route changes. Trend analysis has very few applications (at least in the form used by the transit properties contacted). It can be applied usefully to situations in which the service does not change, but external factors which affect the route ridership change in a regular manner over time.

A fourth criterion is the ease with which one analyst can replicate the predictions of another given the same data, or, in other words, whether the results are dependent on the analyst rather than on the input data. Those techniques with well specified procedures to be followed by the planner, such as in the application of a regression model, a trip rate model, or in a calibrated rule of thumb or a trend analysis, are almost entirely independent of the analyst. In other cases, some basic rules must be followed, but some discretion by the analyst may be required. Surveys, similar route methods, and the development of regression and trip rate models fall in to this category. Finally, judgmental methods are entirely dependent on the individual estimating route level ridership since rules or guidelines are difficult to specify.

The costs of developing and applying models are also important in judging their value. The least expensive approaches include judgment, elasticity, trend, and rule of thumb analyses. The application of similar route approaches, multiple trip rate models and regression models tend to be somewhat more costly due to the increased data collection required. Survey applications and the calibration of regression and trip rate models are the most expensive due to the large amount of data which must be collected and the high cost of some of the data collection techniques. Also affecting the cost is the level of technical sophistication required to develop and/or apply a model.

The simplest models, those requiring the least technical sophistication, include judgment, rules of thumb, and similar route methods. Elasticity approaches, the application of trip rate and regression models, and survey techniques require a moderate degree of sophistication. Finally, calibrating formal statistical regression models and trip rate models is most difficult for the service planner.

A final criterion with which to evaluate these techniques is the model's transferability (i.e., from route to route and from system to system). In general, there is no data to indicate that any model which is developed from data in one community can be used in another community. One may anticipate that those models which include the greatest number of exogenous factors will be more easily transferred, but to date this has not been substantiated.

This review does not indicate that a single model or type of model is significantly better or more useful than any other model. Figure 3-4 illustrates the advantages and disadvantages of each approach. It does, however, illustrate the need for additional evaluations of specific models to determine their ranges of accuracy. In addition, there appears to be a need to alleviate many of the theoretical drawbacks of the models being used. Research to improve the existing models is discussed in the next chapter.

FIGURE 3-4 CHARACTERISTICS OF MODELING APPROACHES

	Accuracy (a)	Sensitivity	Range of Applications	Analyst Dependence	Cost of Application	Technical Sophistication (b)	Transferability (a)
Judgmental		●	●	○	●	●	
Non-Commital Survey		◓	●	◓	○	◓	
Similar Routes		◓	◓	◓	◓	●	
Rules of Thumb		○	◓	●	●	●	
Trip Rate Model		◓	●	●	○ (c)	○ (c)	
Aggregate Regression		●	●	●	○ (c)	○ (c)	
Elasticity		◓	◓	●	●	◓	
Trend Analysis		○	○	●	●	◓	

● better than average; ◓ average; ○ worse than average

(a) approaches not rated by this criterion due to lack of data with which to evaluate them (see text).

(b) a good rating implies the need for a limited sophistication by the service planner; a negative rating implies a high degree of sophistication is required.

(c) negative rating assumes that models would have to be calibrated by the service planner; application of methods require average cost and technical sophistication.

CHAPTER 4: THE RESEARCH

The review of current route level demand prediction techniques indicates that no single model or approach meets all of the criteria set forth in Chapter 2. The most common drawbacks of these approaches are the lack of sensitivity to significant factors affecting route ridership and inaccuracy resulting from inappropriate model specification. In some cases, important factors influencing transit demand are simply not included in the model. (This is the case with those models most commonly used in the industry.) Other models, in which such factors are incorporated, are not structured in a manner consistent with the underlying phenomena. Furthermore, even models which do appear to be well specified are seldom tested in an objective manner, thereby leaving their accuracy in doubt.

A secondary problem, associated whith the use of the more sophisticated techniques discussed previously, relates to data collection. Complex models, based on statistically calibrated equations, usually require costly data inputs both in the calibration and application processes. To obtain usable model inputs, the service planner must often make a number of assumptions which may diminish the capability of any model to produce reliable predictions.

Recognizing that numerous shortcomings exist in current transit ridership prediction methodology, researchers have begun to develop new methods and approaches. The research to date has been in three primary directions. First, some research teams are attempting to improve the theory underlying the model structures in order to better specify the relationships between dependent and independent variables. Others are attempting to improve the methods by which exogenous factors, not directly related to the transit service provided, are included in the models. Finally, several approaches are being taken to improve the quality of and to reduce the cost of data used in the model development and application processes.

