Analysis of Maximum Load Data for an Urban Bus System

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ABSTRACT

Maximum load data are important indicators of transit route performance and are widely used in service planning. Maximum load data for the routes of the San Diego Transit Corporation were analyzed to provide an idea of the characteristics of such data and the range and patterns of variation they display. Major goals were to determine the general characteristics of the data, to analyze relationships between ridership and maximum loads, to compare variations in peak load factors among routes, and to compare successive data sets for the same route to assess the stability of the data over time. The most important characteristics of the San Diego data appear to be their overall variability and the high degree of randomness they display, the wide variation among routes in relationship between ridership and maximum loads, the relative stability over time of overall distributions of maximum loads and peak load factors, and the apparent instability of the exact times of day at which fluctuations in maximum loads occur.

Improvements in the performance of urban bus systems are usually achieved through a continuing process of monitoring and analyzing data about individual routes. Wilson and Gonzalez (1) refer to this process as "short-range transit planning" and identify two possible approaches. One of these, representing common current practice, focuses on identifying substandard route performance (whether it can be corrected or not); the other is based on identifying situations in which certain generic actions can be taken to improve performance. Both approaches involve systematic collection and evaluation of data about transit route performance. Consequently, one key to successful service planning is the ability to properly summarize and evaluate such data.

One important type of route performance data is that related to maximum loads. Peak load factors (ratios of maximum loads to seating capacity) are widely regarded as key indicators of the quality of transit service. In short-range planning, information about maximum loads has an important impact on decisions about scheduling, headway control procedures, and the assignment of equipment, especially where buses with different seating capacities are available. Maximum load data also have important implications for longer range planning decisions, particularly those related to the mix of bus sizes in the fleet.

Despite the evident importance of maximum load data, there is little published information on their characteristics or the best ways to summarize and use them. Discussions of the use of maximum load data [e.g., in the discussion of peak load factors in NCHRP Synthesis of Highway Practice 69 (2)] tend to be presented in general terms and without reference to the statistical characteristics of the data. Furthermore, little attention has been paid to the causes of variation in maximum loads. One study that does bear on this subject is a paper by Shanteau (3) who studied variations in loads at the maximum load point of a single high-frequency bus route and found them closely associated with variations in headway. Beyond this, there appears to be little or no published information; in particular, there do not appear to be any studies of variations in maximum loads for entire transit systems.

This lack of information is addressed here by presentation of an analysis of maximum load data for an entire urban bus system. This analysis involved two separate sets of data covering 27 of the 28 routes of the San Diego Transit Corporation (SDTC). Because the results obviously depend on the peculiarities of this system, they may not be representative of all urban bus systems; they are presented to suggest ways in which maximum load data can be analyzed and to give the reader a feel for the range and patterns of variation to be expected.

Analysis of the data involved comparisons of routes and, for the same route, of successive data sets. Major goals were to determine the general characteristics of the data, to analyze relationships between ridership and maximum loads, to compare variations in peak load factors among routes, and to compare successive data sets for the same route to assess the stability of the data over time.

DATA SOURCES

Primary data sources were summaries of boarding and alighting counts performed by the San Diego Association of Governments (SANDAG) on San Diego Transit Corporation routes. These summaries were available for 27 of the 28 routes in this system including 22 local routes and 5 express routes. In a few cases routes involved two or more branches; where this was the case, data for trips on the different branches were compared to determine whether the different branches should be analyzed separately. As it turned out, separate analysis appeared to be warranted in only one case.

The data summaries cover all scheduled one-way trips on the routes in question and include the dispatch time for the trip, the date the data were collected, the total number of passengers boarding and alighting, the maximum number of passengers on the bus at any point, and the seating capacity of the bus. It should be noted that the location of the maximum load point was not necessarily the same for every trip, so maximum load data in these summaries are not equivalent to load check data taken at maximum average load points.

Two sets of such summaries were analyzed. The first was derived from counts taken between February 1981 and December 1982, and the second from counts taken between September 1982 and April 1984. Surveys of individual routes in the two data sets were taken from 11 to 31 months apart, with an average difference of about 15 months. All data were taken on weekdays. Data for each route were taken over a period of several days and represent different days of the week; in particular, data for successive trips were normally not collected on the same day.

In addition to these summaries, time checks were used in some cases to determine whether headway control problems existed on particular routes, and summaries of the total number of passengers per day boarding, alighting, and remaining on board at each stop were used in selected cases to provide further insight into spatial peaking patterns.

