Headway Deviation Effects on Bus Passenger Loads:
Analysis of Tri-Met's Archived AVL-APC Data

James G. Strathman
Thomas J. Kimpel

Center for Urban Studies
College of Urban and Public Affairs
Portland State University
P.O. Box 751
Portland, OR 97207
(503) 725-4020
strathmanj@pdx.edu
kimpelt@pdx.edu

Steve Callas

Tri-Met
4012 S.E. 17th Ave.
Portland, OR 97202
(503) 962-7502
callasc@trimet.org

January, 2003

The authors gratefully acknowledge the support provided by Tri-Met and the USDOT University Transportation Centers Program, Region X (TransNow). Helpful comments were provided by Rick Gerhart and Ken Turner. The contents of this paper reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the views or policies of Tri-Met or the U.S. Department of Transportation.

Abstract

In this paper we empirically analyze the relationship between transit service headway deviations and passenger loads, using archived data from Tri-Met's automatic vehicle location and automatic passenger counter systems. The analysis employs two-stage least squares estimation to account for the simultaneous relationship between headway deviations and loads. Controlling for the effects of passenger activity on delay, the results indicate that the observed incidence of excess passenger loads is systematically attributable to deviations from scheduled headways. In turn, analysis of the causes of headway deviations served to identify possible operations control actions that would improve service regularity and, consequently, reduce incidences of overloading and forestall the need for additional service.

Introduction

Maintaining reliable service is important for both transit passengers and transit providers. Surveys have shown that reliability is strongly related to passenger satisfaction and perceptions of service quality (TCRP, 1999), while stated preference experiments have found that passengers implicitly value reliability (Bates et al., 2001) and consider it in their mode choice decisions (Prioni and Hensher, 2000). Unreliable service results in additional waiting time for passengers (Welding, 1957; Turnquist, 1978; Bowman and Turnquist, 1981; Wilson et al., 1992a), the unit cost of which has been estimated to exceed the cost of in-vehicle travel time by a factor of three (Mohring et al., 1987).

Unreliable service also has negative economic consequences for transit providers. Effective service capacity is diminished when vehicles become unevenly spaced and platooning, or "bus bunching," occurs. Bus bunching results in more frequent passenger overloads, which necessitates provision of additional service. Such service expansions would not be required if vehicles were more regularly spaced and passenger loads were more evenly distributed. Capital investments in the vehicle fleet are affected because reliability problems are most acute during peak service periods (Strathman et. al., 2000).

There has been considerable research on the underlying causes of unreliable service (Sterman and Schofer, 1976; Abkowitz, 1978; Turnquist and Bowman, 1980; Strathman and Hopper, 1993; Strathman et al., 2002). Primary causes of unreliability have been attributed to route characteristics (e.g., length, the number of signalized intersections, the extent of on-street parking, stop spacing), operating conditions (e.g., traffic volume, service frequency, passenger activity), and vehicle operators (e.g., departure delays, operator-specific behavior differences). Considerable attention has also been devoted to identifying operations control actions to improve reliability (Turnquist and Blume, 1980; Turnquist, 1982; Abkowitz and Engelstein, 1984; Abkowitz and Tozzi, 1987; Levinson, 1991; Wilson et al., 1992b; Strathman et al., 2001). Examples of control actions include vehicle holding, stop-skipping, leap-frogging and short-turning.

While much has been learned about the causes of unreliable service and the corrective actions that can be taken, research on this subject has been hampered by the costs of manual data collection. However, recent deployment of Advanced Public Transit System (APTS) technologies, particularly automatic vehicle location (AVL) and automatic passenger counter (APC) systems, has transformed the data environment for transit providers. Comprehensive data on vehicle operations and passenger activity are now being recovered and archived at very low cost. The new data environment is facilitating more extensive and detailed analysis of transit operations, the benefits of which are reflected in service planning, scheduling, dispatching and operations control improvements (Casey, 2000; Strathman et al., 2002).

This paper explores an application of archived AVL-APC data to analysis of bus bunching and its effects on passenger loads. Tri-Met, the transit provider for the Portland, Oregon, metropolitan region, is the focus of the study. The analysis is complicated by the bi-directional relationship between vehicle spacing and passenger activity during peak service periods. Under conditions of frequent service and constant demand, passenger loads can be expected to vary directly with deviations from scheduled headways. Positive headway deviations produce larger-than-scheduled headways, resulting in larger passenger loads, while negative deviations result in smaller loads. Conversely, passenger activity can also contribute to headway delays. Thus the simultaneity between headways and passenger loads must be reconciled to assess the true consequences of reliability improvements.

The remainder of this paper is organized as follows. In the next section, Tri-Met's automated bus dispatch system (BDS) technology and data recovery environment are described. This is followed by a description of the process used to select routes for analysis. A model relating peak passenger loads to headway deviations is then specified and estimated. Model results are presented along with an evaluation of the effects of progressive reductions in headway deviations. The paper concludes with a discussion of the implications of the findings.