Other significant shortcomings of the current set of models, however, are not being addressed at the present time. To date, no study has begun to develop objective estimates of the accuracy of the various route-level models available based on before/after experiments (in which predictions are compared with actual results). In addition, the question of transferability of specific model formulations between different areas is not the topic of any ongoing research.

The remainder of this chapter briefly introduces six recent or ongoing research efforts aimed at eliminating the drawbacks discussed above. The purpose of the chapter is to describe the approach and purpose of each, rather than providing detailed information on the form and structure of models developed. Those readers interested in more detail on these research studies are referred to the papers and texts cited.

4.1 Simultaneous Equations

Kemp and colleagues from the Urban Institute have completed preliminary efforts aimed at developing a ridership prediction model based on time-series and cross-sectional data.[1] These efforts attempt to eliminate the problem of replicating the scheduler's decision rule rather than estimating the demand curve (see Section 3.4.4). To avoid this common problem encountered in direct route-level demand models, separate equations specifically address the response of demand to supply and that of supply to demand. Using data supplied by the San Diego Transit Corporation, they have calibrated a set of simultaneous equations to predict the supply and demand characteristics of individual routes. By including all important factors (e.g., cost of operations and availability of resources), they hope that the scheduler's decision rules will be entirely captured in the "supply" equations. In this manner, the supply equations should be able to filter out these confounding effects, leaving the demand equations to accurately represent only the causal impacts of service quality changes on the level of ridership.

Three equations in the model system are designed to replicate the response of the amount and quality of service offered on a route with the demand for service and the physical characteristics of the route. The first equation, representing a scheduler's decision rule, determines the capacity requirements of the route. Specifically, bus seat-miles are estimated as a function of:

- the route patronage,
- costs of providing service,
- the availability of vehicles and subsidy,
- the characteristics of the service period (service duration, non-work days and school days in the month), and
- the time since the last major change in the route schedule.

Using:

- this measure of capacity requirements,
- the expected passenger load,

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[1] Alperovich, G., M.A. Kemp and K.M. Goodman, "An Econometric Model of Bus Transit Demand and Supply." The Urban Institute Working Paper No. 5032-1-4, Washington, D,.C., 1977.

Goodman, K. M., M.A. Green and M.E. Beesley, "The San Diego Transit Corporation: The Impacts of Fare and Service Changes on Ridership and Deficits, 1972-1975." The Urban Institute Working Paper No. 5066-5-1, Washington, D.C., May 1977.

Green, M. A., "The San Diego Transit Study Data Base: Reference Manual." The Urban Institute Working Paper No. 5066-5-2, Washington, D.C., 1977.

- the cost of operations, and
- the availability of vehicles and subsidy

the frequency of bus operations (another scheduler's decision) is estimated. In the final supply equation, an average bus speed is calculated based on:

- the number of bus stops along the route,
- the number of passengers at each stop, and
- the congestion of the streets on which the route travels.

Note that all three of these equations are responsive to the level of patronage on the route.

The estimates of the service attributes for the routes become inputs to the actual demand prediction equations. Two separate but interrelated equations predict the volumes of "non-transfer" and "transfer" riders -- that is, those who arrive at the route by some means other than bus and those who transfer from another route. The first demand equation estimates the number of non-transfer passengers. It requires input data describing the route's:

- fare,
- speed,
- headway,
- duration of service, and
- density of bus stops.

The other equation predicts the number of passengers transfering from other routes as a function of:

- total ridership volume, and
- the number of transfer possibilities.

On completion of this preliminary analysis, the research team concluded that the approach appears to be sound and that the five equations which were calibrated look promising. Unfortunately, difficulties with the data set and limitations on the form of individual equations has limited the success of the resultant model. Further effort is needed to improve the quality and size of the calibration data set (in part by bringing it up to date), to include route specific demographic information in the demand equations, to better specify the operating costs associated with route level service changes, and to investigate a broader range of potential model specifications (including non-linear formulations).

4.2 Poisson Regression

Another approach to improving the accuracy of the models used to predict route ridership is to examine the characteristics of the user or potential user rather than those of the route. This change in the frame of reference is intuitively appealing because it more closely addresses the actual process which leads to transit ridership. Specifically, this form of model attempts to replicate each individual's decision rule: whether to use transit, how often to use it, or, possibly, where to go. This "disaggregate" approach is commonly used in system-level transportation demand models. Usually, these models are used to predict mode choice in which several alternatives are available.