GENERAL CHARACTERISTICS OF THE DATA

The data summaries described previously contain three basic items of information for each trip: the total ridership, the maximum load, and the seating capacity of the bus. Two additional measures, the peak load factor and the fraction of passengers on board at the maximum load point, may be derived from these. Let M represent the maximum load, R the number of passengers carried per trip, C the seating capacity, λ the peak load factor, and ϕ the fraction of passengers on board at the maximum load point. Then, $\phi = M/R$ and $\lambda = M/C$. The factor ϕ is an indicator of the degree to which loads peak in space, and λ is the basic measure of the operator's success in matching seating capacity with demand. Note also that R is not merely a function of the demand rate but also reflects the operator's scheduling policies, and that λ is a function of demand, frequency of service, and bus size.

The most striking characteristic of these data is their variability. Maximum loads are expected to vary with ridership and ridership to vary by route, direction, and time of day as demand rates and schedules vary. In addition to these variations, examination of the data showed that ϕ, the fraction of passengers on board at the maximum load point, also varies over a wide range, even for single routes, and that there are large irregular variations in all items of data between successive trips in the same direction on the same route. This suggests that there is a great deal of random variation superimposed on the time-of-day trends in the data.

If all scheduled trips in both data sets are considered, values of R range from 0 to 167, and M varies from 0 up to 81 for standard buses and 112 for 70-seat articulated buses. Values of ϕ are confined to a range of about 0.25 to 1.00 but tend to vary widely within that range, and values of λ range from 0.00 to 1.60. Figure 1, which shows the distribution of maximum loads for all one-way trips on one of the San Diego routes, provides some idea of the typical variation in maximum loads on individual routes.

RELATIONSHIPS BETWEEN RIDERSHIP AND MAXIMUM LOADS

Maximum loads are expected to vary with ridership. The results reported by Shanteau (3), for instance, appear to imply that maximum loads depend on ridership; that ridership, in turn, depends on the actual time separation between buses; and that all other influences make only minor contributions to variations in maximum loads. The San Diego data, on the other hand, appear to indicate that relationships between ridership and maximum loads may vary considerably, both between routes and for a single route. Figure 2 shows distributions of ϕ for two

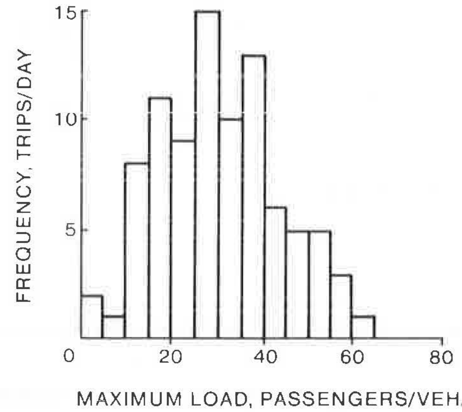

FIGURE 1 Distribution of maximum loads, SDTC Route 2, 1982 data.

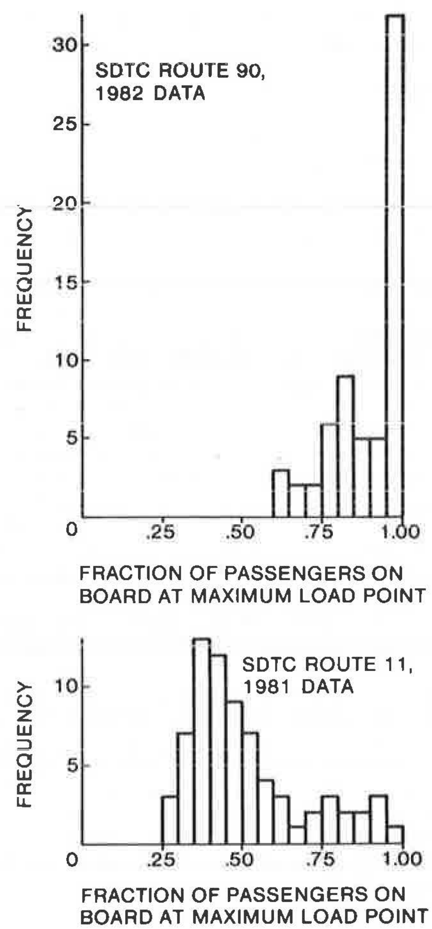

FIGURE 2 Comparison of distributions of fraction of passengers on board at the maximum load point for two San Diego bus routes.

San Diego routes that represent extreme cases. Note both the breadth of the distributions and the differences between them.