Tri-Met's BDS

Tri-Met's BDS became fully operational in 1998. Its main APTS components include the following:

- Automatic Vehicle Location (AVL) using a satellite-based global positioning system (GPS);
- Voice and data communication between operators and dispatchers within a pre-existing mobile radio system;
- On-board computer for temporary data storage, a vehicle control head displaying schedule adherence information to operators, detection and reporting of schedule and route deviations to dispatchers, and two-way, pre-programmed digital messaging between operators and dispatchers;
- Infrared beam-type Automatic Passenger Counters (APCs) installed on approximately 70% of the existing bus fleet and all new bus acquisitions;
- Modern dispatching center containing six CAD/AVL consoles.

With AVL, a vehicle's current status is related to its scheduled status to determine schedule deviation in real time, which is displayed on the vehicle's control head. When schedule deviations exceed pre-determined thresholds, an exception report is automatically transmitted to the dispatch center. Exception reports are also transmitted when vehicles deviate from their routes. Schedule and location exception reports are listed on the dispatcher's CAD screen along with other attention requests (e.g., mechanical problems, traffic and on-board incidents, delays, etc.) that are transmitted by vehicle operators from the control head keypad. In addition to schedule status, the control head screen displays freeform text messages sent by dispatchers to operators. The on-board system also contains a covert microphone and silent alarm key, providing enhanced security.

Operating and passenger data are automatically recorded to a memory card located in the vehicle control head. A data record is written at each bus stop, producing approximately 500,000 stop records per day. In addition, a data record is written at each location where an operator-initiated text message is generated or a schedule exception occurs, producing about 25,000 event records per day. Stop records contain the following information: route number, direction, trip number, date, vehicle number, operator ID, bus stop ID, stop arrival time, stop departure time, boardings, alightings and passenger load (on APC-equipped vehicles), door opening, lift usage, dwell time, maximum speed since the prior stop, longitude, and latitude.

When vehicles return to garages at the end of each day the data are transferred from the memory card to a personal computer and then uploaded to a server on Tri-Met's local area network. A post processing operation then matches the stop records to the schedule database. About 97 percent of the stop records are successfully matched with the schedule database. Tri-Met's data warehouse provides on-line access to data recovered over the prior 6-9 month period (approximately 120 million stop and event records, along with the related schedules). "Older" stop, event and schedule data, extending back to 1998, is archived off-line.

About 30 mid to large-size transit properties have deployed AVL-APC systems (Casey, 1999). However, there are several features that distinguish Tri-Met's system from others. First, its near fleet-wide deployment of APCs contrasts with very limited deployment elsewhere, which facilitates detailed analysis of passenger activity in relation to schedule and headway adherence.

Second, Tri-Met's system utilizes on-board computers for data storage. Other systems typically lack on-board computers, and therefore archive data that is radio-transmitted on a periodic polling cycle (usually 60-90 seconds). Archived polled data have several shortcomings: 1) radio bandwidth limitations constrain both the polling frequency and the amount of data that can be transmitted, and 2) since polled data are temporally rather than spatially-referenced, operational status at specific locations (i.e., bus stops, time points, and route origins and destinations) must be interpolated, which introduces measurement error.

Selection of Study Routes

The study period extended from December 2001 through May 2002, and the focus was limited to weekday bus service. The selection of routes for analysis was based on several factors. Data were obtained for mean passenger loads at the peak load point, the coefficient of variation (CV) of passenger loads, and the number of observations (trips) with valid APC data[1] for all radial and cross-town routes in the Tri-Met system for the peak hour of in-bound service during the mornings and out-bound service during the afternoons. Routes with a high mean and coefficient of variation of passenger loads were identified, under the assumption that these routes would tend to experience the most severe instances of bus bunching and overloading. An effort was also made to identify routes that were generally representative of Tri-Met's service typology, which includes radial routes serving downtown Portland and cross-town routes serving peripheral locations.

Ten of Tri-Met's 99 bus routes were identified for analysis. Table 1 presents relevant passenger statistics for the selected routes. Two of the selected routes (72-Killingsworth/82nd and 75-39th/Lombard) provide cross-town service and the others provide radial service. Samenumbered routes (e.g., 4-Division and 4-Fessenden) represent through-routed service with a changeover point in downtown Portland. Mean peak passenger loads are generally less than bus seat capacity.[2] Coefficient of variation values generally range from .30 to.40, which is fairly substantial for peak hour service. As one would expect, routes with combined high mean loads and CVs tend to experience a higher incidence of passenger overloads (e.g., 4-Division, 14-Hawthorne and 15-Belmont).

(Table 1 about here)

Analysis of Passenger Loads and Headways

Direct examination of route level peak passenger loads in relation to headway delay revealed an expected pattern: vehicles whose actual headways are greater than scheduled headways tend to have larger loads, and vehicles whose actual headways are smaller than scheduled tend to have smaller loads. This pattern is illustrated in Figure 1 for morning peak hour in-bound trips on the 14-Hawthorne.[3] In this case the mean passenger load for trips with positive headway delay is 43.1 persons, while the mean load for trips with negative headway delay is 37.7. This difference in mean loads is significant at the .001 level. It is also apparent in the figure that the relationship between passenger loads and headway delay is approximately linear.