To date, disaggregate models have not often been applied at the route level because of the substantial data requirements. In general, they require a relatively large sample of both users and non-users, thus requiring expensive home-interview data collection techniques. Futhermore, application of these models requires information on the service quality of each alternative mode from origin-to-destination (e.g., data is required for auto service as well as bus) and a table which indicates the total number of trips taken between each origin and destination by all modes.

Gonzales and Lerman at the Massachusetts Institute of Technology have devised an alternative to the standard disaggregate model in which the frequency of transit use is predicted rather than mode choice.[1] The model is based on the Poisson distribution in which the dependent variable is a non-negative integer number of occurences (e.g., transit trips per week). The form is calibrated using a technique called Poisson regression. The major advantage of this type of model is that the coefficients can be calibrated with reasonable accuracy using only information from those individuals who choose to use transit. In other words, there is no need to perform expensive home-interview surveys; conventional on-board surveys are sufficient.

In the application process, the Poisson regression model is easiest to apply on an "incremental" basis. That is, the effects of a system change are measured relative to the base ridership in a manner similar to the way elasticities are applied (See Section 3.5.1).

Poisson regression, however, is not free from drawbacks: it exhibits a significant limitation on the types of applications for which it is useful. Specifically, using only on-board surveys, no information can be included regarding those segments of the population which are not served by a route. Hence, service changes such as route extensions, changes in hours of service (which primarily serve new markets rather than improving service to existing ones), and new routes are extremely difficult to model accurately. The effects of these changes cannot be modeled at all using the "incremental" procedure discussed above.

Using a calibration technique called Poisson Regression, Gonzales and Leman developed the following model in a pilot study based on a 1979 bus survey in Atlanta, Georgia:

$$F = 13.00 - 0.22\ \mathrm{AUTOAV} + 1.43\ \mathrm{POOR} - 1.28\ \mathrm{WHITE} + 1.82\ \mathrm{MEDINC} + 0.83\ \mathrm{NOTRIP} - 1.93\ \mathrm{ELDERLY} - 3.32\ \mathrm{CASH} \qquad (14)$$

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[1] Gonzalez, Sergio L., Responsive Transportation Analysis: Volume 7. Short Range Bus Transit Planning: Demand Prediction at the Route Level, M.I.T. Report No. CTS-RAMP-80-1, Cambridge, MA, February 22, 1980.

Lerman, S.R. and S.L. Gonzalez, "Poisson Regression Analysis Under Alternate Sampling Strategies." M.I.T. Center for Transportation Studies, Cambridge, MA., October 1979.

where F is the number of weekly transit trips and the dependent variables, which are all binary, are defined as follows:

- o AUTOAV = 1 if auto usually available
- o POOR = 1 if income less than $10,000
- o WHITE = 1 if white
- o MEDINC = 1 if income $10,000-$14,999
- o NOTRIP = 1 if trip would not have been made if the bus were not available
- o ELDERLY = 1 if 60 or older
- o CASH = 1 if respondent did not have a transit pass

All coefficient were significant, except AUTOAV which was retained because of its perceived importance. The authors concluded that this approach can provide reasonable model results, but noted that underlying poisson assumption still needs to be submitted to rigorous statistical tests.

4.3 Intervention Analysis

Wang, of the U.S. Department of Transportation's Transportation Systems Center, has identified another potential cause of inaccuracy in route-level demand models. Data employed for calibrating these models often are obtained infrequently over a long period of time, during which ridership may be affected by factors not associated with common model inputs (such as level of service and demographic characteristics). Major factors affecting the system as a whole may mask the direct impacts of route changes or changes in population near the route. For example, the ridership may show some general trend (e.g., growing or declining as a result of factors associated with changes in individual attitudes or on the highway network), and variations by season, by time of month, or even differences by day of week. If the major inputs to the model are correlated with these confounding factors, the true response to changes in the primary factors may be significantly miscalculated in developing the model. As a result, the predictive ability of the model may be diminished.