Values of ϕ for individual trips represent spatial load peaking and result from passengers' travel patterns. In particular, they depend on origin-destination patterns and, for highly dispersed origin-destination patterns, on average trip lengths. At one extreme, ϕ will be 1.00 when all passengers are on board at the maximum load point. For less concentrated origin-destination patterns, a minimum value may be estimated by considering, as an ideal case, the so-called steady-state many-to-many origin-destination pattern, the load profile of which is shown in Figure 3. For this case, all passengers

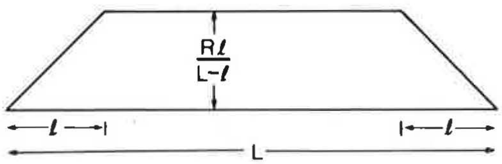

FIGURE 3 Load profile for steady-state many-to-many origin-destination pattern.

are assumed to have equal trip lengths of ℓ and boarding and alighting rates are assumed to be equal except within a distance ℓ of the ends of the route, leading to a trapezoidal load profile. If β represents the ratio of the trip length ℓ to the route length L, the value of ϕ for this case is $\beta/(1 - \beta)$. Assuming that minimum values of β are on the order of 0.20 in San Diego, this implies minimum values of ϕ of around 0.25. Figures 4 and 5 show plots of M versus R for the same routes the ϕ-distributions of which were compared in Figure 2, with the limits discussed previously superimposed for purposes of comparison. Note that the relationship between M and R is not necessarily linear, especially for small values of R, and that there is considerable scatter in the data.

If relationships between ridership and maximum loads depend on passengers' travel patterns, they should vary by route, and these variations should depend on the functions of the various routes in the system and the types of trips they serve. To test this hypothesis, the San Diego routes were divided into four categories: express routes, local routes, terminating in the central business district (CBD), local routes passing through the CBD, and local routes not serving the CBD. To compare these, two alternative measures of the relationship between ridership and maximum loads were calculated for each route. One of these was a weighted value of ϕ, defined as $\hat{\phi} \equiv \Sigma M/\Sigma R$. The other was the regression slope for the line of best fit for M versus R. Because there is apparent nonlinearity in this relationship, especially for trips with small values of R, trips with R less than 10 were arbitrarily excluded. Note that both measures were designed to give more weight to heavily traveled trips than would the mean value of ϕ; this was done because spatial peaking on lightly traveled trips has little impact on the operation of the system.

A summary of the results is given in Table 1. Note that both measures yield similar results, although the regression slopes exhibit a somewhat greater range than the values of ϕ. Both measures are obviously much higher for express routes than for local routes (with the exception of one local route); for local routes, the ranges of both measures are broad and overlapping, although there appears to be some tendency for non-CBD routes to have higher values of $\hat{\phi}$ than CBD-oriented routes and for routes terminating in the CBD to have higher values of $\hat{\phi}$ than those that pass through. The variations among individual local routes do not appear to be closely related to any other route characteristic, such as route length, however.

Values of ϕ for individual routes may vary by time of day, depending on the types of trips served at different times of day, or randomly. If there are definite time-of-day trends, they may affect the timing and magnitude of peaks in maximum loads, depending on whether peaks in ϕ coincide with peaks

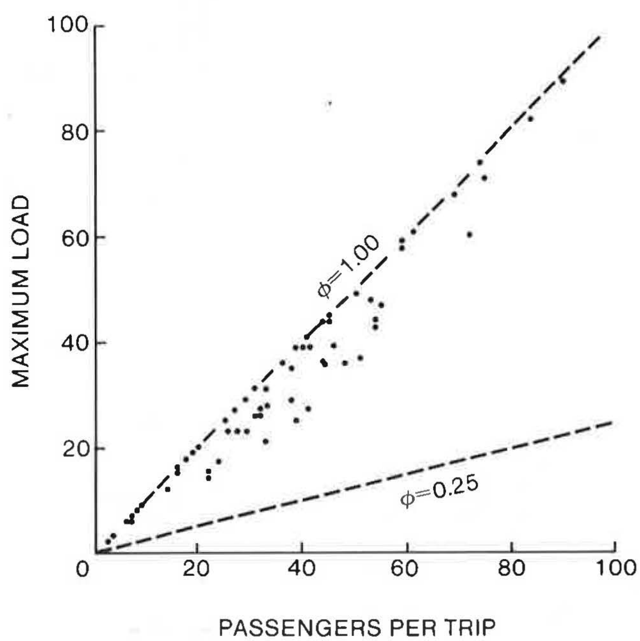

FIGURE 4 Maximum load versus passengers per trip, SDTC Route 90 (express route), 1982 data.

