Comparison of Observed and Coded Network Travel Time and Cost Measurements

Antti Talvitie and Youssef Dehghani, State University of New York, Buffalo

The paper compares two types of measurements of trip times: those provided by the standard network algorithms are compared with trip-time components observed along the traveler's path from home to work and back. The two types of measurements are found to be different. The root mean square errors of the network measurements with respect to observed values are very large (75-135 percent of the mean value) for the non-line-haul travel time components. The means and the variances of the network measured variables, as a rule, are much smaller than the variances or means of the manually coded observed-travel times. Coefficients estimated by using the two types of data are not numerically similar. Statistical tests show that at least the alternative-specific constants' and the level-of-service variables' coefficients are different in the models developed by using the two types of data. Finally, the effect of substantial errors in level-of-service measurements on travel forecasts is discussed. It is also shown that good (short-run) travel forecasts can be obtained from the network-based models provided that consistent network coding conventions are followed and incremental forecasts are avoided.

For several reasons the development and use of disaggregate travel-demand models, and this does not mean logit and probit models only, has increased substantially in recent years. Disaggregate travel-demand models are based on information of individual traveler's choice rather than on percentage choices of groups of travelers. The transportation level-of-service attributes (e.g., travel time and cost components) that enter these travel-demand models have normally been obtained in one of two ways. Either the times and costs have been those that the respondent reported in the interview (often called perceived travel times and costs) or the travel times and costs have been obtained from the coded transportation network by using network models such as the urban transportation planning system (UTPS). These are often termed the network or aggregate travel times and costs because they are in the zone-to-zone values. In a few studies the travel times and costs have been those experienced by the travelers as measured by observation along the paths and the times of day used by the travelers.

In this paper the observed travel time and cost measurements are compared with those obtained from the coded networks. Statistical tests are then conducted to examine whether the coefficients of a mode choice estimated by using the types of data are equal.

Two sets of data were used to conduct the analyses. A subset of home-interview data collected before the opening of the Bay Area Rapid Transit System (BART) in 1972, which contained 142 observations, were originally used to conduct the analyses. The results of this work were reported earlier (1). Since some of the results of this earlier work were statistically inconclusive, a new set of data, collected in 1975, after the opening of BART, were prepared. These data contain approximately 700 observations.

The experienced values of travel times and costs would appear to be preferable to the network-based values. This is because the person included in the sample may not have the same travel characteristics as the average person does and because individual travel behavior is presumably a derivative of one's own rather than the zone's transportation circumstances. However, to obtain observed travel-time and cost components is a time-consuming and expensive process; few researchers have the resources available and the patience to do that. It is far easier to use existing networks to calculate the travel-time components and hope that the errors, if any, are minor.

Given that all the current models used in production planning are based on network information, it is important that the networks yield information on service levels and result in models that are equivalent to the service levels and models obtained by using the observed values of service variables. This assumption of equivalency, now made, needs verification.

COMPARISON OF THE EXPERIENCED AND NETWORK TRAVEL-TIME MEASUREMENTS

The way in which the two types of values were obtained needs to be defined. In the pre-BART data the observed transit travel times were obtained by asking the transit agency's information service to route travelers as if an inquiry call for a transit route was made by the traveler. The observed automobile travel times were based on travel-time runs (moving-vehicle method) made at various times of day and by routing travelers at the minimum time path at their time of travel. In the post-BART data the observed transit travel times were measured along the route travelers reportedly chose or would choose for their transit trip. The observed automobile travel times were obtained as in the pre-BART data.

The network values were obtained through standard network models and associate either peak or off-peak values with the travelers, depending on when the trip took place.

The pre-BART data were prepared independently of the present research. The post-BART data were prepared later under the supervision of Talvitie. Round-trip travel time and cost values are used in both sets of data.

The comparison of the observed (O) and network (N) travel times may be started by listing the means and variances of the travel-time components of interest. These appear in Table 1 for the post-BART data. Examination of the values in Table 1 reveals interesting differences. The variances and the means in the observed data cells appear to be consistently higher than those in the network data. The greatest concern, on the basis of the values in Table 1, appears to be with the out-of-vehicle time components. The average coded walk time to BART is 28.7 min; however, the observed value is more than fourfold, 123.0 min. (Note that this average pertains to all travelers, not just those who chose to use BART with walk access.)