By extending a theoretical framework set up by Box and Tiao,[1] Wang has developed a technique based on systemwide time-series data in which the trend and peaking characteristics are filtered out of the calibration data set. This technique, called "intervention analysis", allows the service planner not only to filter out seasonal and trend affects, but also to eliminate the effects of discrete occurences (e.g., a gas shortage), thereby isolating the "pure" relationships between ridership and service or policy variables. The technique is usually not used directly as a route-level demand model but is used to prepare the data for use in the calibration or application of another actual route-level

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[1] Box, G.E.P. and G.C. Tiao, "Intervention Analysis with Application to Economic and Environmental Problems," Journal of the American Statistical Association, 70, 1975, pp. 70-79.

demand model. However, if sufficient time-series data exists at the route level, the effects of discrete changes in route policies, such as a change in headway, fare increases, or rerouting could be established with this technique.

The development of intervention analysis techniques is important primarily for the following reasons:

1. They permit the planner to filter out confounding factors -- factors which are often not obviously significant before being filtered. Planners can employ these techniques to improve their understanding of causal relationships.

2. They provide a statistical test which can be used to determine whether an intervention (e.g., a fare increase) has had a significant impact on ridership.

3. The calibrated model can be used directly to predict short term changes in transit ridership.

4. The techniques are applicable to a potentially large class of models, thereby allowing many different kinds of dynamic interactions to be considered.

The major drawback to these techniques is that they require a relatively long series of data -- at least 50 observations -- to be calibrated. If a monthly ridership model is being constructed, more than four years of historical data must be available. One year or one and a half months of data are needed for models which deal with weekly or daily volumes, respectively. For service planners attempting to filter out confounding system-level characteristics from route level data, this problem should be relatively minor; however, at the route level, collection of such long term or detailed data may not be feasible.

4.4 Computerized Socio-Economic Characteristics

Another potential source of inaccuracy in route level demand models is the quality of the input data employed in both the calibration and application processes. One specific example involves the estimation of population living near a bus stop. In many models (such as Seattle's rules of thumb and the Pennsylvania Department of Transportation regression described in Chapter 3) the population living within 1/4 mile of the transit route is used as the major determinant of demand. Generally, however, this figure is obtained based on tract-level population from the U.S. Census (or update). An assumption is made that this population is uniformly distributed throughout the tract. This assumption may not be adequate, since it does not account for either heavy concentration of the population (e.g., in large apartment buildings) or undeveloped areas with little or no population.

The Transportation Network Evaluation System (TRANES),[1] a computer system developed by the Comprehensive Planning Organization of the San Diego Region

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[1] Comprehensive Planning Organization of the San Diego Region, "TRANES Technical Report--Draft",San Diego Transit Corporation, San Diego, February, 1978.

addresses this problem. Using a graphical or numerical representation of a bus route as input, the package employs the U.S. Census block level data and information incorporated in the GBF DIME file (a computer file describing the street network at of the city) to determine those Census Blocks lying within 1/4 mile of the transit route. The population and socio-economic characteristics of these blocks are then extracted. Because there are an average of 55 census blocks in each tract, the quality of population estimates is significantly improved.

One problem with this approach is that census data must often be specially updated to reflect changes in the characteristics of urban areas over the ten year period between the collection of census data. Such updates are not performed at the same detailed level as the original collection efforts. At best, the tract level population and socio-economic characteristics are updated; more commonly, only population is updated. Without detailed block level updates, the advantages of the TRANES system may be reduced by the inaccuracy of outdated data in areas where the population has been changing.

4.5 Application Software

Section 4.2 briefly touched on a class of models (disaggregate mode choice models) which require an origin-to-destination trip table to estimate transit ridership. These mode split models have not been used to any great extent for route level analysis in part because of these extensive data input and manipulation requirements. One approach to alleviating these difficulties is to modify the application process rather than model itself. To this end, two research teams have developed application software in which the complex data access and manipulation functions are handled automatically.

The Interactive Graphic Transit Design System (IGTDS)[1] is one of these packages. IGTDS was originally developed by the University of Washington in the early 1970's. Subsequently, modifications were made by the General Motors Transportation Systems Center to the package to improve its capabilities. This new version (IGTDS2) was released in 1978. To use the package, the service planner describes the transportation network, including the street network, parking facilities, transit routes, and transit service characteristics. The model uses these inputs to predict transit patronage and develop performance indicators. Demand prediction is performed using a "logit" mode choice model, taking into account travel time, waiting time, walking time, and costs of travel by transit, auto, and walking alternatives.

The Southeastern Michigan Transit Authority tested the package in the Jeffries Freeway Corridor Transit Design Project. Initial transit ridership predictions were 22% above the observed value. The study team concluded that the time required to use IGTDS in the process was greater than that which would have been used for a manual process, but that much of the time was needed to set up the basic inputs. As a result, they expect subsequent applications to require much less effort. The primary benefit noted was that the package provides a greater ability to examine travelers' responses to a variety of transit service changes.

