the consumption due to speed changes and idling, total fuel consumed has been determined. This value, when calculated for an existing intersection, will be used as the base for determining the percentage reduction for a proposed improvement. For example, at an intersection 1000 gal are consumed. With the construction of a left-turn lane, 100 gal less will be consumed. Therefore, the left-turn bay will reduce consumption by 100/1000, or 10 percent.

For vehicle emissions, Figures 2-4 represent total emissions for vehicles changing speeds. To simplify the analysis, it is assumed that for existing intersections most vehicles will experience a speed change at the intersection. Thus, for congested intersections, the emissions for idling, stopping, and slowing down represent total emissions. Total emissions for the existing intersection would be used just as in the analysis of energy as a base to determine the percentage reduction.

In the case of an improved intersection, total emissions would include vehicles that do not experience a speed change. The number of vehicles that do not stop or slow down can be estimated by equating it to the reduction of vehicles stopping when an existing intersection is improved.

For example, if the addition of a left-turn bay reduced the percentage of vehicles stopping from 80 to 70 percent and 4000 vehicles entered the intersection during the analysis period, it would be estimated that 400 vehicles (10 percent x 4000) will experience little interference when traversing the intersection. Then, to determine vehicle miles, the number of free-flowing vehicles would be multiplied by the distance from the intersection where vehicle movement is affected. This would be the same distance estimated for the energy analysis.

From Figure 5, pollutant emissions in units of 1000 vehicle miles for vehicles traveling at a uniform speed can be obtained. These emission rates multiplied by vehicle miles would determine the emissions for uniform-speed vehicles. The equation is as follows:

$$\begin{aligned}\text{CO, HC, NO}_x &= (\text{TTEI}/1000) \times \text{ER (Figure 5)} \times \text{intersection distance}\\ &\quad \times \text{percent reduction of vehicles stopping}\end{aligned} \tag{25}$$

When these emissions are combined with emissions due to slowdowns, stopping, and idling, the total emissions for an improved intersection can be calculated.

SUMMARY

The procedure described in this paper is designed as a sketch planning tool for planners. Whereas the critical movement technique is a sketch planning tool for analyzing capacity, this methodology is a tool for evaluating vehicle emissions and energy. It can be applied quickly and can provide reasonable estimates of reductions in energy use and vehicle emissions. The quick-response characteristics of the method are demonstrated by the limited amount of data necessary to do an evaluation.

To simplify the application of the technique, the equations given in this paper for pollutant emissions (Equations 9-11, 17-19, 21-23, and 24) and the formats shown in Figures 6 and 7 should be used.

REFERENCES

1. C.W. Dale. Procedure for Estimating Highway User Costs, Fuel Consumption, and Air Pollution. Office of Traffic Operations, FHWA, May 1980.
2. A Manual on User Benefit Analysis of Highway and Bus Transit Improvements. AASHTO, 1977.
3. A Technique for Measurement of Delay at Intersections. Office of Research and Development, FHWA, Rept. FHWA-RD-76-135, Sept. 1976.
4. R. Winfrey. Economic Analysis for Highways. International Textbook Co., Scranton, PA, 1969.
5. Quick-Response Urban Travel Estimation Techniques and Transferable Parameters: User's Guide. NCHRP, Rept. 187, 1978.

Improved Demand Estimation for Rural Work Trips

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A critical review of the most widely accepted rural demand estimation models is performed. Based on data collected in two rural towns, a disaggregate specification for rural work-trip modal choice is proposed. The new model includes a set of socioeconomic and a set of policy-relevant variables and can be used for implementing a wide range of transportation policies to improve rural transit system performance. Model variables produce coefficients consistent with the notion, recently found in the literature, that rural commuters are more sensitive to fiscal variables than are urban commuters. Results from comparison tests suggest that demand prediction with the proposed specification is significantly (up to 88 percent) better than with the best of the existing models.

The evaluation of rural transportation projects that operate with federal or state support has been considered an essential part of government-subsidized transportation programs during the past decade. Transportation policies that can improve the efficiency and effectiveness of rural transit operations have recently been proposed (1), and data on performance measures for evaluating such operations are now available (1-3) and are being compiled by a number of states (4,5). In response to a need for identifying transportation policies that can also enhance rural mobility and the need to determine whether such policies will, in time, cause changes in rural economic development, a project was recently initiated (6). An immediate need for a demand estimation specification to estimate work-trip modal choice was identified.