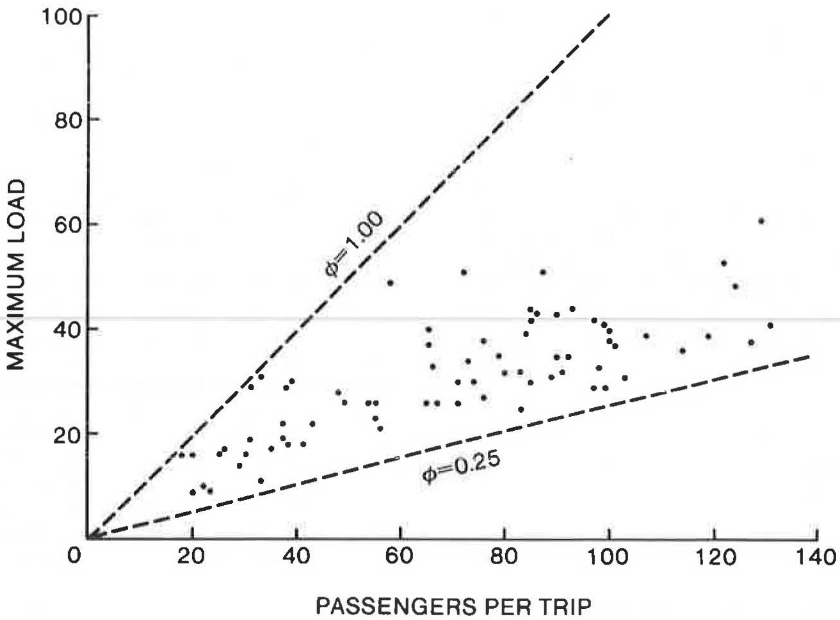

FIGURE 5 Maximum load versus passengers per trip, SDTC Route 11 (long local route passing through CBD), 1981 data.

TABLE 1 Values of $\hat{\phi}$ and Regression Slopes for Maximum Load Versus Ridership for San Diego Bus Routes, 1981-1982

Route	$\hat{\phi}$	Regression Slope
Express		
90	.93	.98
50	.83	.89
110	.75	.88
20	.72	.73
80	.70	.75
Local, non-CBD		
41	.64	.69
13	.57	.59
6	.54	.59
36	.53	.52
33	.53	.49
27	.51	.55
32	.51	.50
Local, CBD terminal		
35	.80	.93
7	.61	.59
15	.60	.47
1	.58	.52
25	.54	.50
43	.54	.53
34	.48	.42
Local, through CBD		
2	.58	.42
16	.53	.52
3	.53	.51
9	.53	.42
4	.49	.37
29	.43	.43
11	.43	.26
5	.42	.30

in R. Time-of-day trends were analyzed by plotting values of R, M, and ϕ versus the dispatch time of the trips in question. Because time-of-day trends were expected to be directional (for example, maximum loads peaking on inbound trips in the morning and outbound trips in the evening), separate plots were prepared for trips in opposite directions on the same route. Because there were large irregular variations between successive trips, moving averages over roughly 1.0 to 1.5 hr (three trips for 30-min headways, five trips for 15-min headways, and so forth) were used to smooth the data and extract the underlying time-dependent trends. Figures 6-8 show examples of such plots in which the solid lines represent the moving averages. As can be seen, the data fall into fairly broad bands about the moving averages. For maximum loads, for example, variations be-

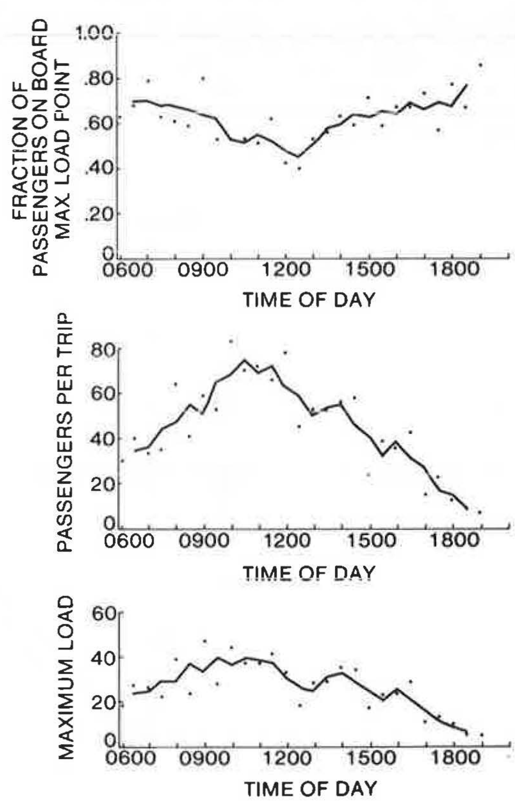

FIGURE 6 Time-of-day trends for SDTC Route 1, inbound, 1981-1982 data; solid lines indicate moving averages.