(Figure 1 about here)

Regression analysis was employed to estimate the effect of headway delay on peak passenger loads for each of the selected routes and time periods. The general form of the specification was as follows:

Load = f(H. Delay, Sch. Hwy, L.F. Bus), where (1)

Load = the passenger load at the peak load point;

H. Delay = headway delay at the peak load point, in minutes;

Sch. Hwy = scheduled headway, in minutes;

L.F. Bus = a dummy variable equaling one for trips served by low-floor buses.[2]

In addition to headway delay effects, passenger loads on a given route in peak hours should be influenced by variations in scheduled headways. In principle, one would expect peak hour scheduled headways to be relatively constant. In practice, however, scheduled headways can vary as a result of selectively adding trips to accommodate peak demand. When these selective adjustments occur, schedulers are reluctant to rewrite time tables for all peak trips, and scheduled headway differences thus emerge. The dummy variable for low-floor buses is included to account for the potentially limiting effect of their smaller capacities compared to Tri-Met's standard 40-foot coaches.

As noted earlier, the passenger load equation is subject to simultaneous equations bias, given the recognition that passenger activity can also be expected to contribute to headway delay.[4] To remedy this problem, the load equation was estimated using two-stage least squares (2SLS). In this approach, an equation relating headway delay to scheduled headways, the low-floor bus dummy, and several exogenous variables is first estimated. A desirable property of the exogenous variables is that they influence headway delay but are unrelated to passenger loads. Estimates of headway delay are then substituted for the observed headway delay values in a second stage estimation of the passenger load equation.

The general form of the first stage headway delay equation is as follows:

$$\text{H. Delay} = f(\text{Sch. Hwy, L.F. Bus, Opr. Exp., Dist. to P.L.P, H. Delay}_o), \qquad (2)$$

where the exogenous variables are defined as

Opr. Exp. = vehicle operator experience, in years;

Dist to P.L.P. = distance from the route origin to the peak load point, in miles;

H. Delay_0 = headway delay at the route origin, in minutes.

It is expected that buses with more experienced operators will tend to be less subject to headway delays, given findings that they require less running time to complete their trips relative to less experienced operators (Strathman et al., 2002). The location of the peak load point tends to vary at the trip level. For morning peak hour in-bound radial trips, the maximum load point is generally centered at a location just beyond the downtown area, while for evening peak hour out-bound trips the maximum load point is generally centered somewhat closer to the edge of the downtown area. For a given trip, we would expect headway delays to be greater when the maximum load point is more distant from the origin, given relatively greater exposure to potential delay-causing factors (Abkowitz and Tozzi, 1987). Finally, it is expected that headway delays that occur at the trip origin will tend to persist through the peak load point.

Estimation Results

The passenger load equation was estimated by 2SLS for each of the 10 routes and for both the morning and evening peak hour periods.[5] The overall sample consisted of 6,393 morning and 6,200 evening peak hour trips. Route and time period-specific parameter estimates are reported in Table 2.

(Table 2 about here)

The parameter estimates for headway delay are significant for eight of the ten routes in the morning peak hour, and for all routes in the evening peak hour. Generally, an increase in headway delay of one minute is estimated to result in an approximate 2.6 person load increase in the morning peak, and a 2.0 person load increase in the evening peak. Alternatively, with respect to the observed variations in headway delay during the morning and evening peaks, an increase of one standard deviation in headway delay (2.7 and 4.0 minutes, respectively) would result in load increases of 7.0 and 8.0 passengers, respectively, or approximately 13 and 15% of the standing capacity of Tri-Met's standard buses.

Compared to headway delay, the estimated effects of scheduled headway variations are not as consistently significant: only two of the morning peak routes and five of the evening peak routes have significant parameter estimates. As one would expect, when significant, the estimated load effect of a one-minute increase in scheduled headway is similar to the effect of an equivalent change in headway delay, given that both of these variables define the spacing between vehicles.

Despite differences in vehicle capacities, only one of the twenty coefficients for the low-floor bus dummy variable is significant with the expected sign. Controlling for the estimated load effects associated with headway delays and scheduled headway variation, this result indicates that there is sufficient vehicle capacity to serve passenger demand, or that instances of overloading (as reported in Table 1) are a consequence of uneven bus spacing rather than an inadequate level of service. This interpretation is illustrated more clearly in Table 3, which shows the estimated effects of progressive reductions in headway delays on the incidence of overloading.[6] Nominally, 10.4 percent of morning peak hour trips and 12.0 percent of evening peak hour trips experienced overloads. Reducing headway delay by 25 percent is estimated to yield an 89.4 percent reduction (to 1.1 percent) in morning peak hour overloads, and a 75.8 percent reduction (to 2.9 percent) in overloads during the evening peak hour. Only the 4-Division in the evening peak hour experiences any appreciable overloading beyond a 25 percent headway delay reduction.