The major objective of this study is to determine the most reliable rural demand estimation model suitable for implementing level-of-service transportation policies and sensitive to long-term mobility and economic changes that may take place in a community. This determination depends on certain basic criteria: (a) the ability of the selected model to estimate modal choice for work trips directly, (b) inclusion of level-of-service independent variables for implementing transportation policies that can improve the efficiency and effectiveness of a transit system, (c) inclusion of mobility and socioeconomic variables so that long-term changes in resident mobility and the local economy can be taken into account when modal choice is determined, (d) data availability, (e) model performance, (f) causally justifiable independent variables, and (g) the potential for model transferability to other rural areas.

A critical review of the most significant existing demand estimation models is performed first. This review includes a summary of performance characteristics that emphasizes effectiveness and the drawbacks of each model from the limited tests found in the literature. Subsequently, a new demand estimation specification for rural work-trip modal choice is proposed and compared with the best of the existing models. The comparison tests are based on six data sets collected in two rural towns over a three-month period.

The major findings can be summarized in two parts. First, results from tests of the performance of the existing rural demand models (7,8) are mostly in agreement with previous studies (7-11). More specifically, the existing models are found to be easy to comprehend but hard to apply to a specific trip purpose, as in work-trip estimation. Furthermore, because of the lack of a strong causal justification and the dearth of appropriate level-of-service variables, their use for policy analysis is not warranted. Finally, they result in significant estimation errors; because of this and the above characteristics, their potential for transferability is questionable at best. These observations reinforce the need for the development of more rigorous and more accurate rural demand estimation specifications.

This is accomplished by the proposed specification, which, in agreement with recent research findings, results in an increased importance of travel cost and household income in rural areas. The tests show that the proposed specification performs better than the existing ones.

BACKGROUND

Review of Rural Estimation Models

The existing approaches to modeling the steady-state demand sector of the rural transportation system fall into three general categories: (a) attitudinal studies, simple survey tabulations, and rough trip-rate estimates (12-15); (b) mathematical techniques based on aggregate analysis (7-9); and (c) disaggregate mathematical techniques (1).

Lack of rigorous analysis does not justify the use of approaches belonging to the first category for reliable policy analysis. Methods in the second category have relied on simple regression techniques (7,9) or used cross-classification techniques in combination with probabilistic assumptions (8). Due to their structure and assumptions, these methods often result in models that are descriptive rather than causal, models with large forecasting errors, questionable transferability properties, and little applicability to policy analysis. When such models are used, the sensitivity of prediction to errors in parameter estimates can be high, and the lack of emphasis on level-of-service variables makes prediction insensitive to proposed changes in transportation policy. On the contrary, disaggregate models are capable of capturing the causal relations between transportation level of service, household socioeconomic characteristics, and travel behavior and therefore provide a more meaningful analysis of various transportation policy options (16).

Aggregate Models

The first comprehensive work in this area (7) aimed "to produce forecasting methods at area-wide and route levels that are specific enough to enable local planners to use [the] method as the basis for initial operations of small-scale transit systems...and simple enough to be applied by local planning staff personnel." Five econometric models were presented, two applicable to fixed-route systems and three to demand-responsive systems. For each kind of system, there are models at the county (macro) level, and at the route (micro) level. By using regression analysis, route ridership is forecast as a (log) linear function of aggregate route characteristics such as total population along routes and route length and destination population.

The choice of independent variables is often arbitrary, and specifications are correlative rather than causal; e.g., excessive attention is paid to achieving a high R^2, but little attention is given to identifying variables that cause a specific ridership to be created. Ridership estimates are not sensitive to changes in transportation policy, household socioeconomic characteristics, or competing alternative levels of service. Furthermore, parameter estimates and statistical measures may be biased due to simultaneity and zone-size variance, respectively; the sensitivity of prediction to errors in parameter estimates can be high. It is concluded that the models are simple and easy to implement but are based on questionable assumptions, have limited applicability, do not contribute to a better understanding of the transit structure, and do not achieve their stated objectives; i.e., they cannot be safely implemented for forecasting purposes, and they cannot form a reliable basis for initial operations in rural areas (1).

The second mathematical approach to modeling rural transit ridership was a response to the deficiencies of the previous approach. Its objective was "to develop techniques of demand estimation which are...simple to understand, easy to apply, and low cost in nature,...offer the possibility of transferability, [and are] capable of identifying the needs generated by specific target populations along routes, such as the elderly, carless, or households with low income" (8).

