

**Evaluation of Transit Operations: Data Applications of
Tri-Met's Automated Bus Dispatching System**

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Introduction

Over the past decade, the adoption of Advanced Public Transportation System (APTS) technology has been motivated by transit providers' desire to improve service reliability as well as to identify potential savings from improvements in scheduling and service planning. Casey (2000) reports that Automatic Vehicle Location (AVL) systems, a cornerstone of APTS, have been deployed by 61 transit agencies as of 1998.

Designing and delivering high quality transit service is an information-intensive undertaking. Service planning depends on spatially detailed demographic and employment data to evaluate potential demand. Detailed operations data is needed to develop schedules that respond to the demand for service, while at the same time conserve scarce agency resources. Effective operations control practice requires access to real time information on the status of vehicles in service. However, relevant information is costly, and transit managers who must weigh the trade-offs between investing in data acquisition or additional service hours have typically been pressured to favor the latter (Fielding, 1987).

With the deployment of APTS technology, transit analysts have begun to recognize potential applications associated with low-cost automated data recovery (Bruun, 2000). There is renewed interest in transit performance monitoring and analysis, a subject that has been essentially dormant since the mid-1980s. Consistent with this development, this paper presents an analysis of operating performance for Tri-Met, the transit provider for the Portland, Oregon metropolitan area. The analysis draws on data recovered by Tri-Met's automated Bus Dispatching System (BDS) and focuses on two main subjects. First, we employ archived trip level running time data to assess schedule efficiency. Second, we use archived data to estimate a fixed effects model addressing operator-related variations in running time.

The remainder of the paper is organized as follows. The next section provides a brief description of Tri-Met's BDS. This is followed by a discussion of the organization of planning, scheduling, operations and analysis functions in the new BDS environment. Subsequent sections present the analysis of schedule efficiency and operator variability. We then conclude with a discussion of the implications of our findings.

Tri-Met's Automated Bus Dispatch System

Tri-Met's BDS was installed in 1997 and became fully operational in 1998. Its main features are as follows:

- Automatic Vehicle Location (AVL) using a satellite-based global positioning system (GPS);
- Voice and data communication within a pre-existing mobile radio system;
- On-board computer and a control head displaying schedule adherence to operators, detection and reporting of schedule and route deviations to dispatchers, and two-way, pre-programmed messaging between operators and dispatchers;
- Automatic Passenger Counters (APCs) (partial);
- New dispatching center containing CAD/AVL consoles.

Compared to other transit providers who have recently implemented AVL technology, the most distinguishing feature of Tri-Met's BDS is the ability to recover and store detailed space-time operating and passenger data (Furth, 2000). This feature has resulted in a substantial improvement in performance monitoring and analysis capabilities (e.g., Tri-Met, 2000b, 2000c).

Integration of Scheduling, Monitoring and Operations Control

One of the most important potential uses of data recovered by BDS technology is in the area of transit service management. Figure 1 illustrates the main activities and inter-relationships involved in service management, which include planning and scheduling, monitoring and analysis of service delivery, and dispatching and operations control.

(Figure 1 about here)

Service planning and scheduling includes two primary activities. The first is route design, wherein service planners lay out routes and locate stops to serve demand. Second, a schedule is designed based on the expected running time needed to traverse the route and the service frequency needed to accommodate passenger demand.

The focus of the second primary function in the management system is on monitoring, or assessing the extent to which the designed service is successfully delivered. Depending on the state of technology and commitment of resources, monitoring activities can include assessment of on-time performance, vehicle running times, headway maintenance, and passenger loads.

The final function of the management system involves dispatching and operations control activities. In an APTS environment the activities associated with this function can include “passive” control and signal prioritization. Also included are activities traditionally implemented by field supervisors to maintain service, such as expressing and holding.

In the service management system, one of the most important benefits of automated data recovery is in reinforcing the linkages between service quality monitoring, planning/scheduling, and dispatching/control functions. In a data-poor environment, planners and schedulers must depend on ad hoc feedback from vehicle operators and passengers to determine appropriate routings, running times, and service frequencies. With automated data recovery, monitoring of

operating performance can yield detailed information on bus running times and passenger loads, providing feedback that can be used to adjust schedules (Furth, 2000). For example, variations in running time can be monitored, which is useful in determining the amount of recovery and layover time needed to maintain the schedule. Also, detailed monitoring of passenger loads can provide information to adjust service frequency.

Sometimes, several performance indicators can be used together to evaluate operating conditions. For example, headway maintenance and passenger load data can be jointly analyzed to determine if heavy load patterns are a consequence of insufficient frequencies or headway maintenance problems. A failure to maintain headways indicates a “bus bunching” problem, with lead buses typically plagued by overloads and following buses carrying few passengers. In this case, control actions taken to maintain headways can forestall the addition of buses to address the overload problem.