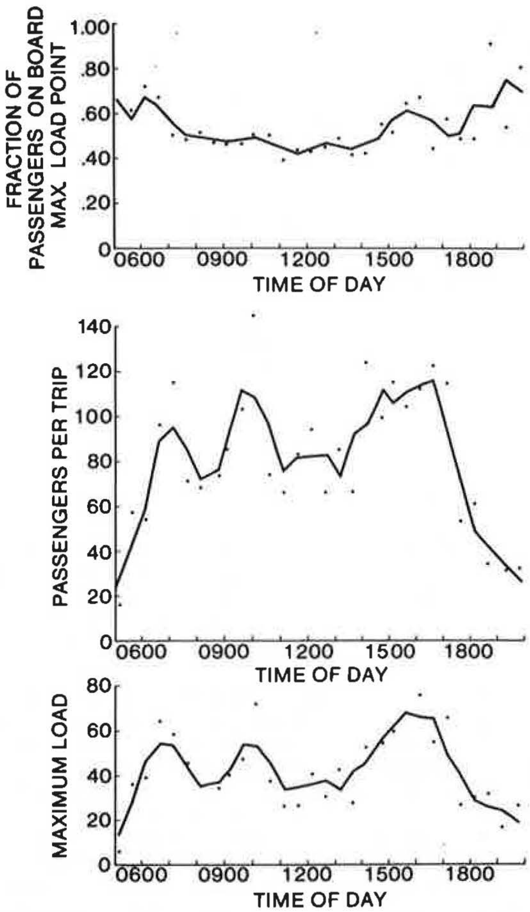

FIGURE 7 Time-of-day trends for SDTC Route 9, northbound, 1981 data; solid lines indicate moving averages.

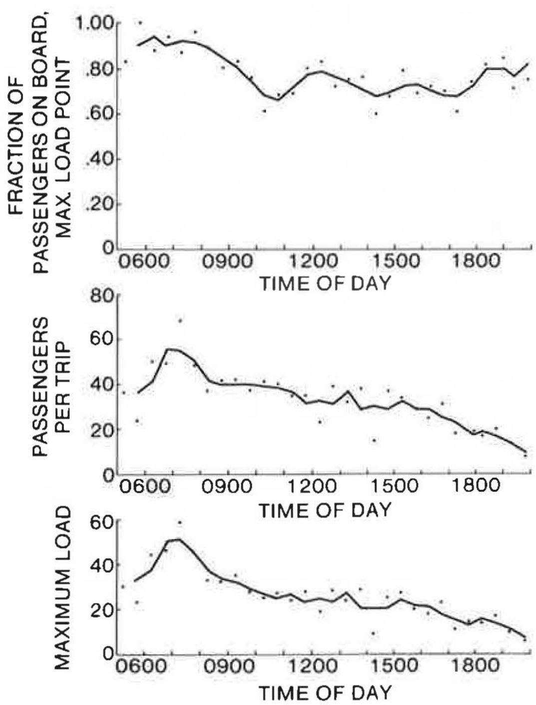

FIGURE 8 Time-of-day trends for SDTC Route 35, inbound, 1982 data; solid lines indicate moving averages.

tween successive trips of 10 to 20 passengers (representing 20 to 40 percent of the seating capacity of a standard bus) are not uncommon.

Table 2 gives a summary of some of the more important features of the time-of-day trends in the San Diego data. The times for the maxima and minima referred to in the table are those of the moving averages, not necessarily the maximum and minimum individual observations. Note that there were fairly large differences between the data sets in the numbers of routes experiencing peak values of R and M during particular time periods. In both cases, however, maximum loads on local routes were more likely to peak in the morning and evening work trip peaks than was ridership. This trend is explained in part by the fact that spatial load peaking is also subject to variations with the time of day, with minimum values of ϕ occurring during the midday period about 75 percent of the time in both data sets. Hence, for routes that have peak values of R during the midday period, there is a tendency for the trips carrying the maximum number of passengers to coincide with those with the least spatial peaking. For express routes, both M and R peak during the morning and evening work trip peaks, and values of ϕ tend to be minimum during the midday period.

TABLE 2 Summary of Time-of-Day Trends for One-Way Trips on San Diego Bus Routes

	Time of Day			
Event	0600-0900	0900-1200	1200-1500	1500-1800
Local routes, 1981-1982				
Maximum R	9	4	24	11
Maximum M	19	5	12	12
Minimum ϕ	7	16	19	6
Local routes, 1982-1984				
Maximum R	14	4	17	13
Maximum M	21	0	10	17
Minimum ϕ	6	18	18	6
Express routes, 1981-1982				
Maximum R	4	0	0	6
Maximum M	6	0	0	4
Minimum ϕ	0	2	8	0
Express routes, 1982-1984				
Maximum R	4	1	0	5
Maximum M	3	1	1	5
Minimum ϕ	1	3	5	1

COMPARISONS OF PEAK LOAD FACTORS

Peak load factors measure the relationship between maximum loads and seating capacity for individual trips. Distributions of peak load factors for individual routes are closely related to distributions of maximum loads but are also affected (sometimes crucially) by bus size. As do the other measures related to maximum loads, peak load factors vary over a considerable range for individual routes, and their distributions for different routes may differ a great deal. Figure 9 shows a comparison of distributions of peak load factors for two routes representing extremes in the San Diego data--one for which peak loads were rarely more than half the capacity of the bus, and another for which there were serious seating capacity problems.