The Poisson model was introduced as a technique superior to ones previously (7) used. It is a simple and appealing model but is subject to criticisms similar to those directed at previous research. Independent variables used for cross classification are rather arbitrary. Ridership estimates are insensitive to changes in transportation policy and to the level of service of competing alternatives. Although regression methods are criticized, they are used to improve on the Poisson model when it proves to be a poor performer (and the specification chosen is correlative rather than causal). Finally, the model is based on questionable assumptions (e.g., that the decision to ride the bus is a random event or that such events for rural households are independent of each other) and does not contribute to a better understanding of the transit structure, a fact acknowledged by its authors (8). Although some of the objectives, such as low cost, ease of application, and need identification, are satisfied, three are not met: The model is confusing, it is not accurate, and it does not have potential for transferability (1).

A more recent modeling attempt (9) used simple regression and was developed for demand-responsive service. It could be criticized along earlier (7) lines. The major existing models developed for fixed daily rural service that were relevant to this study and could be tested are summarized as follows: The macromodel (7) is expressed as

$$\begin{aligned}\mathrm{LOG}\,(\mathrm{RTPASS/MO}) = {} & -0.353 + 0.407\ \mathrm{LOG\ BMILES}\\ & + 0.533\ \mathrm{LOG\ FREQ} + 0.611\ \mathrm{LOG\ RESTRPOP}\\ & - 0.123\ \mathrm{LOG\ COMPBMS}\end{aligned} \tag{1}$$

where

RTPASS/MO = round-trip passengers per month,
BMILES = total vehicle miles per month,
FREQ = average monthly round-trip frequency,
RESTRPOP = people who may use the system (00s), and
COMPBMS = monthly vehicle miles of competing systems in the area.

The micromodel (7) is expressed as

$$\begin{aligned}\mathrm{LOG}(\mathrm{OWPASS/DAY}) = {} & 6.344 + 0.697\ \mathrm{LOG\ FREQ} - 2.547\ \mathrm{LOG\ D}\\ & + \mathrm{LOG\ POP_o} + \mathrm{LOG\ POP_d}\end{aligned} \tag{2}$$

where

OWPASS/DAY = one-way passengers per day on a specific route;
FREQ = round trips per day on that route;
D = round-trip distance from farthest origin point served to main destination (miles);
POP_0 = population of area traversed minus population of largest city, which is defined as the destination population (00 000s); and
POP_d = population of the largest city traversed (00 000s).

The Poisson mode (8) is expressed as

$$T = 0.003\,05\ R^{1.396}\ U^{0.935} \tag{3}$$

where

T = trip ends per operating day,
R = route mileage, and
U = number of dwelling units within 0.25 mile of a route.

Disaggregate Models

The inadequacies of aggregate modeling techniques for rural transportation demand estimation led to an early attempt to formulate rigorous disaggregate specifications (1). A limited analysis was conducted of the effects on ridership of certain transportation level-of-service attributes and of socioeconomic characteristics of individuals. The limited scope of the study could only result in an indication that rural residents are more sensitive to travel cost than urban residents. This was a significant conclusion because previous researchers (7-9), using aggregate analysis, had decided that this particular characteristic did not play a significant role in rural ridership estimation. Furthermore, in the course of the study it became evident that disaggregate demand estimation for rural transportation was feasible. It was determined that more work was needed to measure the effect of a number of level-of-service variables on demand modal choice before such demand models could be used for policy analysis.

PROPOSED MODEL

Because of the disadvantages of the existing models, it was decided that a new model should be developed that should fulfill the criteria set forth at the beginning of this paper. In addition, the new model should make efficient use of data and should be at least as accurate as previous prediction approaches. Given its known characteristics and advantages over aggregate methods, it was decided that a disaggregate formulation should be adopted.

For predicting the choice of transportation mode to work from among three modes--transit, drive alone, and shared ride--a multinomial logit model structure was chosen. The statistical properties of the logit model and its successful application in analyzing discrete modal choice are well documented (17-19) and are not restated here. The particular form of the model used was as follows:

$$P(m{:}M_t) = \exp(X'_{it}\theta) / \sum_{j\epsilon M_t} \exp(X'_{jt}\theta) \tag{4}$$

where

$P(m{:}M_t)$ = probability of worker t selecting mode m from choice set $M_t \equiv$ {transit, drive alone, rideshare},
X_{mt} = vector of independent variables for alternative m and worker t, and
θ = vector of coefficients estimated by using the maximum likelihood method (17).

The vector of independent variables (X_{mt}) can be expressed in the general form

$$X_{mt} = X_m(L_m, S_t) \tag{5}$$

where L_m is a vector of level-of-service characteristics of mode m and S_t is a vector of socioeconomic characteristics of worker t.