In order to gain more knowledge of the similarities

Table 1. Means and SD of travel time and cost components by mode and type of measurement—post-BART data.

Time or Cost Component (min)	Type	Automobile		Bus with Walk Access		BART with Walk Access		BART with Bus Access		BART with Drive-Park Access	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
On-vehicle time	N	45.2[a]	24.6[a]	68.5[a]	34.7[a]	44.2	21.4	45.0	20.1	41.3	24.9
	O	50.5[a]	28.7[a]	77.3[a]	35.8[a]	37.3	22.5	48.1	24.1	48.1	25.4
Walk time	N	NA	NA	18.4	5.1	28.7	8.6	25.3	8.3	13.5	5.7
	O	8.6	25.2	23.0	24.8	123.0	109.0	19.6	18.3	25.3	31.9
Headway	N	NA	NA	29.0	18.5	18.5	8.0	20.4	15.5	18.5	8.0
	O	NA	NA	29.0	18.1	20.7	9.1	30.4	18.8	20.7	9.1
Transfer time	N	NA	NA	19.1	13.4	12.8	6.9	23.1	16.7	12.8	6.9
	O	NA	NA	35.4	23.4	26.8	15.7	37.2	20.1	26.8	15.7
Number of transfers	N	NA	NA	2.7	1.1	2.9	1.4	4.6	1.3	2.9	1.4
	O	NA	NA	2.6	0.9	2.3	0.7	2.6	0.9	2.9	0.7
Cost per wage	N	37.3	33.5	14.8	14.4	16.7	10.3	21.7	14.3	17.3	10.5
	O	31.9	29.4	14.8	14.4	17.4	10.3	20.8	11.4	24.3	13.9

[a] Pre-BART data value.

Table 2. Correlation coefficients, intercepts, and slopes for regressions between the observed and network measurements—post-BART data.

Travel Time Component and Mode	Correlation Coefficient	Intercept a	SE	Slope b	SE
On-vehicle time, BART and walk	0.74	3.1	0.77	0.77	0.04
On-vehicle time, BART and bus	0.77	5.8	3.0	0.92	0.06
On-vehicle time, BART and park	0.61	22.4	2.0	0.62	0.04
Walk time, bus	0.22	3.5	1.1	1.06	0.26
Walk time, BART and walk	0.31	10.0	20.3	3.94	0.68
Walk time, BART and bus	0.24	6.0	4.6	0.54	0.17
Walk time, BART and park	0.26	5.3	4.4	1.48	0.30
Headway, bus	0.39	18.0	1.6	0.38	0.05
Headway, BART and walk	0.40	12.3	1.1	0.45	0.06
Headway, BART and bus	0.27	23.7	2.4	0.32	0.09
Headway, BART and park	0.40	12.3	1.1	0.45	0.06
Transfer time, bus	0.28	25.9	2.8	0.49	0.12
Transfer time, BART and walk	0.28	18.8	3.3	0.63	0.22
Transfer time, BART and bus	0.36	27.4	2.6	0.43	0.09
Transfer time, BART and park	0.28	18.8	3.3	0.63	0.22

between the experienced and network travel-time values, regressions were run to obtain correlation coefficients, intercepts, and slopes. Ideally, we would like to obtain a correlation coefficient of one, an intercept of zero, and a slope of unity. The more we deviate from these values the less equal are the two sets of data. The correlation coefficients, intercepts, and slopes are given in Table 2 for post-BART data.

Examination of the numbers in Table 2 shows that, except for some isolated time components, the desired values for correlation, intercepts, and slope are not achieved. Statistically speaking, the hypotheses that the slopes should equal unity and the intercepts are zero must be soundly rejected for all variables, except in two or three isolated cases. In fact, the numbers of Table 2 do not appear to represent regressions between two types of measurements of the same variable.

The information produced so far about the similarities and dissimilarities of observed and network measurements of travel times can be conveniently summarized by using two measures: the root mean square error (RMSE) and Theil's U-coefficient. The former is often used as an all-around measure of goodness of fit; the latter measure is zero for perfect measurements (or forecasts) and has an upper bound of one. Furthermore, Theil's U-coefficient can be decomposed to three components (denoted U^M, U^S, and U^C), which indicate the proportional loss in accuracy due to differences in means, standard deviations, and covariances, respectively. These useful summary measures are given in Table 3 for the post-BART data.