In comparing distributions of peak load factors, it is useful to have a simple measure to summarize them, similar to those used in the preceding section to compare relationships between ridership and maxi-

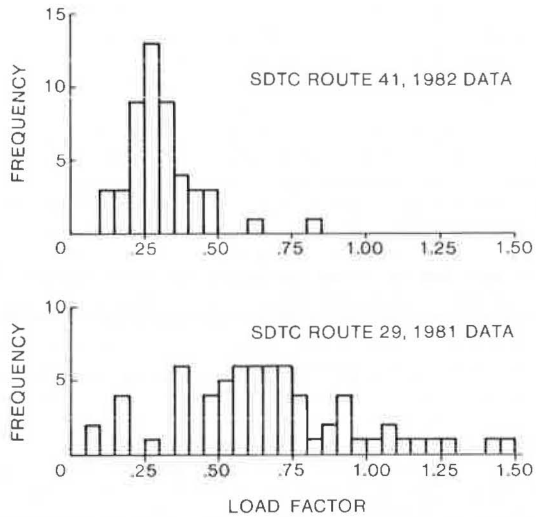

FIGURE 9 Comparison of load factor distributions for two San Diego bus routes.

mum loads. In this case, the ability to summarize the characteristics of the distribution also has practical value in service planning because the resulting measure may be used to set service standards and to identify the most serious seating capacity problems.

The most commonly used measures for summarizing peak load factors are average peak load factors. These are ratios of the sum of maximum loads on a route during some time period to the total number of seats dispatched. Both the time periods used to define average peak load factors and the standards with which they are compared vary among transit operators. In the case of SDTC, the time period is the hour for which the average peak load factor is greatest, whenever this occurs, and the standard is 1.00; a general idea of standards used elsewhere may be gotten from the recommended standards in NCHRP Synthesis of Highway Practice 69 (2).

Comparisons of average peak load factors, as defined by SDTC, with overall peak load factor distributions indicated that average peak load factors were a poor measure of the frequency and severity of standing loads. Specific problems were that they were inconsistent because they involved averaging over different numbers of trips where frequencies of service were different, and that they were dependent on the concentration in time of heavily loaded trips--in particular, they tended to understate the severity of problems where overloading resulted from irregular fluctuations in loads over comparatively long periods of time, such as exist on some San Diego routes where demand peaks during the midday period.

Consequently, an alternative measure of compliance with peak load standards was devised. Let Λ be the peak load standard, defined in terms of the peak load factor for an individual trip, and n be the number of trips surveyed. Then an overload index (ψ) may be defined as

$$\psi \equiv (100/n)\Sigma(\lambda/\Lambda - 1) \qquad \text{for all } \lambda > \Lambda$$

This index is sensitive to both the frequency and the severity of violations of the peak load standard and avoids the problems associated with using average peak load factors. It is not subject to an obvious intuitive interpretation, however, as is the average peak load factor; comparisons of the values of ψ with overall distributions for λ for San Diego routes indicated that values of ψ in excess of 2.00 represented significant violations of the standard, values less than 1.00 indicated only minor violations, and values between 1.00 and 2.00 represented borderline cases. Table 3 gives a summary of the frequency with which the various ψ-scores occurred in the two San Diego data sets.

TABLE 3 Distribution of Values of Overload Index (ψ), 1981-1982 Data Versus 1982-1984 Data

	ψ for Data Set				
	0.00	0.00-1.00	1.00-2.00	2.00-3.00	3.00-4.00
1981-1982	13	9	1	2	2
1982-1984	8	11	6	2	0

COMPARISONS BETWEEN DATA SETS

Two sets of data for each route were compared to assess the stability of the data over time. Specific comparisons involved total ridership, distributions of maximum loads and peak load factors, values of the overload index (ψ), and time-of-day trends for R, M, and Φ.

Contingency tables were used to compare frequency distributions derived from successive data sets. This method is based on the hypothesis that the relative frequencies with which the data fall into given ranges are independent of the data set considered--in effect, that the distribution of the underlying population has not changed over time. If the hypothesis is true, the joint probability that event j is observed in data set i is the product of the marginal probabilities that event j occurs and that the observation belongs to data set i. If x_{ij} represents the number of times event j is observed in data set i, then the expected value of the number of times it is observed is given by

$$E(x_{ij}) = \Sigma_i x_{ij} \Sigma_j x_{ij} / \Sigma_i \Sigma_j x_{ij}$$

These expected frequencies may be compared with the actual frequencies by means of a chi-square test to determine the probability that differences as large as those observed occurred by chance. Table 4 is an example of a contingency table to compare a route's maximum load distributions for two successive data sets.