On-time performance (or schedule adherence) is monitored by most transit providers. Tri-Met defines a departure to be on time if it is one minute early to five minutes late. Although it is probably the most widely-used performance indicator in the transit industry, on-time performance is mainly relevant in situations where riders consult schedules or when timed transfers occur. Passengers tend to time their arrival at a stop when service is infrequent, indicating that on-time performance is more important in off-peak periods. Random passenger arrivals at stops are associated with high frequency service, and in this context headway maintenance is a more relevant performance measure.

The linkages between service monitoring and operations control are defined both in real time and “after the fact.” Passive control takes place in real time by reporting schedule adherence to operators on the vehicle control head and in pre-programmed text messaging

between operators and dispatchers. BDS technology is also capable of supporting real time control actions, such as signal prioritization for late-running buses, as well as initiating traditional control actions, such as vehicle holding and expressing. The effects of control actions on operating performance can also be evaluated. Holding or expressing, for example, can result in improvements in headway maintenance and better balancing of passenger loads. At the same time, such actions can also negatively affect on-time performance and running time variation.

Most large transit providers have defined standards to guide the design and delivery of service (Benn, 1995). While the determination of standards may be considered a desirable objective, it can also be an empty exercise in the absence of comprehensive performance monitoring. Service quality monitoring provides evidence of the extent to which the adopted standards are being met. Fielding (1987) has developed a comprehensive framework that illustrates how service monitoring and evaluation should be incorporated in transit planning and management.

Service standards defined by Tri-Met are summarized in Table 1. The standards are grouped into four general categories covering route/service design, level of service, service delivery, and service effectiveness. Service planners follow a shortest path objective in designing routes, deviating only when the addition of passengers is sufficient to justify the associated increase in travel time. Stop spacing along the route is guided by the density of development as well as requests for service. Schedule design is based on running times that are sufficient for an average operator to complete a trip under normal conditions. For express and limited service, running times are targeted at specified proportions of their regular service values. Both route and schedule design activities seek to maximize revenue service in relation to layover, recovery and deadhead time. To ensure coverage, a threshold level of service is defined

for routes or time periods where demand is limited. Related to passenger comfort and convenience, maximum load factors that vary by time of day and location are applied in setting service frequencies.

(Table 1 about here)

The only standard presently defined for service delivery at Tri-Met relates to on-time performance. Following BDS implementation, however, a number of other performance-related indicators have been monitored and reported. These include actual run time and run time variation, headway maintenance, the number of stops passed up due to overloading, and an estimate of the amount of excess passenger waiting time at stops due to headway variation.

Service effectiveness is defined by standards related to farebox recovery and boarding rides per revenue hour. Accident frequency is monitored and reported, although a standard has not been established. Riders and the general population are periodically surveyed to assess satisfaction and awareness of services and programs.

Analysis of Running and Recovery Times

One area where service delivery monitoring is enhanced by automated BDS data recovery is the analysis of bus running time. At Tri-Met, scheduled running times are set to accommodate the average operator. Adjustments are periodically made in response to operator feedback and evaluation of schedule adherence. These adjustments reflect the fact that variations in running time can occur across trips on any given route as a result of traffic conditions, random incidents, passenger activity and operator behavior. As a result, sufficient recovery time must be built into the schedule to ensure that the delays encountered on one trip do not carry over on subsequent trips. Schedulers guard against setting running time too high because it increases the

need for holding, which irritates passengers. They can be more generous in allocating recovery time because any excess is experienced when the bus is empty at the end of the route. Overall, schedulers seek to minimize the combination of running and recovery time.

The determination of appropriate running and recovery times for a hypothetical route is illustrated in Figure 2, which is based on Levinson's (1991) synthesis. The figure shows a frequency distribution of running times for a route, and identifies the median as well as the 95th percentile value. Levinson contends that the running time for the route should be set at a value slightly less than the median/mean in order to avoid the situation where a majority of operators have to "kill time" to maintain the schedule. Whether the running time is set at the mean, median, or some smaller value, the appropriate recovery time is defined as the difference between the chosen running time and the running time associated with the 95th percentile trip in the frequency distribution. Thus, sufficient running and recovery time is allocated to accommodate 95 percent of scheduled trips (recognizing that the 95th percentile trip will have zero recovery time), and it is nearly assured that the schedule will be maintained on a round-trip basis under normal operating conditions.

(Figure 2 about here)

With automated data recovery it is feasible to monitor bus running times and assess the correspondence between the service actually delivered and what was designed. Such an analysis was undertaken for Tri-Met's Spring 2000 sign-up, a service period extending from March 5 through June 3. To reflect the scheduling practice of setting running times for the typical operator, the median observed running time was chosen as a key benchmark point in the frequency distributions.