The results in Table 3 are interesting. Except for the line-haul travel times, BART and walk or park headways, and the cost variables, the RMSEs are roughly equal in magnitude to the means of the observed times and costs, which indicates large errors in measurement. The same result is conveyed by the Theil's U-coefficient; the U-coefficient obtains very large values for out-of-vehicle time components. If we impose an arbitrary but reasonable U-coefficient value of 0.20-0.25 for acceptably accurate measurements, then even some on-vehicle and travel-cost measurements fail to meet the standard. The components of the U-coefficient indicate that, with some exceptions, the largest share of the error comes from the covariances between the network and observed values.

As a final item before actually estimating choice models by using the two types of measurement, it is instructive to examine typical frequency plots of some of the travel variables. The analysis performed by McFadden and Reid (2) tells that zonal averages will yield consistent estimates for coefficients, given that the distributions of variables are not skewed. Thus, the distribution of the variables for the entire sample (one can envision it to be one large zone) ought not to be skewed either if good coefficients are to result from using zonal averages. In examining the frequency plots it is good to keep in mind that most of the difference between the two types of measurements is due to covariances. Thus, the frequency plots for the two measurements can look similar without the measurements being similar because measurements in any given interval may not pertain to the same individuals.

It is natural to start with the plots of on-vehicle times. An automobile on-vehicle time plot is shown in Figure 1. An examination of the plot in Figure 1 suggests that there is a great deal of similarity between the two types of measurement; the only noticeable difference is the fat tail of the observed automobile on-vehicle time distribution. One might suspect that the lack of fat tail in the network times distribution is due to improper accounting of congestion effects. A χ^2 test against the null hypothesis (that the distributions of the two measurements are the same) was, however, rejected at the 0.95 level of confidence.

The walk time (bus with walk access) frequency distribution in Figure 2 indicates that the network-coded walk time has a highly peaked distribution; however, the

Table 3. RMSE and Theil U-coefficients of travel time components—post-BART data.

Variable	Mean (Observed)	RMSE	Theil U			
			U	U^M	U^S	U^C
On-vehicle time						
BART and walk	37.2	17.4	0.26	0.16	0.00	0.84
BART and park	48.1	23.2	0.32	0.09	0.00	0.91
Automobile (pre-BART)	50.5	13.1	0.17	0.16	0.10	0.74
Bus (pre-BART)	77.2	18.8	0.16	0.22	0.00	0.78
Walk time						
Bus	23.0	24.5	0.63	0.03	0.64	0.33
BART and walk	123.0	143.1	0.85	0.43	0.50	0.07
BART and bus	19.6	19.1	0.50	0.09	0.27	0.64
BART and park	25.3	33.1	0.77	0.13	0.63	0.25
Headway						
Bus	29.0	20.3	0.42	0.00	0.00	1.00
BART and walk	20.7	9.7	0.32	0.05	0.01	0.94
BART and bus	30.4	23.2	0.53	0.18	0.02	0.80
BART and park	20.7	9.7	0.32	0.05	0.01	0.94
Transfer time						
Bus	35.4	28.6	0.59	0.33	0.12	0.55
BART and walk	26.8	20.8	0.60	0.45	0.18	0.37
BART and bus	37.2	25.4	0.50	0.31	0.24	0.45
BART and park	26.8	20.8	0.60	0.45	0.18	0.37
Cost per wage						
Automobile	31.9	19.2	0.30	0.08	0.05	0.87
BART and walk	17.4	4.6	0.16	0.03	0.00	0.97
BART and bus	20.8	8.0	0.23	0.01	0.13	0.86
BART and park	24.3	11.3	0.33	0.38	0.09	0.53

Figure 1. Frequency plot—automobile in-vehicle time.