Use of contingency tables, as opposed to direct comparisons of the distributions by means of chi-square tests, was considered appropriate because neither sample could be said to represent the "true"

TABLE 4 Contingency Table for Comparisons of Maximum Load Distributions for SDTC Route 2, 1982 Versus 1983

	Data Set						
	0-10	11-20	21-30	31-40	41-50	>50	Total
Maximum Load (observed)							
1982	3	19	24	23	11	9	89
1983	15	21	31	14	14	6	101
Total	18	40	55	37	25	15	190
Maximum Load (expected)							
1982	8.43	18.74	25.76	17.33	11.71	7.03	89.00
1983	9.57	21.26	29.24	19.67	13.29	7.97	101.00
Total	18.00	40.00	55.00	37.00	25.00	15.00	190.00

Note: Chi-square = 11.428. Significant difference for $\alpha < .05$.

distribution and because the contingency tables allowed the comparison of samples of different sizes. There was some concern about the statistical validity of the comparisons, however, because the real null hypothesis in the chi-square test is that the two data sets represent randomly drawn samples from the same population. In the case of the San Diego data, it was clear that the trips were not sampled at random with respect to time of day because each scheduled trip was surveyed once. If the probabilities that the data fall into given ranges vary a great deal with time of day, the chi-square test would tend to overstate the probability that two samples were drawn from the same population. This possibility was checked after the fact by comparing the actual chi-square scores with their expected distributions. These proved to be reasonably similar, so it was concluded that contingency tables did provide statistically valid tests for differences in distribution.

In general, the data in the two sets were found to be quite similar. Overall ridership had declined by about 2 percent, which is not significant, being well within the normal variation in daily ridership for the system as a whole. Of the 27 routes surveyed, 10 experienced increases in ridership and 17 experienced decreases. In all but three cases the increase or decrease in ridership for individual routes was less than 20 percent; there were increases of 24 and 34 percent, respectively, on two lightly traveled routes and a decrease of 58 percent on one route (Route 9) where there had been major routing and scheduling changes due to cancellation of a service contract with a suburban jurisdiction.

Contingency table comparisons detected five cases in which distributions of maximum loads were significantly different at the 5 percent level. Of these, three were lightly traveled routes where the changes were of no practical significance, one (Route 2) was the result of increased night service (which resulted in a comparatively large increase in lightly loaded trips), and one (Route 9) was due to a large decrease in ridership, as discussed previously.

Differences in peak load factor distributions that were significant at the 5 percent level were also found in five cases. Of these, two (Routes 2 and 9) were associated with differences in maximum load distributions that were significant at the same level; the others involved cases in which differences in maximum load distributions were significant at the 10 to 25 percent levels. Of these three routes, one (Route 25) was a lightly traveled route that had experienced a comparatively large increase in ridership; a second (Route 32) had experienced a comparatively large decrease in ridership that resulted in downward shifts at the lower ends of the distributions of maximum loads and peak load factors; and the third (Route 34) had experienced a large increase in trips for which maximum loads exceeded seating capacity.

Where routes had peak load factors exceeding 1.00 for a total of 10 or more trips (counting both data sets), contingency tables were also used to compare the frequencies with which this event occurred. In two cases the difference was significant at the 5 percent level: Route 9 had experienced a significant drop in the number of trips for which λ exceeded 1.00 and Route 34 had experienced a significant increase.

Summaries of the distributions of values of the overload index (ψ) for the two data sets were given in Table 2. Despite the overall decrease in ridership, there was a small increase in the number of routes with peak load factors exceeding 1.00; values of the index increased for 13 routes, decreased for 6, and remained the same (zero both times) for 8 routes. For a variety of reasons, however, all but one of the four highest ψ-scores in the 1981-1982 data set had declined, so that, even with the addition of Route 34, only two routes in the 1982-1984 data set had ψ-scores greater than 2.00, compared with four in the 1981-1982 set.

Comparison of plots of time-of-day trends showed that overall peaking patterns tended to remain stable but that there were fairly substantial shifts in the exact times and magnitudes of fluctuations in ridership and maximum loads, even where there were no significant differences in the overall distributions of M, R, and ϕ. Figure 10 shows a comparison of time-of-day trends in maximum loads for a route that appeared to have no significant changes in the overall distribution of M; as can be seen, the magnitude of the fluctuations in the moving averages is similar, but the times of occurrence do not correspond very well, except during the morning peak.