Figures 3 and 4 show the running time distributions for AM Peak (in-bound) and PM Peak (out-bound) trips on the 14 Hawthorne, a radial route serving downtown Portland from the east side. Route 14 is characterized by frequent service (5 minute headways in the peak), heavy passenger loads, moderate-to-heavy traffic, numerous signalized intersections, on-street parking over most of the route, and sporadic delays in crossing the Willamette River from bridge openings to accommodate river traffic. For the 1199 AM Peak (in-bound) trips in the distribution, running times ranged from 31 to 58 minutes, with a median value of 40.5. The median observed run time is two minutes (5.2%) longer than the mean scheduled run time of 38.5 minutes. The 95th percentile observed running time is 47.9 minutes. The difference between the 95th percentile running time and the median running time is defined to be the optimal recovery time. This value is 7.4 minutes, which is 3.5 minutes (32.1%) less than the mean scheduled recovery time of 10.9 minutes. Thus the observed performance indicates a need to add running time and reduce recovery time.

(Figures 3 and 4 about here)

Turning to Figure 4, the PM Peak (out-bound) running time distribution of 1026 trips ranges from 38 to 67 minutes, with a median value of 50.4. This is 7.4 minutes (17.2%) greater than the mean scheduled running time of 43.0 minutes. Conversely, the optimal recovery time of 11.1 minutes is 9.8 minutes (46.9%) less than the mean scheduled recovery time of 20.9 minutes. Compared to the AM in-bound situation, the needed adjustments suggested by the observed performance of PM out-bound trips are more substantial.

Summary findings by time period and direction for the 14 Hawthorne are presented in Table 2. In comparing the median observed run times to their scheduled values, it appears that insufficient running time is scheduled for out-bound trips. With respect to scheduled recovery

times, surplus amounts are observed in all instances except for PM Peak in-bound trips. The pattern of running and recovery surplus times in the table is generally consistent with the scheduling practice of setting running times low enough to avoid having operators kill time, while setting generous recovery times to avoid late departures on subsequent trips. Nevertheless, the values in the final column of the table indicate that the total amount of time scheduled for combined running and recovery is generally excessive. In the case of Early AM (in-bound) trips, for example, the excess is determined to be 6.9 minutes per trip. This implies that schedule adjustments could be made that would effectively “add a trip” over a 6-trip cycle, with sufficient running and recovery time to maintain reliable service at no additional cost.

(Table 2 about here)

The values in the final column of Table 2 should be interpreted as the maximum potential time savings because there are several constraints that need to be considered in developing schedules. One possible limitation pertains to the contract between Tri-Met and the bus operators union. The contract stipulates that schedules must contain five minutes of recovery/layover time for each hour of running time. However, the contract also states that a layover cannot be guaranteed for each trip. The optimal recovery times reported in Table 2 appear to satisfy this condition. For example, for PM Peak outbound trips, the minimum total time needed to satisfy the contract would be about 55 minutes (50.4 running and 4.6 recovery), while the optimal total is 61.5 minutes (50.4 running and 11.1 recovery). The distribution of running times for this period (see Figure 4) indicates that, for the optimal schedule time, the probability of completing a trip and experiencing a 4.6 minute layover exceeds .80, well above the “average operator” threshold probability of .50. A second potential limitation is associated with the schedule development process. This process must incorporate factors that impose

additional running and recovery time, including the need to coordinate transfers with other routes, timing service to match known passenger demand at key locations (e.g., schools), coordinating operator shift changes and assigning blocks of service among operators (“runcutting”), and setting consistent, predictable frequencies (“clock headways”). In each instance, the outcome can result in more schedule time and never less (Pine, Niemeyer and Chisholm, 1998).

While the 14 Hawthorne analysis is useful in illustrating the correspondence between service delivery and schedule design, it still suffers from the fact that its level of aggregation is too great to be meaningful in schedule design. For example, the run time distributions are partly affected by differing types of service (express versus local) and service pattern changes (i.e., some trips are short-turned while others traverse the full length of the route). The ideal unit of analysis is the individual bus trip, with run time distributions developed for each scheduled trip over a designated service period. Such an approach was employed in analyzing week day service for the Spring 2000 sign-up. This analysis encompassed 5,479 scheduled daily trips on Tri-Met’s 104 route bus system over 65 week days. Archived running time data for 281,305 actual trips were employed in the analysis.

Three alternative recovery/layover benchmarks are considered in the analysis. The first is Levinson’s optimal recovery, or the difference between the median and 95th percentile running time. The second is the value associated with the operators’ contract requirement, or 10% of the median run time. The third reflects the “rule of thumb” standard (18% of median running time) that is generally applied in the schedule development process at Tri-Met.

Table 3 reports system-level results. The median observed running time of 52.06 minutes per trip is .71 (1.4%) minutes less than the average scheduled running time. This conforms with

Levinson's recommended run time target. Alternatively, the average scheduled recovery time is found to exceed the three recovery benchmarks by fairly substantial amounts. The greatest difference between scheduled and required recovery is associated with the operators' contract standard. In this case, the implied recovery is 5.13 minutes per trip, which is 8.64 minutes less than the average scheduled recovery of 13.77 minutes. Even in the case of the rule of thumb benchmark, there is an average excess in scheduled recovery of 4.53 minutes per trip.