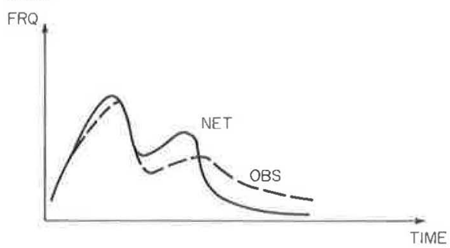
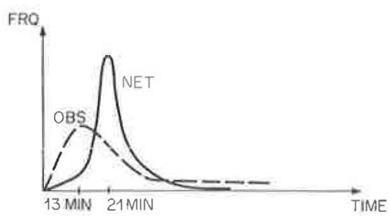


Figure 2. Frequency plot—walk time.



distribution of the observed walk times both peaks earlier and is much fatter. The appearance of the two distributions is as expected. Traffic zones are connected to network with relatively few common values and the observed values show a scatter, which relates to the location of individuals with respect to the bus-line configuration.

The frequency plot for bus headways (round trip, directional headway summed) appears in Figure 3. Note that the network headways are shorter in duration; their distribution also has a noticeably thinner tail than that of the observed headways. The apparent reason for this is that zones have been connected to trunk-line streets on which many bus lines operate and have low headway for consecutive buses. In actuality the travelers' origins and destinations are dispersed within the zones, and by taking note of schedules the travelers can gain the advantage of nearer bus lines in spite of their lower service frequency.

The frequency plot for transfer time in Figure 4 shows similar characteristics on the distribution of headways. Again, it appears that the majority of network paths use trunk-line streets that have frequent bus service and, where transfers are necessary, the transfer times are quite short. The observed transfer times show, in contrast, that travelers use routes that are convenient for them on some other grounds besides the headways of transfer buses. The distributions of transfer times also show that paths built by network algorithms do not coincide with paths actually taken by travelers—a fact well known to most transportation planners.

The two types of measurements (observation and network) of travel-time variables are certainly different. On the basis of the correlation analysis and the frequency plots we would not expect to obtain similar models with the two types of data. This is because there were large differences in the measurement and because the frequency distributions were not normal but were highly skewed. This latter result also enables the conclusion that the coefficients obtained with the aggregate network data are biased.

COMPARISON OF MODE CHOICE MODELS DEVELOPED WITH SERVICE MEASUREMENTS

The model specifications used in the tests reported in this section is a minor variant of the model specification developed by the urban travel demand forecasting project (UTDFP) at the University of California, Berkeley (3). The larger post-BART sample of 700 observations will be used. The earlier paper (1), which used only the small pre-BART data set, resulted in inconclusive answers. Even so, the main hypotheses seemed to be supported by the previous analyses.

First, the coefficients of both system and socioeconomic variables were found to be numerically different, though the statistical evidence to support the existence of such differences was inconclusive. The reason for these differences was ascribed to the correlations between the socioeconomic and service attributes, which correlations were taken to be manifestations of people's travel and other choices. It was then concluded that the observed service-level calculations preserve these correlations and are likely to yield unbiased coefficients and demand elasticities (given a good model specification) while the network calculations do not appear to preserve these correlations and, by simple logic, must yield coefficients that are statistical artifacts. An example clarifies this. Assume that two

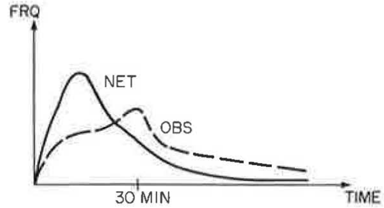


Figure 3. Frequency plot—headway.

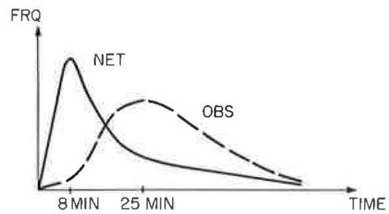


Figure 4. Frequency plot—transfer time.

Table 4. Chi-square statistics for various tests of coefficient equality in models developed by using observed and coded network-based service attribute data.

Hypothesis	χ^2-statistic	Critical χ^2 [a]	Accept or Reject
1. Equality of alternative specific constants	35.4	12.6	Reject
2. Equality of coefficients of service variables	53.0	12.6	Reject
3. Equality of coefficients of socioeconomic variables	33.0	14.1	Reject[b]
4. Equality of coefficients of service variables given unequal alternative specific constants	29.0	12.6	Reject
5. Equality of coefficients of socioeconomic variables given unequal alternative	5.2	14.1	Accept[b]

[a] At 0.05 level.
[b] For these tests the assumption of statistically independent samples may not have been strictly met.

travelers who have different socioeconomic attributes reside in the same zone and go to work in the same destination zone. The network algorithms assign these two people identical values for the service attributes. The choice model in turn attributes the choice to the different socioeconomic attributes (because the service attributes are equal) even though the service levels may contribute to the choice.