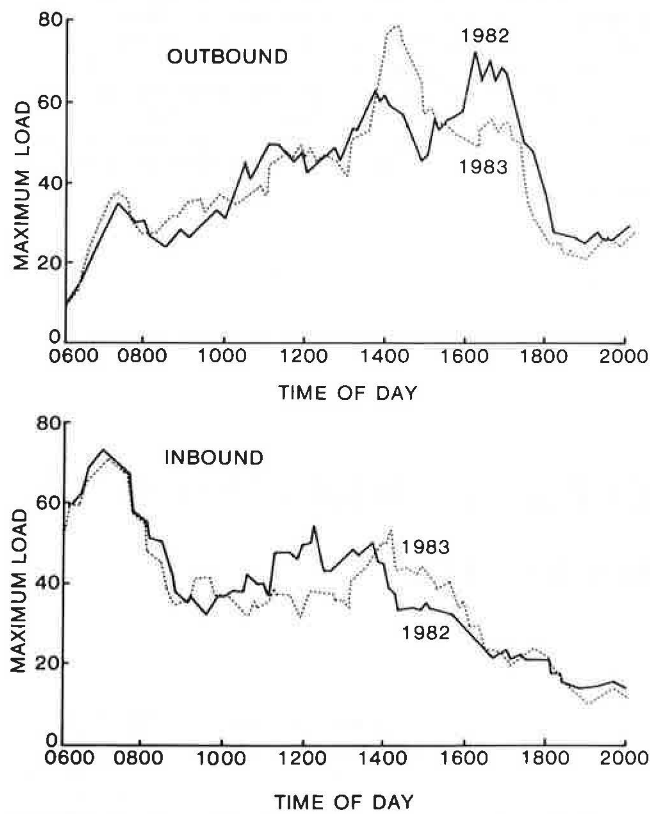

FIGURE 10 Time-of-day trends in maximum loads on SDTC Route 7 for successive data sets; plots represent moving averages over seven trips.

CONCLUSION

The most important characteristics of the San Diego maximum load data appear to be their overall variability and the high degree of randomness they display, the wide variation among routes in relationships between ridership and maximum loads, the relative stability over time of overall distributions of maximum loads and peak load factors, and the apparent instability of the exact times of day at which fluctuations in maximum loads occur.

These characteristics suggest that, for most planning purposes, overall distributions of maximum loads, peak load factors, and the like should be used instead of data for individual trips or data averaged over short time periods. In addition, the high degree of variability and randomness suggests that caution should be exercised in interpreting maximum load data; statistical analyses of such data are unlikely to alert planners to problems and changed conditions they would otherwise miss, but they are likely to cast doubt on the reality of apparent problems and changes. The variability of the data also implies that it will always be impractical to achieve close matches between seating capacity and demand, because considerable overcapacity must be provided to prevent serious overcrowding. For instance, if all scheduled one-way trips are considered, no route in either San Diego data set had more than 74 percent of its seats occupied at its maximum load point, despite several cases of fairly serious overloading.

When viewed from the standpoint of the system as a whole, the causes of variations in maximum loads appear to be quite complex. Variations in ridership are obviously the most important influence, but there are also wide variations, both for individual routes and between routes, in spatial peaking patterns and time-of-day trends in total ridership and the fraction of passengers on board at the maximum load point. Although some of the reasons for these variations are fairly obvious (for instance, the marked differences between express routes and most local routes), much of this variation remains unexplained.

ACKNOWLEDGMENT

The data used in this study were furnished by the staff of the San Diego Transit Corporation. The author would particularly like to thank Richard Murphy and Janet Braaten of the SDTC for their assistance in providing access to the data and in discussing some of the results.

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Publication of this paper sponsored by Committee on Bus Transit Systems.

O-Bahn: Description and Evaluation of a New Concept

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ABSTRACT

The O-Bahn system, developed in the Federal Republic of Germany in recent years, consists of conventional diesel buses equipped with a special guidance mechanism that can be extended or retracted. The vehicles thus can run on regular streets or on special guideways that have two simple vertical guidance surfaces. The O-Bahn concept is intended to combine the advantages of low-investment bus operation on streets in low-density areas with the advantages of narrower right-of-way and greater highway safety of guided-mode operation on higher density route sections. However, because the basic vehicle is the standard (or articulated) diesel bus, the most important advantages of guided modes--high-capacity vehicles, ability to form trains, electric traction with a number of superior aspects, and fail-safe running--are not captured. A systematic analysis of all characteristics shows that the O-Bahn is much more similar to semirapid bus (bus lines that use busways and other separated ways on individual sections) than to light rail transit (LRT). In comparison with semirapid bus, the O-Bahn offers the advantages of narrower right-of-way, somewhat greater comfort and safety, guaranteed permanent retention of the exclusive right-of-way for buses only, and greater suitability (O-Bahn with dual-traction vehicles) for operation in tunnels. These advantages must be weighed against the higher investment cost and lower capacity and operating flexibility of the O-Bahn, which is due to the inability of O-Bahn vehicles to overtake or bypass each other on the guideway. O-Bahn represents a higher cost, higher quality system than semirapid bus, which may be advantageous for use in such special cases as areas with narrow rights-of-way. It is not suited for lines that require high-capacity, low-cost transit systems, which are typical of cities in developing countries.