VARIABLES AND DATA

Three level-of-service variables and six socioeconomic variables were included in the logit formulation. These variables and their expected coefficients are summarized in Table 1. The level-of-service variables are defined as in urban work-trip modal-choice models (16). Of the socioeconomic variables, the variable automobiles per household worker is introduced as a replacement for automobiles per licensed driver and workers per household; it is hypothesized that the former is of direct and overriding concern in rural areas, where individual workers have been found to be increasingly dependent on the automobile (10). A dummy variable is introduced to associate home ownership with driving alone, which is a significant expense in rural areas and would most likely be expected of homeowners. Finally, length of residence is introduced to account for long delays involved in the decision to ride a transit vehicle or share a ride in rural areas, a sociological characteristic also pointed out in the literature (1,10). Automobile availability per licensed driver for shared ride is not assigned an expected sign in Table 1 as a result of two observations: (a) It has been shown that in urban areas the effect of this variable on shared ride is less than it is on drive alone, and (b) across-the-board increased automobile availability in rural areas, when combined with the previous observation, may result in an unpredictable effect on shared ride.

Approximately 500 households from the rural towns of Cloquet and Le Sueur, Minnesota, were contacted, and household characteristics were recorded for those who were potential riders of the commuter rural transit service. Sample demographic and socioeconomic characteristics are summarized in the following table:

Characteristic	Cloquet	Le Sueur
Estimated population	12 000	4200
Estimated population growth (%)	5	12
Percentage of total population		
Age (years)		
18-64	51.6	50.4
≥ 65	13	12.2
Below poverty level (1970 Census)	6.5	4.2
Household income	19 190	20 120
People per household	2.9	3.8
Workers per household	1.4	2.4
Licensed drivers per household	1.9	2.5
Automobiles per household	1.6	2.1
Own residence (%)	98	78
Length of residence (years)	22	8.7

These data were supplemented by information on level-of-service characteristics of the transportation system. To minimize the effect of a variety of trip choices on the choice of mode to work, only simple home-based trips were considered, i.e., trips from home to work to home. The final sample of 77 observations was divided into two subsamples: 40 Cloquet observations and 37 Le Sueur observations. A disaggregate model was then developed for each subsample to allow evaluation of model transferability. Finally, a model was developed for the complete sample so that higher statistical significance could be obtained.

ESTIMATED COEFFICIENTS

Three basic disaggregate models to estimate rural work-trip modal choice were derived from the Minnesota data--one from the Cloquet sample (model 1), one from the Le Sueur sample (model 3), and one from the combined Minnesota sample (model 5). These models are presented in Table 2. The previously stated hypotheses about the positive influence of home ownership on driving alone and of length of residence on using transit and carpooling are reflected by the parameters associated with variables DROWN and RESL, respectively. The two parameters have the expected sign and, in the combined sample model, are significant at the 8 and 7 percent levels, respectively. The two variables were not included in the Cloquet model, since almost all Cloquet respondents owned their home and length of residence was uniform across individuals. A third hypothesis being entertained--that automobile availability per worker has a positive influence on driving alone and carpooling--is reflected in model 5 by the parameter associated with variable AAPW. That parameter is also of the expected sign and is significant at the 5 percent level.

For all estimated coefficients, significance improved drastically when the sample size increased, as seen in Table 2, with the exception of the in-vehicle travel time coefficient (IVTT). All other coefficients in the combined Minnesota model are significant over the 8 percent level. Very short commuting trips in Le Sueur probably account for the perceived lack of importance of IVTT in that town.

For the convenience of prospective model users, two alternative models were derived for each town and these are also presented in Table 2. Models 2 and 4 differ from models 1 and 3, respectively, in that the former two do not use the variable AAPW but, rather, its components. In addition, automobile availability per licensed driver (AALD) was not found to be significant for work-trip modal choice in Cloquet and was not included in any demand model for that town.

The combined Minnesota rural work-trip modal-choice model is again presented in Table 3 along with two existing urban models. An inspection of the model coefficients confirms the observation found in the literature (1) that rural residents are more sensitive to travel cost than urban residents. Furthermore, remaining household income (RHINC) is seen as having an influence on rural modal choice greater than in urban areas by an order of magnitude, which also indicates the increased importance of financial considerations for transportation decisions in rural areas. Finally, it should be noted that the increased importance placed by urban commuters on OVTT in relation to IVTT is also observed in rural commuting and is of the same order of magnitude.