(Table 3 about here)

In order to implement operations control actions to reduce headway delay, it is necessary to identify the root causes of the problem. In this respect, it is worthwhile to examine the first-stage regression results for the headway delay equation. Although the primary reason for estimating this equation was to address simultaneity bias in the passenger load model, the results also shed light on the causes of headway delay. To illustrate, Table 4 presents the results of the first-stage route-level headway delay regressions for evening peak hour trips.

(Table 4 about here)

It is apparent that a primary determinant of headway delay at the peak load point is the headway delay status at the beginning of the trip. Generally, a one-minute headway delay at the route origin is estimated to result in an approximate delay at the peak load point of 45 seconds. The distance from the route origin to the peak load point is also a generally significant determinant of headway delay, with each mile increment contributing to additional delay of more than one-half minute. Given that passenger load profiles vary from trip to trip, it is hard to consider how operations control actions could address this phenomenon.

Headway delay is estimated to be significantly related to operator experience for four of the ten routes. With the exception of a cross-town route, more experienced operators achieve shorter delays. It is worth recognizing that in peak periods, operators with substantial experience are often interspersed with operators with the least experience when regular service is augmented by peak service trips (i.e., "trippers"). Thus, experience-related differences in operator performance on a given route tend to be greatest during the very times when other operational disruptions also tend to be most prevalent.[7] The service regularity consequences of operator experience mixing are not accounted for in the runcutting and sign-up processes, which link operators to trip blocks. For routes with high demand and frequent service, it may be worthwhile to constrain assignments to achieve greater homogeneity among operators with respect to experience. More generally, experience-related differences among operators point to a hidden cost of relying on part-time operators to service peak demand.[8]

Finally, headway delay is estimated to be inversely related to scheduled headways for half of the routes in Table 4. There is no obvious rationale for interpreting this finding. If headways are set to match service capacity with demand, then passenger activity per vehicle (a potential cause of delay) should be invariant with respect to the size of the headway. However, we did observe that the coefficient of variation of peak loads was smaller for trips with larger scheduled headways, suggesting that the estimated greater delay for trips with shorter headways could be the result of greater passenger activity variance.

Regarding operations control, the results of the headway delay regressions indicate that field supervisors should concentrate their efforts to maintain regularity at the route origins. The effects of reducing headway delay at the origin should carry through to the peak load point. The control actions required to address headway delay at the origin would depend on differences in service design. Through-routed service, for example, does not include scheduled layovers at the downtown changeover point. Reducing departure delays for evening out-bound trips on these routes would require active headway management at the changeover location to improve service regularity. Strategies such as Turnquist's (1982) "prefol" would likely be the most effective in reducing headway delay. In this strategy, lead buses would be held to equalize headways among the sequence of affected trips. For trips with scheduled layovers, headway delays at the route origin can be traced to two basic causes: 1) the carry-over of a delay from a previous trip; and 2) a late departure following an excessive layover. When delay from a previous trip exceeds the scheduled layover, headway control will be necessary to improve regularity. The existence of a systematic pattern of delay due to insufficient layover suggests a schedule that contains inadequate running or recovery time. When delay is smaller than the scheduled layover, field supervisors can restore regularity by limiting layover time. Such action would be subject to working condition provisions in the agency's agreement with the operators.[9]

With the implementation of AVL technology, patterns of headway delay and excessive layover can be readily documented from archived operations data. Operations managers should be provided with regular reports on headway delay patterns as part of an overall performance monitoring program focused on service quality improvement.

Conclusions

This paper has examined variations in bus passenger loads in relation to deviations from scheduled headways. Transit analysts have generally recognized that the relationship is subject to simultaneity, with passenger loads positively affected by delay and delay positively affected by passenger activity. Using a two-stage least squares approach, we controlled for the latter effect in order to estimate the effects of headway delay on peak passenger loads. The substantial data requirements for estimating the relationship between passenger loads and headway delay were met as a result of Tri-Met's deployment of AVL and APC technology, and the comprehensive archiving of data recovered by these systems.

Estimation results indicate that headway delays are a primary cause of passenger overloads, and that a modest reduction in headway delay would lead to a substantial reduction in overloads. Further analysis revealed that headway delay at the peak load point was strongly related to headway delay status at the route origin, thus pin-pointing where field supervisors should be targeting operations control efforts. A pattern of origin headway delay on a route may indicate a schedule problem rather than a need for operations control.

The implementation of APTS technologies has provided the transit industry with an improved means of monitoring and analyzing operations activity. In the area of operations control, well-established practices focusing on maintaining service regularity can potentially become much more effective, given access to AVL and APC information. The benefits from service regularity improvements will be shared between transit passengers (through reduced waiting time and uncertainty) and transit providers (through lower operating and capital costs).