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[1] Gallio, L.D., and J. Maslanka, "Jeffries Freeway Corridor Transit Design Project Using the Interactive Graphic Transit Design System (IGTDS), Southeastern Michigan Transportation Authority, August 1981.

There are two drawbacks to this system. First, it is designed for routes which serve a single common terminus. Unfortunately, this restriction significantly reduces the range of applications to which the software can be applied. Second, there is a lack of flexibility in the software which makes it difficult to modify the basic mode split equation. This is likely to be necessary if the software is to be used in an area other than that for which it was calibrated. Since the capability exists to alleviate these problems through program modification, this is probably not a major deterrent to the eventual use of IGTDS by the industry.

Another computerized transit forecasting system, produced by Volvo,[1] provides a similar but expanded set of capabilities. The Volvo system is based on a direct demand model rather than a mode split approach. Using graphical displays extensively and conversational communications with the user, this computer package develops ridership estimates for an entire transit system. Based on a detailed representation of the transit network, including route location, frequencies, running times, transfer points, and fare structure, this software applies a direct demand model in which an origin-destination table of transit trips is generated as a function of service quality and the attraction and generation potential of the zone. (The attraction and generation potential are measured in terms of population, employment and socio-economic characteristics.) The estimated transit travel patterns are then automatically assigned to individual routes. These routes are either designed by the transit planner or optimally selected from the coded street network. The routes and network are then evaluated in terms of loadings, productivity, costs, and travel characteristics for users (e.g., wait time, ride time, transfers, etc.).

The demand model used in the software package can be specified and calibrated by the user; therefore, little can be said in the way of evaluating the quality of the predictions made. The system is designed primarily to be applied to systemwide changes: its usefulness in the examination of changes to individual routes has never been tested. Volvo recommends using the evaluation reporting capabilities of the software to investigate several dozen alternative networks (which may include minor changes to individual routes). This process may take several days to several weeks. Although the time is still more than that devoted by many transit properties, the reliability of the results may be significantly better using this software. Another advantage is that the interaction of the single route change on the remainder of the transit network may be examined. A full evaluation of the system's capabilities must await further experimentation on route-level applications.

4.6 Conclusion

This chapter has identified the key problems with the current practice of route level ridership prediction and presented recent and on-going research to improve the state of the art. The primary problems associated with current practices include:

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[1] Andreason, I., "The Volvo Approach to Transportation Planning," AB Volvo, Bus Division, Goteborg, Sweden 1979.

1) models which lack sensitivity to important factors which affect transit ridership,
2) improper specifications of model forms,
3) a lack of objective testing to determine the accuracy of these models,
4) the inability of transit properties to collect and use extensive data sets necessary to exercise more complex models, and
5) insufficient understanding of the transferability of models between communities or even within various parts of the same communities.

To date, the models and tools developed to address these problems are still in the formative stage. Most have not been tested in actual transit property planning applications. Furthermore, few have been examined sufficiently to indicate whether they can be ex½ected to improve the ridership prediction capabilities in the transit industry.

Once new methods have been developed, the task of convincing transit operators to employ the methods will remain. Several difficulties can be anticipated when trying to gain acceptance for an individual model. First, it will be necessary to prove that a new approach will predict better than methods already available. An objective validation of new approaches and models will be a necessity in on-going and future research efforts. In addition, the costs of model application and the technical sophistication required of the service planner must be within acceptable limitations of transit authorities. All efforts should be made to reduce the complexity of applying new methods within the constraints of the theoretical designs of new models. The use of computers and user-friendly software may prove integral to the acceptance of the more sophisticated approaches. Of course, the successful application of a new model at one site should enhance its broader acceptance.

Based on this review, in appears that little research is being performed by the transit operators. Although several properties indicated that they would be interested in improving their techniques, only three had actually experimented with new models. Furthermore, these efforts were not as advanced as those presented in this chapter. It appears that continued efforts from the Department of Transportation and independent research teams will be necessary to further advance the state of the art.

Finally, although there is significant room for improvement in current methods, it is unlikely that the "ideal" model, one which meets all the criteria established in Chapter 2, will ever be produced. Professional judgment will remain an integral input into the prediction of ridership on transit routes.