Second, the models that were developed by using travel times and costs from networks were observed to have coefficients whose relative values were approximately equal to those used in building the network paths. For example, if walk and wait times were weighed two in building the paths, then this same ratio (two to one) was observed in the choice model. Variable specification also seemed to have an effect; the arguments to support it are lengthy and not repeated here. The obvious hypothesis then was that the conventions used to build the paths and create the variables procreate the choice models based on coded network service data. We conjectured that if (a) networks in two or more cities are coded by using similar conventions, (b) paths are built by using similar weights, and (c) variables are created by using same type of rules (e.g., wait time is one-half of the headway up to 10 min of headway and one-fourth thereafter) then, with normal low percentage of transit users, the resulting choice models for those cities should indeed be identical. The models so obtained are not, of course, really behavioral or transferable travel-demand models, but only reflections of the coding procedures.

Third, the socioeconomic and system attributes were found to increase the predictive power of the models only slightly.

The more ample post-BART data support these hypotheses, which were arrived at by use of the small pre-BART data set. The appropriate statistical test for many of the hypotheses presented in this paper is a nested (Chow-like) likelihood ratio test. McFadden (4) has shown that if we have two independent samples (A and B), a test for the equality of the coefficients is possible. Let L_A and L_B be the maximum log likelihood levels attained for the samples A and B and L_{AB} be the maximum log likelihood for the combined sample, then $\chi^2 = -2(L_{AB} - L_A - L_B)$ is distributed χ^2 with K degrees of freedom, where K is the number of parameters. The same test can be used to test the equality of a subset of coefficients (e.g., coefficients of the service attributes).

The results of the various tests are shown in Table 4, and the models are estimated by using the observed and network variables that appear in Table 5. In Table 4 the tests on subsets of coefficients all lead to rejection of equality of coefficients (tests 1-3). Tests 4 and 5 follow orthodox statistical testing of hypothesis. That is, given the inequality of alternative-specific dummies (test 1), a test is made about whether the system variables have equal coefficients (test 4) with negative results. Finally, given the inequality of alternative-specific dummies and system variable coefficients, a test is made for the equality of socioeconomic variables' coefficients (test 5) with affirmative results. Thus, the tests unequivocally show that the models developed by using the observed and coded network service data are different. This is not a surprising finding, given the large discrepancies in the two types of measurements found in the first section.

Turning then to the model coefficients, we were unable to reproduce the coefficients of the UTDFP model, which was developed by using the network measurements. The greatest discrepancy is in the automobile and driver and drivers variables. In the UTDFP model these coefficients were between 3.0 and 5.0 and 1.0 and 2.0, respectively; coefficients of this magnitude were also estimated by Atherton and Ben-Akiva (5). On the other hand, models developed observed service-level attributes that seem consistently to produce coefficients similar to those in our study, which are substantially smaller (6, 7). This discrepancy was not investigated in depth at this time. It is suspected that one of the chief reasons for discrepancies is the possibility of having choice-based samples. Network coding and manual coding exclude different travelers from the sample. Another reason may be the use of different rules to exclude alternatives. A third reason may be the use of different model specification. How these three causes affect model coefficients will be investigated later.

Note that, by using the observed data, the out-of-vehicle time components do not seem to be valued more dearly than the in-vehicle time components. In contrast, when the network data are used the ratio of walk time to in-vehicle time is 1.9. This is approximately the same as used in building the paths in the network, where this ratio was 2.0. These same ratios are not observed for the wait times. However, there were substantial perturbations to these data after the paths were run, which makes the analysis of the effect of coding and pathbuilding conventions to model impossible with the present data (8, 9, 10).

Third and finally, the models have a low explanatory power over and above the explanatory power contained in the alternative-specific dummies. The overall proportion of successful predictions increased little more than 10 percent, or from 54 to 67 with observed service

Table 5. Model specification, coefficients, and t-values.