MODEL TESTING AND EVALUATION

Method

In testing the demand estimation models, six data sets were used. The following table summarizes these data sets and gives the monthly transit ridership for each data set:

Location	Data Set	Transit Route	Round-Trip Passengers per Month
Cloquet	1	Cloquet-Potlatch	292
	2	Cloquet-Diamond Match	
Le Sueur	3	Le Sueur-Green Giant	157
	4	Le Sueur-Hospital	
	5	Le Sueur-Telex	268
	6	Henderson-Telex	268

Because of its small size, data set 2 could not be used alone but only in combination with data set 1. Similarly, data set 4 had to be used in combination with data set 3. Six estimation models were tested: Macromodel (7), Micromodel (7), Poisson model (9), disaggregate Cloquet model 1, disaggre-

Table 1. Rural work-trip modal-choice model: definition of variables.

Variable Code	Definition	Expected Sign of Coefficient
D_a	1 for drive alone, 0 otherwise	
D_s	1 for shared ride, 0 otherwise	
OPTC/HINC	Round-trip out-of-pocket travel cost (¢) ÷ household annual income (1968$)	Negative
IVTT	Round-trip in-vehicle travel time (min)	Negative
OVTT/DIST	Round-trip out-of-vehicle travel time (min) ÷ one-way distance (miles)	Negative
$AALD_a$	Number of automobiles per licensed driver for drive alone, 0 otherwise	Positive
$AALD_s$	Number of automobiles per licensed driver for shared ride, 0 otherwise	Unknown
WPH_s	Number of workers in the household for shared ride, 0 otherwise	Positive
$AAPW_{a,s}$	Number of automobiles per household worker for automobile and shared ride, 0 otherwise	Positive
$RHINC_{a,s}$	Household annual income − 800 (number of persons in the household) for drive alone and shared ride (1968$), 0 otherwise	Positive
$DROWN_a$	1 for own residence and drive alone, 0 otherwise	Positive
$RESL_{t,s}$	Length of residence (years) for transit and shared ride, 0 otherwise	Positive

Note: a = drive alone, s = shared ride (carpool), and t = transit.

Table 2. Work-trip modal-choice model for rural Minnesota.

Variable	Cloquet Model 1[a]	Cloquet Model 2	LeSueur Model 3[a]	LeSueur Model 4	Combined Minnesota Model 5[a]
D_a					
Coefficient	-2.390	-1.854	-6.525	-5.912	-6.356
t-statistic	-0.715 3	-0.793 1	-2.340	-2.036	-2.933
D_s					
Coefficient	-3.192	-3.497	-8.694	-5.639	-6.832
t-statistic	-0.899 8	-1.209	-3.150	-1.311	-3.378
OPTC/HINC					
Coefficient	-77.620	-69.541	-114.72	-155.88	-136.99
t-statistic	-0.513 1	-0.492 4	-0.732 8	-0.974 2	-1.437
IVTT					
Coefficient	-0.059 46	-0.059 00	-0.013 85	-0.015 48	-0.029 31
t-statistic	-1.199	-1.198	-0.274 5	-0.311 3	-0.983 3
OVTT/DIST					
Coefficient	-0.589 0	-0.582 4	-0.494 9	-0.461 6	-3.583
t-statistic	-2.266	-2.284	-2.324	-2.454	-3.583
$AALD_a$					
Coefficient	-	-	-	1.166	-
t-statistic				0.571 7	
$AALD_s$					
Coefficient	-	-	-	-3.208	-
t-statistic				-0.692 8	
WPH_s					
Coefficient	-	0.597 4	-	0.247 7	-
t-statistic		0.643 0		0.409 9	
$AAPW_{a,s}$					
Coefficient	0.290 1	-	1.673	-	1.286
t-statistic	0.215 2	-	1.536	-	1.667
$RHINC_{a,s}$					
Coefficient	0.000 183	0.000 155 8	0.000 508	0.000 542	0.000 427 5
t-statistic	0.573 8	0.513 2	1.679	1.778	2.057
$DROWN_a$					
Coefficient	-	-	1.214	0.852 9	1.471 7
t-statistic			0.887 6	0.637 5	1.406
$RESL_{t,s}$					
Coefficient	-	-	0.037 46	0.040 94	0.012 37
t-statistic			0.530 9	0.576 0	1.500
Sum of chosen probabilities	21.83	21.89	26.64	27.74	49.27
$L^*(\theta)$	-29.11	-28.98	-16.14	-16.80	-47.14
$L^*(0)$	-43.94	-43.94	-40.65	-40.65	-84.59
$\rho^2 = 1 - [L^*(\hat{\theta})/L^*(0)]$	0.34	0.34	0.60	0.59	0.44

Note: $L^*(\hat{\theta})$ = log likelihood at convergence and $L^*(0)$ = log likelihood at zero.