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APPENDIX

TRANSIT PROPERTIES CONTACTED

Transit Agency (City)	Peak Buses	Annual Ridership (millions)	Annual Revenue Bus-Miles (millions)	Route-Level Ridership Prediction Techniques Used: Judgment	Non-Committal Survey	Similar Routes	Rules of Thumb	Regression	Elasticity	Non-Forecast	None
Capital District Transit Authority (Albany, NY)	200	14.0	6.0	X					X		
MARTA (Atlanta, GA)	700	99.0	34.7			X	X				
Greater Bridgeport Transit District (Bridgeport, CT)	50	5.6	--				X		X		
Calgary Transit (Calgary, Alberta)	471	49.0	15.0			X					
Regional Transportation Authority (Chicago, IL)*	625	40.0	14.4	X							
Central Ohio Transit Authority (Columbus, OH)	227	16.4	7.6			X	X				
Dallas Transit System (Dallas, TX)	406	37.0	14.5			X	X				
SEMTA (Detroit, MI)	272	9.3	10.0		X		X	X			
Edmonton Transit (Edmonton, Alberta)	525	65.0	--							X	
CITRAN (Ft. Worth, TX)	92	6.0	3.1			X	X		X		
Grand Rapids Area Transit Authority (Grand Rapids, MI)	54	4.5	2.5		X						
City and Country Bus Service (Honolulu, HI)	310	60.0	--							X	
Metropolitan Transit Authority of Harris Co. (Houston, TX)	416	39.0	--	X							

*Does not include the Chicago Transit Authority

APPENDIX: TRANSIT PROPERTIES CONTACTED (continued)

Transit Agency (City)	Peak Buses	Annual Ridership (millions)	Annual Revenue Bus-Miles (millions)	Route-Level Ridership Prediction Techniques Used: Judgment	Non-Committal Survey	Similar Routes	Rules of Thumb	Regression	Elasticity	Non-Forecast	None
SCRTD (Los Angeles, CA)	2006	376.0	--	X							
Transit Authority of River City (Louisville, KY)	223	20.0	--	X							
Madison Metro (Madison, WI)	150	14.0	4.7								X
Milwaukee County Transit System (Milwaukee, WI)	515	70.0	21.0				X				
Tidewater Regional Transit (Norfolk, VA)	136	13.5	5.9								X
AC Transit (Oakland, CA)	712	66.0	30.5			X	X				
North County Transit District (Oceanside, CA)	116	8.5	6.7			X	X				
Ottawa - Carleton Regional Transit (Ottawa, Ontario)	678	73.0	27.4			X	X				
Greater Peoria Mass Transit District (Peoria, IL)	42	2.2	1.6		X						
SEPTA (Philadelphia, PA)	1800	240.0	--	X							
Phoenix Transit System (Phoenix, AZ)	165	14.1	9.4		X					X	
Rhode Island Public Transit Authcrity (Providence, RI)	207	20.0	8.2		X						
Sacramento Regional Transit District (Sacramento, CA)	187	18.8	--								X

APPENDIX: TRANSIT PROPERTIES CONTACTED
(continued)

Transit Agency (City)	Peak Buses	Annual Ridership (millions)	Annual Revenue Bus-Miles (millions)	Route-Level Ridership Prediction Techniques Used: Judgment	Non-Committal Survey	Similar Routes	Rules of Thumb	Regression	Elasticity	Non-Forecast	None
Metropolitan Transit Commission (St. Paul, MN)	865	94.0	31.2							X	
Utah Transit Authority (Salt Lake City, UT)	260	20.0	10.4	X							
San Diego Transit (San Diego, CA)	241	36.0	11.5			X	X	X	X		
MUNI (San Francisco, CA)	--	--	--								X
Santa Clara County Transit (San Jose, CA)	260	24.0	--							X	
Santa Cruz Metropolitan Transit District (Santa Cruz, CA)	53	6.0	--								X
Seattle Metro (Seattle, WA)	700	58.0	27.6		X		X			X	
South Bend Public Transportation Corp. (South Bend, IN)	42	3.5	1.7								X
CNY Centro (Syracuse, NY)	144	13.0	--				X				
Toronto Transit Commission (Toronto, Ontario)	1079	346.0	47.5				X			X	
WMATA (Washington, DC)	1578	172.4	54.0	X							
Wichita Metropolitan Transit Authority (Wichita, KS)	57	3.6	--								X
Winnipeg Transit System (Winnipeg, Manitoba)	472	61.3	16.7							X	

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