Variable	Alternative Entered, Zero Otherwise[a]	Observed Service Coefficients	Observed Service t-value	Network Service Coefficients	Network Service t-value
Income	1	-0.0000674	2.5	-0.0000246	1.0
Drivers in household	1,3,6	0.788	4.5	0.929	5.1
Drivers in household	7	0.717	3.6	0.854	4.8
Head of household	1	0.192	0.9	0.658	3.5
Employment density	1	-0.00144	3.1	-0.00166	3.8
Automobiles per driver	1,3,6	1.781	3.9	1.976	4.3
Automobiles per driver	7	1.021	2.0	1.340	3.1
Cost per wage (min)	1-7	-0.0469	6.4	-0.0304	5.2
In-vehicle time (min)	1-7	-0.0122	1.7	-0.0329	4.4
Walk time (min)	1-7	-0.0170	4.3	-0.0634	3.6
Headway (min)	3-6	0.00735	0.7	-0.0186	2.3
Transfer time (min)	3-6	-0.0173	1.3	-0.00039	0.03
Number of transfers	3-6	-0.393	2.1	0.0288	0.3
Alt 1 dummy	1	-1.116	1.6	-2.910	3.4
Alt 3 dummy	3	-5.206	7.7	-5.502	8.5
Alt 4 dummy	4	-0.579	1.7	-1.154	3.1
Alt 5 dummy	5	0.0842	0.3	-1.285	4.1
Alt 6 dummy	6	-2.744	4.9	-3.769	6.5
Alt 7 dummy	7	-2.993	4.6	-3.690	6.1
Number of observations		676		700	
Log likelihood at zero		-904.95		-1134.2	
Log likelihood at maximum		-614.50		- 711.58	
Proportion successfully predicted		0.67		0.61	

[a]Alternatives: 1 = drive alone, 2 = bus with walk access, 3 = bus with automobile access, 4 = BART with walk access, 5 = BART with bus access, 6 = BART with automobile access, and 7 = shared ride.

variables and from 54 to 61 network measurements when both the socioeconomic and the service variables were added to the model. This has to be considered a low payoff—too much of the behavior is explained by the unobserved variables.

CONCLUSIONS

The conclusions of this paper are obvious. On the level-of-service side, substantial errors are possible and can result both in inaccurate forecasts and biased model coefficients. On the demand side, incremental forecasts should be avoided by using models based on network information because of biased coefficients. However, it is not concluded that ball-park travel prognoses cannot be made by using current network-based model systems.

The forecasting accuracy of the models is nearly identical, regardless of the type of data used. The saying "data do not matter" has, apparently with justification, circulated among travel-demand modelers. The network-based models seem to have simple aggregation properties. Koppelman's (11) careful in-depth study on aggregation shows that predictions with zonal averages seem to perform remarkably well. There are two reasons that cause this to be the case. First, networks ignore the within-zone variances, the source of aggregation bias. Table 1 shows that between-zone variance (network data) accounts for 10-60 percent of the total variance (observed data) for the excess time components and about 70-90 percent of the on-vehicle time variances. Thus, by using the networks there is not much left to aggregate as far as the service variables are concerned. Second, assume that the network travel times and costs are errors-in-variables-type variables or

$$Z = X + v \tag{1}$$

where

Z = the network values,
X = the true values, and
v = a (random) error.

Let us then assume that X and v are independently and normally distributed with means m_x and zero and variances of σ_x^2 and σ_v^2. These are reasonable assumptions. Any time a trip is taken but the trip time is not known exactly, it is a random variable; and this random variable is independent of the traveler's location within the traffic zone. The hypothesis in disaggregate travel-demand models is that the choices of travelers depend on the true values or, in a regression sense,

$$Y = \alpha + \beta X + e \tag{2}$$

The use of linear regression is justified because of the clarity of the result and because of the fact that the logit curve is nearly linear for small coefficient values, or over the relevant range (due to both the small variances in the networks and variable defintions, e.g., automobile and drivers varies between 0 and 1; however, variable number of drivers may introduce a serious nonlinearity).