[a]Selected for testing and evaluation.

gate Le Sueur model 3, and disaggregate combined Minnesota model 5.

Four error measurements were computed for each data set and model. These measurements included (a) absolute error (AE) and (b) percentage of absolute error (PAE), defined as a percentage of actual ridership. For data sets that were themselves combinations of other data sets, the sum absolute error (SAE) was computed to measure the total absolute error of the component data sets. Percentage of sum absolute error (PSAE) was also calculated for SAE as a percentage of actual ridership. These error measurements are defined as follows:

$$AE = |\text{actual ridership} - \text{estimated ridership}|,$$

$$PAE = |\text{actual ridership} - \text{estimated ridership}| / \text{actual ridership},$$

$$SAE = \sum_{i=1}^{N} |\text{actual ridership} - \text{estimated ridership}|_i, \text{ and}$$

$$PSAE = \sum_{i=1}^{N} |\text{actual ridership} - \text{estimated ridership}|_i / \sum_{i=1}^{N} \text{actual ridership}_i$$

where N is the total number of component data sets within a data set.

In testing the three aggregate models (Macro, Micro, and Poisson) certain application problems were encountered. For example, in both Le Sueur and Cloquet, the transit systems only serve work trips at specific destinations. The market for these systems is therefore smaller than the general population. The aggregate models tested do not seem to be suited for handling these cases since the values of independent variables such as RESTRPOP, POP_0, and POP_d in the Macromodel and Micromodel become very small and may lead to inaccurate results.

Other variables in the aggregate models also appear to be unclear in some applications. The variable BMILES in the Macromodel makes no distinction between deadhead miles and miles driven with passengers aboard. In certain cases, such as the Le Sueur system, which has one route between Le Sueur and Henderson 6 miles away, the deadhead miles are a significant portion of the total bus miles. In Cloquet, all service is within the city and deadhead miles are also further reduced as twice a day the bus drops off workers of one shift and leaves with workers from the previous shift without having to deadhead to the plant. These two situations are quite different, and it is unlikely that this model accurately handles both cases. Similar problems exist in applying the variable R, used by the Poisson model to account for system route mileage. Finally, it should be noted that, when applying the Macromodel and Micromodel, no corrections were made for fare, since in both cities the transit fare is the "base fare".

Results

The absolute error (AE) measurement for the six models tested is presented in Table 4 in two ways.

Table 3. Transferability of work-trip modal-choice model: rural versus urban.

Variable	Rural Minnesota	Urban[a] New Bedford	Urban[a] Los Angeles
D_a			
Coefficient	-6.356	-2.198	-2.746
t-statistic	-2.933	-2.648	-4.85
D_s			
Coefficient	-6.832	-1.535	-1.830
t-statistic	-3.378	-1.535	-3.95
OPTC/HINC			
Coefficient	-136.99	-87.33	-24.37
t-statistic	-1.437	-1.576	-2.07
IVTT			
Coefficient	-0.029 31	-0.019 9	-0.014 65
t-statistic	-0.983 3	-0.484 9	-2.25
OVTT/DIST			
Coefficient	-0.480 8	-0.101 3	-0.186 0
t-statistic	-3.583	-2.903	-4.02
$AALD_a$			
Coefficient	-	2.541	3.741
t-statistic		3.674	7.19
$AALD_s$			
Coefficient	-	0.449 9	0.609 3
t-statistic		0.847 8	1.58
WPH_s			
Coefficient	-	0.187 4	0.081 0
t-statistic		1.249	0.46
$AAPW_{a,s}$			
Coefficient	1.286	-	-
t-statistic	1.667		
$RHINC_{a,s}$			
Coefficient	0.000 427 5	0.000 072	0.000 083
t-statistic	2.057	1.279	2.31
$DROWN_a$			
Coefficient	1.471 7	-	-
t-statistic	1.406		
$RESL_{t,s}$			
Coefficient	0.012 37	-	-
t-statistic	1.500		
BW_a[a]			
Coefficient	-	1.026	0.810 1
t-statistic		3.769	3.28
$DTECA_s$[a]			
Coefficient	-	0.000 60	0.000 27
t-statistic		0.766 5	2.23
Sum of chosen probabilities	49.27	N.A.	N.A.
Log likelihood at convergence	-47.14	-256.5	-391.2
Log likelihood at zero	-84.59	-436.4	-930.0
ρ^2	0.44	0.41	0.58

[a]Models and variables introduced in report by Atherton and Ben-Akiva (16).