Assuming that the optimal run time is represented by the median, the total run-plus-recovery excess per trip is found to range from 3.82 minutes in the rule-of-thumb case to 7.92 minutes in the operator contract case.

(Table 3 about here)

An estimate of the annualized cost associated with the alternative excess schedule times is presented at the bottom of Table 3. These values represent the expected cost savings from strict adherence to the alternative recovery standards. The values reflect an assumed marginal operating cost of \$42.00 per platform hour and 255 days of week day service. The expected annual savings range from \$7.7 million under contract recovery to \$5.7 million for adherence to the rule-of-thumb recovery standard.

There is some uncertainty associated with annualizing the findings from a three month service period. For example, there may be seasonal differences in the run time distributions. Tri-Met schedulers have noted that service operations during the Spring sign-up tend to be more stable than operations in other times of the year. Recognizing that the scheduling process is itself expensive and disruptive to passengers, it would be prudent to extend this analysis from a single sign-up to an annual time frame.

The summary results discussed above mask interesting details at the trip and route levels. To illustrate, in Figure 5 the trip level results relating to excess schedule time for the 18 percent standard have been aggregated to the route level. As the figure shows, 81 of the 104 routes were found to exhibit excess schedule time, while 23 routes were found to have an insufficient amount. The routes with the greatest excess were the 158 Stevens Road, the 60 Leahy Road and the 46 North Hillsboro, while the routes with the greatest deficits were the 99 McLaughlin Express, the 61 Marquam Hill/Beaverton and the 66 Marquam Hill/Milwaukie (see Appendix 2 for a complete listing). The former routes have been recently introduced to provide suburban feeder service, while the latter routes all provide single trip peak express service and thus have no scheduled recovery or layover.

(Figure 5 about here)

While it may be demonstrated that excess time exists in a schedule, there are concerns that removing this time will negatively affect service reliability. Efforts to streamline schedules must recognize that effective field supervision is needed to ensure that service reliability is maintained. Levinson (1991) suggests that at least five supervisors per hundred operators are needed to ensure reliable service delivery, and he emphasizes that their attention should be mainly focused on maintaining operations. Presently, Tri-Met's road operations staff consists of 31 individuals and the agency employs 1,135 FTE operators, yielding 2.7 field supervisors per 100 FTE operators. During weekday PM Peak periods, deployment falls to 1.8 field supervisors per 100 operators. This implies that reductions in recovery time would need to be accompanied by additional field supervision staff.

To justify adding field supervisors, it would have to be established that the associated cost would be more than offset by savings from schedule time reductions. It is also expected that

the BDS will improve the effectiveness of field supervision over time, which would result in the need for less personnel than suggested by Levinson's standard.

Analysis of Operator-Related Effects on Running Time

Prior research has provided a clear understanding of the various determinants of bus running time (Abkowitz and Tozzi, 1987; Strathman et al., 2000). These determinants include route length, route characteristics (e.g., the number of signalized intersections and the extent of on-street parking), the number of stops made, the volume of passenger activity, seasonality, time of day, and direction of travel. However, the influence of bus operator behavior on running time has not been seriously studied. Transit analysts recognize that driving practices vary among operators, but it is not known how much of the total variance in running times is attributable to operator-related variations versus other determinants. Up to this point, the data requirements to investigate this question have been too expensive. But AVL-APC systems are capable of generating the large volume of data necessary to undertake such an analysis.

Using Tri-Met AVL-APC data on bus trips for the Summer and Fall 2000 service periods, a running time model consisting of a standard set of operations and passenger activity variables, augmented by a set of operator-specific dummy variables, is developed. The operator dummy variables are analogous to fixed effects, which have been employed in a variety of other applications (e.g., Gabriel et al., 1995; Rhoads and Gerking, 2000). The general specification of the running time model is as follows:

Run Time = f(Distance, Lifts, Stops, Early AM, AM Peak, PM Peak, Night, Feeder, Crosstown, Peak Express, Ons+Offs, Ons+Offs², Headway, Summer, O₁, ... O_n), where

Run Time	=	Actual running time, in seconds;
Distance	=	Length of the route, in miles;
Stops	=	Actual passenger stops made;
Early AM	=	A dummy variable equaling one for trips initiated before 7:00 am, and zero otherwise;
AM Peak	=	A dummy variable equaling one for trips initiated between 7:00 and 9:00 am, and zero otherwise;
PM Peak	=	A dummy variable equaling one for trips initiated between 4:00 and 6:00 pm, and zero otherwise;
Night	=	A dummy variable equaling one for trips initiated after 6:00 pm, and zero otherwise;
Feeder	=	A dummy variable equaling one if the route provides feeder service to a transit center, and zero otherwise;
Crosstown	=	A dummy variable equaling one if the route provides lateral service, and zero otherwise;
Peak Express	=	A dummy variable equaling one if the trip provides express service during peak periods, and zero otherwise;
Ons+Offs	=	The sum of trip-level boardings and alightings;
Ons+Offs ²	=	The quadratic value of Ons+Offs;
Headway	=	The scheduled time between buses at the peak load point, in minutes;
Summer	=	A dummy variable equaling one for trips that occurred during the Summer 2000 service period (June-September), and zero otherwise;
O ₁ , ... O _n	=	Operator-specific dummy variables identifying operators for which at least ten valid trip records were recovered for the Summer (June-September) and Fall (September-December) 2000 service periods.