Archived operations data are an essential ingredient in the design and monitoring dimensions of effective operations control programs. The information from archived data can help in identifying operations problems and deciding on appropriate control actions. More generally, the data can also support decision-making on resource allocation between the supply and management of transit service. In this respect, managers need to determine what constitutes an "optimal" level of operations management activity, recognizing that dedicating resources to operations control comes at the expense of reductions elsewhere (primarily in the number of scheduled trips). Analytically, it can be demonstrated that optimality is achieved when the marginal cost of operations management is just equal to the marginal benefit to passengers from improved regularity plus the marginal avoided cost of unnecessary additional service. In the pre-APTS era, operations managers faced considerable uncertainty in weighing such trade-offs. Presently, however, there is a growing wealth of information at their disposal to facilitate these decisions. As a result, the gap between the analytical and the applied decision-making contexts has shrunk dramatically with the emergence of comprehensive operations data produced by new technology.

Footnotes

1. Although 70% of the bus fleet is APC-equipped, the assignment of buses to routes results in some routes having near-complete APC coverage and others having more limited coverage. Also, equipment malfunctions and post-processing checks result in the loss of 30-40% the APC trip level records. For example, total daily passenger boardings and alightings per vehicle are compared and if the difference exceeds 10% of total boardings, all of the day's APC trip records are screened out.
2. Two vehicle types are assigned in varying mixes to the study routes. One type is a standard 40 foot bus with a 43-person seat capacity, and the other type is a 40 foot low-floor bus with a 39-person seat capacity.
3. Similar patterns were observed for the other nine routes during the morning and evening peak hour periods.
4. If estimation involved pooling of data across routes, or over time for a given route, it could also be argued that scheduled headways are subject to simultaneous equations bias. For example, service planners take passenger loads into account in determining service frequency. In the present study, our intent is to estimate route-specific passenger load equations for a single service period, and under these conditions we would not expect simultaneity to be a problem for the scheduled headway variable.
5. Initial analysis employing the Hausman test (Pindyck and Rubinfeld, 1981) confirmed the systematic presence of simultaneous equations bias involving passenger loads and headway delay, thus justifying the choice of 2SLS estimation.

6. These estimates are based on passenger load predictions using the associated headway delay, scheduled headway, and low-floor bus parameter estimates applied to the observed values of the variables, and progressively reducing the observed values of headway delay.

7. It is generally believed that the "experience effect" related to shorter delays for more senior operators is attributable to their abilities to process passengers more quickly and to better recognize where and how to recover time in their runs. However, it is also possible that differences in work assignments between junior and senior operators are being confounded with experience. For example, a part-time operator with a tripper assignment may be less concerned about delay if they are returning to the garage after the trip and are compensated ("time-slipped") for any additional time needed to complete their assignment. Moreover, dispatchers and field supervisors are less concerned about delays by trippers because they know there are no subsequent trips that will be affected.

8. In larger transit agencies, additional service during peak periods is often assigned to part-time operators. Because part-time operators are compensated less, this practice reduces operating costs. However, operating cost savings are undermined if part-time operators experience higher accident rates or greater absenteeism and attrition. Lower operating costs are also undermined if greater headway delays by part-time operators lead to additional waiting time for passengers. It has been noted that runcutting software is very sensitive to small wage differences across types of operators (Charles Rivers Associates, 2001). When various offsetting costs are taken

into account, runcuts that minimize operating costs by designing peak service to rely more heavily on part-time operators may not minimize total agency costs and the time-related costs to transit passengers.

9. The agreement between Tri-Met and the operators union requires schedules to contain five minutes of layover time for each hour of running time, but also states that a layover cannot be guaranteed for each trip.

References

Abkowitz, M. 1978. Transit Service Reliability. Cambridge, MA: USDOT Transportation Systems Center and Multisystems, Inc. (NTIS No. UMTA/MA-06-0049-78-1).

Abkowitz, M. and I. Engelstein. 1984. Methods for maintaining transit service regularity. Transportation Research Record 961, 1-8.

Abkowitz, M. and J. Tozzi. 1987. Research contributions to managing transit service reliability. Journal of Advanced Transportation, 21, 47-65.

Bates, J., J. Polak, P. Jones and A. Cook. 2001. The valuation of reliability for personal travel. Transportation Research, Part E, 37, 191-229.

Bowman, L. and M. Turnquist. 1981. Service frequency, schedule reliability and passenger wait times at transit stops. Transportation Research, Part A, 15, 465-471.

Casey, R. 1999. Advanced Public Transportation Systems Deployment in the United States. Report No. DOT-VNTSC-FTA-99-1. Volpe National Transportation Systems Center, Cambridge MA.

Casey, R. 2000. What have we learned about Advanced Public Transportation Systems? In What Have We Learned About Intelligent Transportation Systems? Volpe Transportation Systems Center, Federal Highway Administration, US Department of Transportation, Chapter 5.

Charles Rivers Associates. 2001. Part-Time Operators: The Trends and Impacts. TCRP Report 68. Washington, DC: Transportation Research Board, National Research Council.

Levinson, H. 1991. Supervision strategies for improved reliability of bus routes. NCTRP Synthesis of Transit Practice 15. Washington, DC: Transportation Research Board, National Research Council.

Mohring, H., J. Schroeter and P. Wiboonchutikula. 1987. The values of waiting time, travel time, and a seat on the bus. Rand Journal of Economics, 18 (1), 40-56.