First, the error value is given so that conclusions on model performance can easily be drawn; evidently, lower errors indicate better model performance. Second, each model is compared with the Micromodel, and the deviation of its error with respect to that of the Micromodel is presented. A negative deviation means that the model in question has a greater error than the Micromodel and is therefore less desirable. A positive deviation implies that the model has a smaller error than the Micromodel and is therefore more desirable. Table 4 also includes a relative error measurement (PAE), which indicates the relative size of the absolute error with respect to the actual ridership value.

From the test results and the relative performance comparisons of Table 4, the following conclusions can be drawn:

1. At all times and for any individual data set, the proposed disaggregate specification performs substantially (up to 88 percent) better than the Micromodel. To be sure, this conclusion is drawn from testing the disaggregate models on a town different from that used in model development.

2. In testing model performance on combined data sets, the sum absolute error (SAE) again reveals the superiority of the disaggregate models. This conclusion can be drawn from the following table in which the Cloquet model, when applied to combined Le Sueur data sets, performs substantially better than the Micromodel (data sets 3 and 4 are treated as one data set):

Data Set	Estimation Model	SAE	PSAE	Improvement Over Micromodel (%)
3 and 4, 5	Micro	365	86	--
	Cloquet	113	27	69
	Le Sueur	73	17	80
	Combined	77	18	79
3 and 4, 5, 6	Macro	652	94	-4
	Micro	627	91	--
	Cloquet	235	34	63
	Le Sueur	113	16	82
	Combined	127	18	80

3. At all times and for any data set, the proposed disaggregate specification developed by using the combined Minnesota data performs substantially better than the Micromodel.

4. The Macromodel and Poisson model perform substantially (up to 78 percent) worse than the Micromodel. Although not indicated in Table 4 and the table above, the error always represents underestimation. This observation supports previous remarks on the performance of the Poisson model (8,9) but not on that of the Macromodel (9,11).

Table 4. Estimation errors of six demand models.

Location	Data Set	Estimation Model	AE	PAE	Improvement Over Micromodel (%)
Cloquet	1 and 2[a]	Macromodel[b]	230	79	-58
		Micromodel[b]	146	50	-
		Poisson[c]	260	89	-78
		Cloquet[d]	0	0	100
		Le Sueur[e]	47	16	68
		Combined[f]	18	6	88
Le Sueur	3 and 4[a]	Micro	275	176	-
		Cloquet	32	21	88
		Le Sueur	56	36	80
		Combined	50	32	82
	5	Micro	90	34	-
		Cloquet	81	30	10
		Le Sueur	17	6	81
		Combined	27	10	70
	6	Micro	262	98	-
		Cloquet	122	46	53
		Le Sueur	40	15	85
		Combined	50	19	81

[a]Treated as one data set.
[b]Developed by Burkhardt and Lago (7).
[c]Developed by Newman and Byrne (8).
[d]Developed with disaggregate data from Cloquet (model 1).
[e]Developed with disaggregate data from Le Sueur (model 3).
[f]Developed with disaggregate data from the combined Cloquet-Le Sueur sample (model 5).

CONCLUSIONS

A disaggregate demand specification was developed to estimate rural work-trip modal choice. The inclusion of a set of policy-relevant variables allows the use of the model for implementing a wide range of transportation policies to improve transit system performance. The inclusion of mobility and socioeconomic variables allows one to take into account long-term changes in resident mobility and the local economy when determining modal choice. Although parameters did not change appreciably across the models developed for different towns, their statistical significance in general increased as the sample size increased.

When the rural specification is compared with existing disaggregate urban specifications, it is seen that variables associated with financial considerations are more important to rural commuters than they are to urban commuters. However, the increased importance placed on OVTT over IVTT is found to apply to rural and urban commuters in a similar fashion.

The test results suggest that, in the prediction of rural work-trip modal choice, the disaggregate specification developed here performs better (up to 88 percent better) than the best existing aggregate models for all locations and at all times. Of the existing models, the Micromodel appears to perform better than the Macromodel or the Poisson model, which consistently underestimate the demand.