Based on previous research, the expected effects of the non-operator variables are as follows. Running time is expected to increase with route distance and the number of stops made. The time period of operation dummy variables reflect running time differentials relative to the mid-day period (9:00 am-3:00 pm). Generally, peak period service requires more running time

due to traffic congestion, but Strathman et al. (2000) found that congestion-related delays were limited to the evening peak in an earlier Tri-Met study. Compared to radial service, routes providing feeder and crosstown service are expected to require less running time because they do not operate in the down-town area, where average speeds are reduced by numerous signalized intersections and heavier traffic volumes. Passenger activity is specified in both linear and quadratic form. Depending on passenger loads, the effect of the quadratic term could be either positive or negative. With large passenger loads and many standees, boarding and alighting times per passenger would likely be greater, implying positive linear and quadratic effects. With smaller passenger loads, it is possible that diminishing boarding and alighting times per passenger would be observed, implying positive linear and negative quadratic effects. Running times are expected to be inversely related to headways due to “bus bunching” effects. Bus bunching is more likely to occur when headways are small, and the consequence of this phenomenon is greater running time either as a result of impedance due to platooning or to holding actions imposed to improve bus spacing. Running times are expected to be lower during the Summer service period than in the Fall as a result of lower traffic volumes observed during that period.

The model specification includes 910 operator-specific dummy variables. Omitted operators are those who generated fewer than ten valid trip records during the study period, which could result from several causes. First, screening of AVL and APC data reduces the number of valid trip records. Second, operators with non-standard work assignments (e.g., relief, tripper, or extraboard) make fewer trips and are thus less likely to be included. If the excluded operators are disproportionately comprised of those with non-standard assignments, it is expected that the typical included operator will require less running time due to experience

(operators with non-standard assignments are usually the least experienced) or greater familiarity with their assigned work.

The study sample is limited to weekday service. Fifteen routes were selected for the analysis. The routes are representative of Tri-Met's service typology, which is comprised of radial, crosstown, feeder, and peak express service (a list of routes is provided in Appendix 2). A total of 110,743 valid trip records were recovered, which represents 49.7 percent of the total scheduled weekday trips for the selected routes.

Parameter estimates for the various route, service, and passenger variables are reported in Table 4. Given that running time is measured in seconds, the coefficients in the table can be interpreted as the change in seconds of running time associated with a unit change in a given variable. Thus running time is estimated to increase by 206 seconds for each mile increase in route length, which implies an average speed of about 20 mph. Stop activity involves a combination of variables. A stop involving a lift operation is estimated to require 68 seconds (8.1 seconds for the stop plus 59.8 seconds for the lift operation), while a stop involving a single boarding or alighting is estimated to require about 11 additional seconds. Compared to mid-day service, Early AM trips are estimated to require 257 fewer seconds of running time (7.7%). The estimated differential for Night trips is similar. As observed before, AM Peak trips require less (100 seconds, or 3%) running time than mid-day trips. The estimated differential for PM Peak trips is 138 seconds (4.1%).

(Table 4 about here)

Regarding service typology, Feeder service is estimated to require less running time (418 seconds, or 12.5%) than radial service, while the estimated differentials for Crosstown and Peak Express service are -506 (15.1%) and -1089 (32.5%) seconds, respectively. The estimated

consequence of a one minute reduction in headway is an increase of about 11 seconds in running time. Seasonality effects are evident in the finding that Summer period trips are estimated to require about half a minute less running time than trips in the Fall service period.

Turning to the results for the 910 operator-specific dummy variables, the mean value of the estimated coefficients is -40.61 , which means that the identified operators typically ran about two-thirds of a minute faster than the excluded operators. The standard deviation of the estimates is 212.6 seconds, which is fairly substantial. Based on a standard normal distribution, it can be concluded that the 95th percentile running time interval (which encompasses the running time differentials for 864 of the 910 operators) is ± 417 seconds, or about 12 percent of the mean running time. This value can be related to the recovery-layover standards employed in schedule development, addressed in the previous section. Given a recovery-layover standard of 18 percent of mean running time, about 605 recovery-layover seconds would generally be needed to accommodate the sampled trips in the running time model. The estimated 95th percentile running time interval related to operator behavior amounts to nearly 70 percent of the recovery-layover time implied by the standard. Thus, it appears that the most important reason for adding recovery-layover time is to accommodate variations in operator behavior rather than non-recurring operations-related factors.