Pindyck, R. and D. Rubinfeld. 1981. Econometric Models and Economic Forecasts. New York: McGraw-Hill Book Co.

Prioni, P. and D. Hensher. 2000. Measuring service quality in scheduled bus services. Journal of Public Transportation, 3, 51-74.

Sterman, B. and J. Schofer. 1976. Factors affecting reliability of urban bus services. Transportation Engineering Journal, 102, 147-159.

Strathman, J. and J. Hopper. 1993. Empirical analysis of bus transit on-time performance. Transportation Research, Part A, 27, 93-100.

Strathman, J., K. Dueker, T. Kimpel, R. Gerhart, K. Turner, P. Taylor, S. Callas and D. Griffin. 2000. Service reliability impacts of computer-aided dispatching and automatic vehicle location technology: a Tri-Met case study. Transportation Quarterly , 54, 85-102.

Strathman, J., K. Dueker, T. Kimpel, R. Gerhart, K. Turner, P. Taylor, S. Callas and D. Griffin. 2001. Bus transit operations control: review and an experiment involving Tri-Met's automated Bus Dispatching system. Journal of Public Transportation, 4, 1-26.

Strathman, J., T. Kimpel, K. Dueker, R. Gerhart and S. Callas. 2002. Evaluation of transit operations: data applications of Tri-Met's automated bus dispatching system. Transportation, 29, 321-345.

Transit Cooperative Research Program (TCRP). 1999. A Handbook for Measuring Customer Satisfaction and Service Quality. TCRP Report 47. Washington, DC: Transportation Research Board, National Research Council.

Turnquist, M. 1978. A model for investigating the effects of service frequency and reliability on bus passenger waiting times. Transportation Research Record, 663, 70-73.

Turnquist, M. and S. Blume, S. 1980. Evaluating potential effectiveness of headway control strategies for transit systems. Transportation Research Record 746, 25-29.

Turnquist, M. and L. Bowman. 1980. The effects of network structure on reliability of transit service. Transportation Research, Part B, 14, 79-86.

Turnquist, M. 1982. Strategies for Improving Bus Transit Service Reliability. Evanston, IL: Northwestern University. (NTIS Report No. DOT/RSPA/DPB-50-81-27). USDOT, Research and Special Programs Administration.

Welding, P. 1957. The instability of close interval service. Operational Research Quarterly, 8, 133-148.

Wilson, N., D. Nelson, A. Palmere, T. Grayson and C. Cederquist. 1992a. Service quality monitoring for high frequency transit lines. Paper presented at the 71st Annual Meeting of the Transportation Research Board, Washington, DC.

Wilson, N., R. Macchi, R. Fellows and A. Deckoff. 1992b. Improving service on the MBTA Green Line through better operations control. Transportation Research Record 1361, 10-15.

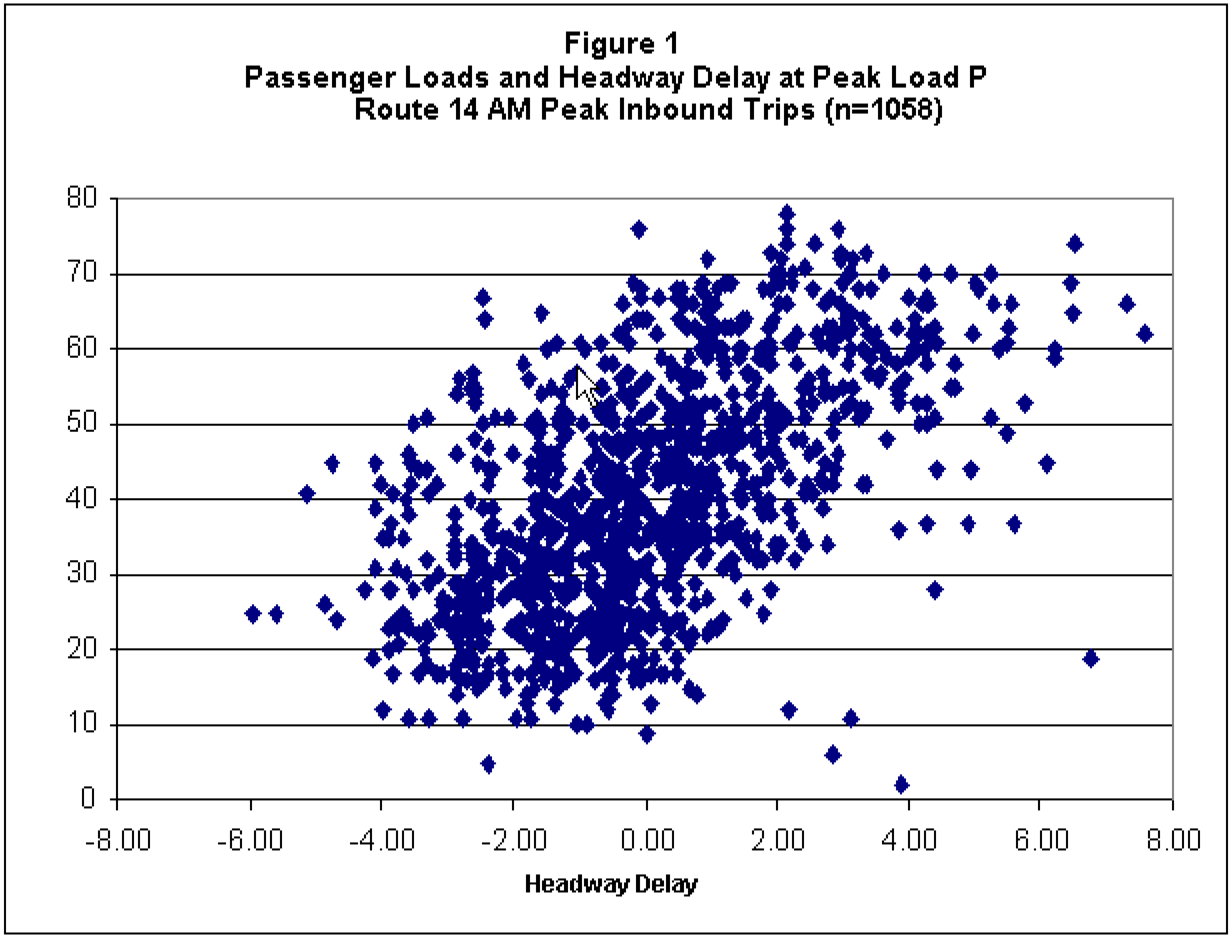
Figure 1
Passenger Loads and Headway Delay at Peak Load P
Route 14 AM Peak Inbound Trips (n=1058)
80
70
60
50
40
30
20
10
0
-8.00
-6.00
-4.00
-2.00
0.00
2.00
4.00
6.00
8.00
Headway Delay