Future work will include further testing of the disaggregate specification developed here. In particular, larger data samples will make it possible to identify a system of market segmentation so that the model can be tested on aggregate data with small aggregation bias. Research is planned toward developing improved specifications to increase the model sensitivity to a larger variety of policy options. For example, the model could be extended to handle additional modes of work travel or to include additional policy and socioeconomic variables. Research is also needed in developing similar specifications for additional trip purposes so that a more complete set of travel patterns for rural residents can be estimated.

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REFERENCES

1. T.J. Adler, S.R. Stearns, and Y.J. Stephanedes. Techniques for Analyzing the Performance of Rural Transit Systems. Office of University Research, U.S. Department of Transportation, Final Rept. DOT-RSPA-DPB-50/80/23, Vol. I, 1980.
2. E. Poka, G. Maring, P. Davison, and R. Benacquista. Rural Highway Public Transportation Demonstration Program Evaluation: First Progress Report. TRB, Transportation Research Record 661, 1977, pp. 28-31.
3. J.E. Burkhardt. Results of the Rural Highway Public Transportation Demonstration Program. Presented at 59th Annual Meeting, TRB, 1980.
4. R.L. Brown. Evaluating Performance of Demand-Response Systems. Presented at 58th Annual Meeting, TRB, 1979.
5. Recommendations for Transit Performance Measures. Applied Resource Integration, Ltd., Boston, 1978.
6. Y.J. Stephanedes, D. Eagle, and A.S.J. Amin. Analyzing the Impacts of Transportation Policies on Rural Mobility and Economic Development. Office of University Research, U.S. Department of Transportation, Final Rept. (in preparation).
7. J.E. Burkhardt and A.M. Lago. Methods of Predicting Rural Demand. Ecosometrics, Inc., Bethesda, MD, 1976.
8. E.S. Newmann and B.F. Byrne. A Poisson Model of Rural Transit Ridership. TRB, Transportation Research Record 661, 1978, pp. 21-27.
9. Potential Demand for Rural Public Transportation. ITE Journal, 1981, pp. 29-31.
10. Y.J. Stephanedes. Performance Indicators and Policy Evaluation in Rural Transit. Thayer School of Engineering, Dartmouth College, Hanover, NH, Ph.D. dissertation, 1978.
11. R.L. Smith, Jr. Evaluation of Rural Public Transportation Demand Models Which Include Level of Service Measures. TRB, Transportation Research Record 638, 1978, pp. 49-51.
12. C.V.S. Mix and J.W. Dickey. Rural Public Transportation in Virginia. TRB, Transportation Research Record 519, 1974, pp. 56-65.
13. J.E. Burkhardt and W.W. Millar. Estimating the Cost of Providing Rural Transportation Service. TRB, Transportation Research Record 578, 1976, pp. 8-15.
14. R.J. Popper, C.B. Notess, and R.N. Zapata. The Demand for Special Transit Systems to Serve the Rural Elderly. TRB, Transportation Research Record 618, 1976, pp. 1-6.
15. W.R. Ugolik and R.G. Knighton. Estimating the Effects of Alternative Levels of Service on Rural Transit Ridership. TRB, Transportation Research Record 718, 1979, pp. 34-39.
16. T. Atherton and M. Ben-Akiva. Transferability and Updating of Disaggregate Travel Demand Models. Center for Transportation Studies, Massachusetts Institute of Technology, Cambridge, Rept. 76-2, 1976.
17. D. McFadden. Conditional Logit Analysis of Qualitative Choice Behavior. In Frontiers in Econometrics (P. Zarembka, ed.), Academic Press, New York, 1973.
18. T.A. Domencich and D. McFadden. Urban Travel Demand. North-Holland, Amsterdam, Netherlands, 1975.
19. M.G. Richards and M.E. Ben-Akiva. A Disaggregate Travel Demand Model. Saxon House, D.C. Heath, Ltd., Westmead, England, 1975.

Synthesized Through-Trip Table for Small Urban Areas

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Research performed to develop an improved and simple-to-use set of models that would facilitate the synthesis of a through-trip table for urban areas of less than 50 000 population is described. The effects of functional classification, average daily traffic, percentage of trucks, route continuity, and urban area population were determined to be significantly correlated with through-trip patterns. A least-squares analysis led to the development of a set of simple multiple regression expressions that estimate (a) the percentage of through-trip ends at each station and (b) the distribution of these trip ends among stations. The relations developed are simple to apply. The introduction of the new parameters, especially route continuity, appears to have improved the accuracy of the resulting trip table as compared with previous applications of the technique.