A frequency distribution of the estimated operator-specific coefficients is shown in Figure 6. In constructing this distribution the coefficients were rescaled in relation to their mean value. The operator effects on running time appear to be normally distributed, which has important implications. For example, had the distribution exhibited an extended right tail, it would have pointed to the existence of a sub-group of “foot-draggers” who use excessive amounts of running time and are thus more likely to start their trips late as their work assignment

progresses. Alternatively, an extended left tail would have indicated the existence of a group of “jack rabbits” who tend to run ahead of their schedules with the likely intent of maximizing layover time.

(Figure 6 about here)

Another way of interpreting the operator effect is by decomposing the variation in observed running time into components associated with operator effects, route-passenger-service effects and random (unexplained variation) effects. Given the standard deviations of observed running times, operator coefficients, and the error term, the result is that the operators account for 17 percent of running time variation, while route-passenger-service, and random effects account for 79 and 4 percent, respectively.

Given the estimate of a substantial amount of operator-related running time variation, this raises the question of whether there are any traits of the operators themselves that could explain performance differences. Attribute data on operators is limited, but some insight might be gained from information that is readily available. Such information includes length of service, the type of work assignment, a history of customer complaints, and the extent to which their trip departures were on time. With this information the following model was specified:

$\beta_i = f(\text{Experience, Complaints, Departure Delay, Tripper, Extraboard, Relief})$, where

β_i = The running time model coefficient for operator i ;

Experience = Length of service, in months;

Complaints = The number of customer complaints over the past year.

Departure Delay = Average delay in departure over the sampled trips, in seconds;

Tripper = A dummy variable equaling one if the operator work assignment is for tripper service, and zero otherwise;

Extraboard = A dummy variable equaling one if the operator has an extraboard work

assignment, and zero otherwise;

Relief = A dummy variable equaling one if the operator has a relief work assignment, and zero otherwise;

An operator's relative running time is expected to be inversely related to experience as a result of experience-related factors such as driving skill, familiarity with equipment and operating conditions on routes, and the ability to process boarding passengers. The number of customer complaints may reflect an operator's commitment to delivering good service, part of which involves adhering to the schedule. In this regard, however, the effect of customer complaints is not clear because a lack of commitment could be manifested in running consistently early or late, or in simply being less predictable. Given sufficient scheduled running times, regular delays in trip departures are a signal that an operator is padding his/her layover and makes up this additional layover time by running faster on ensuing trips. This implies an inverse effect of departure delay on relative running time.

Three non-regular work assignment dummy variables are specified in the model. Tripper assignments are typically filled by part-time operators for service that is added during peak periods. The assignment may be limited to a single trip. It is expected that these operators will require more running time. Extraboard assignments are made to cover absences and are filled only by full time operators. Controlling for experience, there is no clear basis for hypothesizing how these operators will perform relative to their peers filling regular work assignments. Relief assignments are made to cover vacation leaves and gaps from regular work assignments, and are usually filled by newer operators. It is expected that these operators will require more running time than their extraboard counterparts, and probably less than tripper operators.

Attribute data were recovered for 883 of the 910 operators. Regression results are presented in Table 5. The explanatory power of the regression is fairly low, with an R^2 value of .09, and experience is the only attribute found to have a clearly significant effect on operator performance. The model estimates that an operator's relative running time decreases by .57 seconds for each month increase in experience. Other model specifications were estimated to test whether experience effects were subject to variable returns, but results indicated that the effect is linear. Although the marginal effect of experience is small, its impact is not trivial given the substantial variation in experience among operators. For example, the difference in running time between operators with three and twelve years experience (values which are well within one standard deviation of the mean) is slightly more than a minute. In situations where service is frequent, a difference of this magnitude can be disruptive.

(Table 5 about here)

The model results indicate that relative running time decreases by about 12 seconds for each minute delay in trip departure. While this is consistent with expectations, the parameter estimate is not significant. Of the work assignment effects, only trippers are arguably significant (at the .08 level). These assignments are estimated to consume 40 additional seconds of running time. Given that trippers are interspersed with regular service assignments, this implies that the operator-related difference in running time between a given tripper and regular trip assigned to a typical full time operator would be about 90 seconds. With peak headways under ten minutes, these differences can easily contribute to bus bunching problems.

Discussion and Conclusions

The analysis of bus running times in this paper has focused on two principal questions. First, how compatible are scheduled running and recovery times with field experience? Second, how much of the variation in running time can be attributed to operator behavior? Regarding the first question, it was found that scheduled and observed running times are in general correspondence, but that scheduled recovery times typically exceed the amounts that operating experience indicate would be sufficient. Regarding the second question, it was found that there is a substantial amount of variation in running times that can be linked to variations in operator behavior. In terms of their implications, the two questions are closely related. If either recovery times or operator variation can be reduced, schedule efficiency will improve and the delivery of bus services will become more cost effective.