Table 1. Passenger Activity on Study Routes

	Mean Peak Passenger Load		Load Coefficient of Variation		Trips Exceeding MLF (%)*	
Route	AM In-bound	PM Out-bound	AM In-bound	PM Out-bound	AM In-bound	PM Out-bound
4-Division	38.7	44.9	.32	.27	14.8	34.1
4-Fessenden	32.5	34.7	.35	.37	6.6	10.2
9-Powell	35.2	32.7	.30	.32	2.7	1.1
9-Broadway	36.0	37.9	.35	.32	8.4	7.1
14-Hawthorne	41.0	42.3	.39	.33	19.2	19.3
15-Belmont	40.1	36.2	.37	.37	22.8	13.5
12-Sandy Blvd.	39.4	40.3	.29	.27	9.6	17.5
19-Glisan	40.4	38.3	.30	.33	5.9	8.7
72-Killingsworth/82nd	33.1	38.2	.42	.31	12.2	15.4
75-39th/Lombard	27.9	27.4	.42	.35	1.8	0.6

* MLF is Tri-Met's maximum load factor, or 130% of bus seat capacity.

Table 2. Peak Load-Headway Model: 2SLS Parameter Estimates

	AM Peak Hour In-Bound Service					
Route	Constant	H. Delay	Sch. Hwy	L.F. Bus	R^2	n
4-Division	31.53	2.31	.30	4.51	.21	364
	(5.00)	(3.67)	(1.24)	(.76)		
4-Fessenden	32.06	3.19	-.13	1.76	.31	739
	(15.01)	(4.13)	(-1.78)	(.85)		
9-Powell	34.38	2.86	.12	-.43	.28	624
	(25.83)	(9.80)	(.90)	(-.27)		
9-Broadway	37.54	2.89	-.07	-3.19	.37	370
	(21.15)	(6.47)	(-.63)	(-2.02)		
14-Hawthorne	21.46	3.21	4.34	-3.71	.40	1058
	(12.04)	(4.01)	(10.86)	(-1.62)		
15-Belmont/NW23rd	36.28	3.03	.09	1.50	.37	517
	(14.01)	(1.22)	(.35)	(.56)		
12-Sandy Blvd	35.50	2.36	-.03	2.49	.18	282
	(15.30)	(4.76)	(-.28)	(1.28)		
19-Glisan	38.86	-.78	-.39	-2.77	.11	579
	(10.05)	(1.39)	(-4.79)	(-.75)		
72-Killingsworth/82nd	34.42	2.69	-.59	3.18	.01	941
	(5.45)	(7.75)	(-1.76)	(.55)		
75-39th/Lombard	1.29	1.34	1.88	2.15	.28	919
	(.29)	(9.04)	(8.45)	(.61)		