In predicting, we do not know the true value X but the network value Z, and thus, we need to obtain E (X|Z), but this is equal to

$$E(X|Z) = (\sigma_v^2 m_x + \sigma_x^2 Z)/(\sigma_v^2 + \sigma_x^2) \tag{3}$$

and

$$E(Y|Z) = \alpha + \beta[(\sigma_v^2 m_x + \sigma_x^2 Z)/(\sigma_v^2 + \sigma_x^2)] \tag{4}$$

where α and β are the consistent errors-in-variables estimators for α and β. On the other hand, the least-squares predictor is

$$Y = \bar{Y} + b(Z - \bar{Z}) \tag{5}$$

where b is just an ordinary least-squares (OLS) estimator of Y on Z. It can be shown that

$$b = \beta/(1 + \sigma_v^2/\sigma_x^2) \tag{6}$$

or

$$Y = \bar{Y} + b(Z - \bar{Z}) \tag{7}$$

$$Y = \alpha + \beta m_x + \beta(Z - \bar{Z})/(1 + \sigma_v^2/\sigma_x^2) \tag{8}$$

Because E (v) = 0, $\bar{Z}$ is an unbiased estimate for m_x, and

$$Y = \alpha + \beta[(\sigma_v^2 m_x + \sigma_x^2 Z)/(\sigma_v^2 + \sigma_x^2)] \tag{9}$$

But this is exactly what was obtained by using the consistent errors-in-variables coefficients α and β, Equation 4.

Even though the OLS coefficients b in Equation 7 are not unbiased they yield unbiased forecasts. Thus, for prediction purposes the network-based models, whether aggregated or disaggregated, can be used with success, provided that conventions for network coding and path building are not changed and out-of-range predictions not made. Note that incremental forecasts cannot be made because the demand elasticities are not unbiased.

A good example of how poorly done network coding results in wrong travel forecasts is provided by the BART patronage predictions. In the UTDFP sample the following shares were observed for BART patronage, and predicted by using the network information; in the third line revised predicted shares are shown by using the average observed service levels where they differ from the network values by more than 5 min.

Share	Drive	Shared Ride	Bus	BART
Observed	0.595	0.22	0.12	0.065
Predicted (network service variables)	0.53	0.21	0.135	0.125
Revised (observed service variables)	0.60	0.24	0.11	0.05

The error in prediction is almost totally due to network coding; the remainder can be attributed to unforeseen land-use changes and other highly unpredictable items, such as reliability; aggregation error may also be present.

Discussions of the difficulties in validating demand models, of which the Metropolitan Transportation Commission (MTC) model system discussion serves as a good example, are exclusively directed to the problems associated with the demand models to the total neglect of the service side. Webber (12) discusses at length the mistakes made by planners for not knowing that supposedly out-of-vehicle time is valued in people's minds two to three times more than the in-vehicle time and attributes, among other things, the 100-percent mistake in BART patronage forecasts to this lack of knowledge about travel behavior.

Given that (a) the bulk of the explanatory power is in the constant terms of the demand model, (b) presumably the unobserved attributes that underlie these constants change only slowly, and (c) travelers do not seem to be very sensitive to travel times and costs (and, hence, minor errors in service variables, say 5 min, do not substantially affect the predictions), it should be hard to make a bad prediction in the short run—provided, of course, that the service levels are not predicted wrongly.

Although networks can be used to give adequate ballpark travel forecasts in many planning situations, their usefulness is limited. We mentioned that incremental forecasts could not be made by using network-based models because of their biased coefficients. Careful coding of networks is also costly and time consuming and depends on good human judgment. This heavy reliance on human judgment in network coding can be a two-edged sword. On one hand it can be used to guard against foolish mistakes, often attendant with the blind use of models, but on the other hand human judgment lends itself too easily to errors of commission. Planners who want demand figures to justify, for example, a rail transit link should code short-access links and weigh them heavily in building network paths and also in travel-demand models. In case of BART, the access walk times were underestimated more than fourfold (123 min versus 28 min). Such errors are going to show up in predictions even if the behavioral weights are not guessed correctly. Furthermore, there is evidence that no mistake was made by using equal weights for the travel-time components.

It seems to us that academicians and planners alike have been too attracted to debating and estimating statistically the mysteries of human behavior (with little success one might add) to pay attention to the obvious, which is directly observable and requires really no insight to human behavior—the level of service provided by the transportation system. A good effort to improve our capabilities in the entire supply side of transportation is desirable.

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