Excessive recovery time results in a shift from revenue to non-revenue service. When excess recovery time is found to exceed the scheduled headway, a reduction can save a trip without affecting the level of service provided to passengers. However, several factors need to be taken into account in evaluating recovery time. First, recovery time requirements tend to be larger when clock face schedules are employed. While such schedules are convenient for passengers, their usefulness is diminished when service is frequent or when passengers do not consult schedules. These conditions are more likely to exist during peak periods, when running time variation also tends to be greater. Thus if clock face schedules were adopted only for low frequency service, transit providers could save resources without affecting the quality of service perceived by passengers. Second, the run time analysis in this paper took contract layover requirements into account, but did not consider other constraints that affect the blocking of trips in the schedule writing process. For example, shift changes must be accommodated. Third,

running times are subject to seasonal variation. The analysis in this paper focused on a single three-month service period, and the extent to which the variation in this period is consistent with annual variation is unknown. Given that most transit agencies employ scheduling software that can be used to assess work rules and clock face schedules, simulations could be done to determine their effects on recovery times.

The options available for reducing operator-related variability are essentially two-fold. The first option is structural in that it focuses on the characteristics used in the model assessing relative operator performance. The results indicate that part-time operators contribute to greater running time variability. Greater reliance on full-time operators would thus reduce running time variation. Such a shift has labor cost implications that would need to be assessed in relation to savings from recovery time reductions. Among full-time operators, the model results indicate that service regularity would likely improve if the work assignments of operators with similar experience were grouped together. However, this contrasts with the present seniority-based system in which operators select their work assignments. Also, given the finding that running times improve with seniority, there may be an opportunity to enhance the performance of less experienced operators through training.

The second option in dealing with operator variability is operational in nature. Here, operator characteristics are taken as given and a greater emphasis on operations control is made. In this case, additional field supervision would focus on ensuring that operators departed on time and maintained their schedules at least through the maximum passenger load points. As with the structural option, this has cost implications that would need to be assessed relative to recovery time savings.

This paper provides an example of how AVL-APC data can be used to monitor and evaluate service performance in relation to adopted standards. Its focus has been limited to standards governing running and recovery times employed in scheduling. Clearly, opportunities exist to assess a variety of other standards used in service planning. It should be noted that, in the absence of detailed space-time data, the service standards themselves are usually based on experience and professional judgement. As AVL-APC data become more widely available, it will be possible for analysis of operational performance to regularly feed back to the standard-setting process, providing either validation or a basis for change.

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Appendix 1

Schedule Excess Under 18% Recovery Standard, By Route

Route No.	Schedule Excess
158	47.8
60	37.87
46	37.68
49	34.29
81	29.26
59	28.16
144	26.32
53	25.9
48	25.34
41	25.07
34	21.8
25	21.7
67	21.35
154	19.72
22	19.69
58	18.57
50	17.99
39	17.09
70	16.09
201	14.49
155	14.4
23	13.86
26	13.32
24	13.3
89	12.98
180	12.75
37	12.42
56	11.24
9	11.13
128	11.07
35	10.97
68	10.7
52	10.69
83	10.51
31	10.45
6	10.4
29	10.06
54	10.03
20	9.47
88	9.4
27	9.31
78	8.87
62	8.76
115	8.64

140	8.44
85	7.7
76	7.47
156	6.95
108	6.06
57	5.93
14	5.91
63	5.77
101	5.72
77	5.5
119	5.32
19	5.23
72	5.02
84	4.86
105	4.49
179	4.15
33	4.14
152	4.03
133	3.95
5	3.92
87	3.5
32	3.29
112	2.56
82	2.55
157	2.46
1	2.37
47	2.31
4	2.09
96	2.05
117	1.95
17	1.52
75	1.49
104	1.43
8	1.19
40	1.04
71	0.45
15	0.32
51	-0.38
12	-0.59
109	-1.13
36	-1.2
18	-1.43
42	-2.27
43	-3.02
110	-3.54
55	-4.4
97	-4.85
45	-4.95
10	-5.19

16	-5.65
65	-11.35
95	-11.42
38	-11.47
64	-12.22
92	-13.82
44	-20.14
74	-20.25
66	-20.85
61	-22.75
99	-23.12

Appendix 2

Routes Selected for Running Time Estimation

Radial Routes

4-104 Fessenden-Division

14 Hawthorne

15-115 Belmont-NW 23rd Ave.