Table 2. Peak Load-Headway Model: 2SLS Parameter Estimates, Continued

	PM Peak Hour Out-Bound Service					
Route	Constant	H. Delay	Sch. Hwy	L.F. Bus	R^2	n
4-Division	87.78	1.03	-3.77	2.27	.25	370
	(8.56)	(9.07)	(-5.18)	(.38)		
4-Fessenden	21.70	2.11	1.92	-.01	.14	695
	(5.17)	(10.34)	(10.35)	(-.00)		
9-Powell	25.02	1.71	.83	-1.76	.29	459
	(18.55)	(12.66)	(6.56)	(-1.19)		
9-Broadway	15.09	1.61	2.45	.58	.21	567
	(6.37)	(10.79)	(9.60)	(.42)		
14-Hawthorne	26.85	3.56	2.79	2.32	.28	814
	(9.69)	(6.17)	(5.18)	(.98)		
15-Belmont/23rd	36.93	3.18	-.58	2.60	.23	768
	(14.87)	(16.80)	(-1.43)	(2.00)		
12-Sandy Blvd	41.72	1.15	-.03	-1.62	.15	303
	(8.32)	(5.78)	(-.05)	(-.97)		
19-Glisan	20.02	1.81	1.27	3.71	.10	346
	(2.46)	(7.23)	(1.80)	(1.15)		
72-Killingsworth/82nd	18.44	2.11	2.04	.67	.24	987
	(5.34)	(9.26)	(8.74)	(.23)		
75-39th/Lombard	15.02	1.20	.24	7.38	.15	891
	(2.90)	(9.94)	(1.21)	(1.60)		

Table 3. Percentage of Trips Exceeding the Maximum Load Factor Standard* For Alternative Headway Delay Scenarios

	AM Peak Hour In-Bound Service			
		Reduction in Headway Delay		
Route	Observed	25%	50%	75%
4-Division	14.8%	2.2%	0.3%	0.0%
4-Fessenden	6.6	1.5	0.0	0.0
9-Powell	2.7	0.3	0.0	0.0
9-Broadway	8.4	0.5	0.0	0.0
14-Hawthorne	19.2	0.9	0.3	0.0
15-Belmont/NW23rd	22.8	2.5	0.2	0.0
12-Sandy Blvd	9.6	2.5	1.1	0.0
19-Glisan	5.9	0.0	0.0	0.0
72-Killingsworth/82nd	12.2	2.1	0.7	0.0
75-39th/Lombard	1.8	0.0	0.0	0.0
Overall	10.4	1.1	--	--

* The load factor standard is 130% of vehicle seating capacity.

Table 3. Percentage of Trips Exceeding the Maximum Load Factor Standard* For Alternative Headway Delay Scenarios, Continued

	PM Peak Hour Out-Bound Service			
		Reduction in Headway Delay		
Route	Observed	25%	50%	75%
4-Division	34.1	19.5	12.4	1.9
4-Fessenden	10.2	2.3	0.3	0.0
9-Powell	1.1	0.2	0.0	0.0
9-Broadway	7.1	0.2	0.0	0.0
14-Hawthorne	19.3	2.3	0.4	0.0
15-Belmont/23rd	13.5	4.0	0.1	0.0
12-Sandy Blvd	17.5	2.0	0.0	0.0
19-Glisan	8.7	0.9	0.3	0.0
72-Killingsworth/82nd	15.4	3.2	0.6	0.0
75-39th/Lombard	0.6	0.0	0.0	0.0
Overall	12.0	2.9	0.1	--

* The load factor standard is 130% of vehicle seating capacity.

Table 4. Headway Delay: First-Stage Parameter Estimates, PM Peak Hour Out-Bound Service*

	Route Number									
Variable	4-Div.	4-Fess.	9-Pow.	9-Broad.	14	15	12	19	72	75
Scheduled Headway	-.69	-.13	-.06	-.53	.02	-.10	-.17	-1.29	-.09	-.10
	(-2.13)	(-2.25)	(-1.27)	(-7.20)	(.19)	(-1.33)	(-1.26)	(-7.89)	(-1.51)	(-.91)
Low Floor Bus	1.28	2.86	-.32	-1.25	-.78	-.16	-.49	-1.46	-.55	-.34
	(.48)	(2.46)	(-.67)	(-3.00)	(-1.76)	(-.65)	(-1.20)	(-1.60)	(-.74)	(-.14)
Operator Experience	-.01	.01	-.03	-.10	-.03	.01	-.08	-.02	-.02	.04
	(-.39)	(.45)	(-.80)	(-5.65)	(-2.55)	(.39)	(-2.52)	(-.61)	(-1.27)	(2.37)
Distance to Peak Load Pt.	.97	.52	.74	.76	.23	.79	.53	.01	.27	.20
	(6.21)	(5.49)	(3.85)	(8.24)	(1.58)	(6.46)	(4.36)	(.07)	(7.56)	(6.14)
Headway Delay at Origin	.79	.57	.75	.76	.36	.76	.81	.76	1.01	.78
	(18.71)	(15.67)	(21.61)	(16.60)	(8.28)	(28.47)	(19.60)	(14.04)	(15.53)	(15.11)
Constant	5.72	-2.74	.26	4.48	-.19	.08	2.34	14.33	.54	.22
	(1.26)	(-2.21)	(.59)	(6.99)	(-.33)	(.18)	(1.78)	(7.51)	(.60)	(.08)
R^2	.53	.31	.53	.54	.09	.52	.59	.48	.25	.22
n	370	695	459	567	814	768	303	346	987	891

* Student's t-statistics are reported in parentheses.