19-119 Glisan-Woodstock

54 Beaverton-Hillsdale

56 Scholls Ferry

Crosstown Routes

72 Killingsworth-82nd Ave.

75 39th Ave.-Lombard

Feeder Routes

24 Halsey

26 Stark

52 Farmington/185th

88 Hart/198th

Peak Express Routes

64 Marquam Hill/Tigard

96 Tualatin I-5

99 McLoughlin Express

Table 1: Tri-Met Service Standards

Category	Standard
Route and Service Design	
Directness	Additional travel time for all through passengers should not exceed 5 minutes for each boarding/alighting rider along a deviation.
Running Time	Sufficient for an “average operator” to complete a trip safely and reliably under normal operating conditions.
Express Service	Sched. Run Time should be 25% less than local service.
Limited Service	Sched. Run Time should be 10% less than local service.
Missed Trips	0.2% of all scheduled trips, based on “pull-outs”
Schedule Efficiency	Revenue Hrs / Platform Hrs * 100 \geq 75% (system); 60% (route); Recovery/layover: 18%; Deadhead: 7%
Stop Spacing	80+ units/acre: 400-600 ft. 22-80 units/acre: 500-750 ft. 4-22 units/acre: 600-1000 ft. L.T. 4 units/acre: “as needed”
Level of Service	
Threshold Service	Establishes maximum (“policy”) headways by day, time period and route type.
Load Factors	Small Bus (25’): 130% of vehicle seating capacity Standard Bus (40’): 145% of vehicle seating capacity Light Rail (88’): 218% of vehicle seating capacity Loads should not exceed 100% for more than 20 minutes outside Fareless Square. Off Peak: Load Factor should not exceed 100% outside Fareless Square on three consecutive trips.
Service Delivery	
On-Time Performance	75% of all trips on a line at each time point 75% of all “meets” at transit centers.
Run Time Variation/ Run Time	Monitored and reported (quarterly)
Regularity/Headway Maintenance	Monitored and reported (quarterly)
No. of “Pass-ups”	Monitored and reported (quarterly)
“Excess” Passenger Waiting Time	Monitored and reported (quarterly)
Service Effectiveness	
Farebox Recovery	30% at the system level
Boardings per Revenue Hour	Routes periodically sorted to identify “poor performers”
Awareness	Periodically Surveyed
Rider Satisfaction	Periodically Surveyed
Accidents	Monitored and reported

**Table 3: Summary Results of Trip-Based Run and Recovery Time Analysis:
Spring 2000 Sign-up**

Category	Value	Excess Per Trip
Average Scheduled Run Time (min.)	51.35	
Median Actual Run Time	52.06	-.71
Average Scheduled Recovery Time (min.)	13.77	
Levinson Optimal Recovery	5.76	8.01
Contract Minimum Recovery (10%)	5.13	8.64
“Rule-of-Thumb” Recovery (18%)	9.24	4.53
Average Scheduled Run + Recovery Time (min.)	65.12	
Levinson Optimal Run + Recovery	57.82	7.30
Contract Minimum Run + Recovery	57.20	7.92
“Rule-of-Thumb” Run + Recovery	61.30	3.82
Annual Excess Schedule Cost (\$ millions)*		
Levinson Optimal	\$7.1	
Contract Minimum	\$7.7	
“Rule-of-Thumb”	\$5.7	

* Annual cost estimates are based on marginal operating costs of \$42.00/hr. applied to 5,479 daily trips over 255 week days.

Table 4: Run Time Model Parameter Estimates

Variable	Mean Value (Standard Deviation)	Coefficient (t-value)
Intercept	--	573.09 (17.20)
Distance	12.87 (4.84)	206.00 (576.43)
Lifts	.25 (.70)	59.80 (54.56)
Stops	35.81 (16.78)	8.10 (58.09)
Early AM	.07 (.25)	-256.66 (-73.48)
AM Peak	.15 (.36)	-99.84 (-40.08)
Mid-Day	--	--
PM Peak	.13 (.33)	138.43 (47.12)
Night	.30 (.46)	-248.04 (-81.34)
Radial	--	--
Feeder	.08 (.27)	-418.47 (-69.17)
Crosstown	.22 (.42)	-506.14 (-146.46)
Peak Express	.01 (.10)	-1088.9 (-73.65)
Ons+Offs	98.73 (56.65)	3.36 (54.64)
Ons+Offs ²	12957 (14802)	-.0016 (-8.63)
Headway	16.99 (10.57)	-10.76 (-99.37)
Summer	.51 (.50)	-26.40 (-14.98)
R ²		.96
n		110743

* For the run time dependent variable, the mean value is 3354.9 and the standard deviation is 1225.2.

Table 5: Operator Model Parameter Estimates

Variable	Mean Value (Standard Deviation)	Coefficient (t-value)
Intercept	--	25.15 (1.07)
Experience	94.3 (88.7)	-.57 (-5.69)
Complaints	3.9 (4.5)	-1.43 (-.92)
Departure Delay	101.2 (54.9)	-.19 (-1.49)
Regular Service	--	--
Tripper	.20 (.40)	40.01 (1.78)
Extraboard	.21 (.41)	-5.54 (-.26)
Relief	.18 (.39)	29.8 (1.34)
R ²		.09
n		883

* The values of the mean and standard deviation of the dependent variable are -40.61 and 212.6, respectively.