Beyond Generating Transit Performance Measures: Visualizations and Statistical Analysis Using Historical Data

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Abstract. In recent years, the use of performance measures for transit planning and operations has gained a great deal of attention, particularly as transit agencies are required to provide service with increasing demand and diminishing resources. The widespread application of intelligent transportation systems (ITS) technologies in transit systems has opened the window for automating the generation of comprehensive performance measures. In Portland Oregon, the local transit provider (TriMet) has been on the leading edge of the transit industry since they implemented their bus dispatch system (BDS) in 1997. The BDS is comprised of automatic vehicle location (AVL) on all buses, a radio communications system, automatic passenger counters (APCs) on most vehicles and a central dispatch center. Most significantly, TriMet had the foresight to develop a system to archive all of its stop-level data that is then available for conversion to performance indicators. In the last decade TriMet has extensively used this system to generate performance indicators through monthly, quarterly, and annual reporting. TriMet currently generates a number of performance indicators, yet the road is still open to explore more opportunities beyond general transit performance measures. In particular, based on an analysis of one year of archived BDS data, this paper demonstrates the power of using visualization tools to understand the abundance of BDS data. In addition, several statistical models are generated to show the power of statistical analysis in conveying valuable and new transit performance measures (TPMs) beyond what is currently generated at TriMet or in the transit industry in general. It is envisioned that systematic use of these new visualization methods and TPMs can assist TriMet and any other transit agency in improving the quality and reliability of its service, leading to improvements to customers and operators alike.

INTRODUCTION

The deployment of surveillance, monitoring and management systems as part of the intelligent transportation systems (ITS) programs has enabled monitoring the performance of existing transit systems in real time or in retrospect. The cost of collecting the data is no longer an obstacle and currently it is possible to design, extract and test specific, relevant, and dynamic measures of actual system performance. In the area of public transportation, many agencies have implemented systems that collect a wealth of operational information that can be used to evaluate and improve the operating efficiency of the transit fleet. In fact, there is so much data collected that digesting the abundant amount of data obtained from ITS archives is becoming an issue.

One agency that makes extensive use of these technologies is the Tri-County Metropolitan Transportation District of Oregon (TriMet), the local transit operator in the Portland, Oregon metropolitan region. TriMet has had a long history and extensive experience with advanced public transportation operations. The bus dispatch system (BDS), which includes global positioning system (GPS) based automatic vehicle location technology (AVL), automated passenger counters (APC), traffic signal priority (TSP) systems, radio communication capabilities, and computer aided dispatching, was installed on TriMet buses in 1997. TriMet's scheduled regular weekday service contains nearly 10,000 trips and on a typical weekday the BDS records about 500,000 entries. TriMet's entire fleet is currently equipped with the BDS system. The amount of data being archived per day is beyond the capabilities of an analyst to understand without the help of visualization and summarization aids.

Archived TriMet BDS data has been extensively used during past decade in several studies. For example assessing the effects of the BDS on operations and reliability (*1*, *2*), relating service reliability to passenger demand (*3*, *4*), assessing the accuracy of the APC technologies (*5*), measuring the effects of TSP on service operations (*6*), generation of various run time and dwell time models (*7*, *8*), using the BDS data as probe vehicles to monitor arterial performance (*7*), assessing the accuracy of next arrival systems (*9*), measuring the effect of bus stop consolidations on demand and operations (*10*), and generation of transit performance measures (*11*). All these studies have revealed the power of using the BDS system as a tool in planning and operations. Most of these studies led to substantial improvements in the way TriMet is serving its customers.

TriMet itself has a set of talented personnel who generate performance measures internally, as shown in Table 1 (*12*). It is clear that TriMet is intensively using its BDS data to generate a variety of performance measures, including those in the Transit Capacity and Quality of Service Manual (*13*). The research described in this paper attempts to go beyond this list and also utilize the time and space dimensions of the BDS data.

Due to the size and complexity of the transit data obtained from ITS a second tier of performance measures that is built on visualizations and summarizations and not just displaying numbers in tables is a must. We will be discussing various performance measures with focus on transit service reliability as a key element. Accordingly the objective of this paper is to describe how archived BDS data can be used to generate complex performance measures and present them visually and in the context of a statistical analysis. The research concentrates on service variability and the amount of valuable information that can be retrieved when studying the variance in several aspects of the transit service. This is a pilot research effort and it is hoped that these visualization and statistical analyses can be fed directly into the transit operations environment for use in revising schedules and operations strategies. In addition in this research paper data obtained from the TriMet BDS system are combined with other data sources such as weather to highlight certain aspects of service interruptions, due to precipitation and/or seasonal effects.

TABLE 1 TriMet Performance Reports

Performance Report Type	Summary Level	Day	Reporting Frequency
Route Performance			
Route Ridership [1]	Rte	All	Quarterly
Peak Period Ridership	Rte-Dir-Peak Period	All	Quarterly
Time of Day Route Performance [2]	Rte-Dir-Time of Day	All	Quarterly
Service Delivery [3]	Rte	All	Quarterly
Time of Day Performance	Rte-Dir-Time of Day	All	Quarterly
Time of Day Ridership [4]	Rte-Dir-Time of Day	All	Quarterly
Trip Level Performance	Rte-Dir-Trip	All	Quarterly
Service Standards			
Hourly Capacity [5]	Rte-Dir-Trip	All	Biannual
Trip Level Hourly Capacity [6]	Rte-Dir-Trip	All	Biannual
Hourly Excess Capacity [5]	Rte-Dir-Trip	All	Biannual
Trip Level Hourly Excess Capacity [6]	Rte-Dir-Trip	All	Biannual
Deadhead Trips with Excess Capacity [7]	Rte-Dir-Block	Weekday	Biannual
Less Productive Tripper [8]	Block-Piece	Weekday	Biannual
Route Level Ridership			
Route Level Ridership [9]	Route	All	Quarterly
Route Level Ridership	Route	All	Annually
Weekly Route Level Ridership [10]	Route	Weekly	Annually
Route Level Ridership [*]	Route	Weekday	Annually
Route Level Ridership & Veh Hours [*]	Route	Weekday	Annually
Passenger Censuses			
Time Point Segment Ridership	Rte-Dir-TP Segment	All	Biannual
Time Point Segment Ridership	Rte-Time of Day-TP Segment	All	Biannual
Route & Stop Level Passenger Census	Rte-Dir-Stop	All	Biannual
Stop Level Passenger Census	Stop	All	Biannual
Stops All [*]	Stop	All	Biannual
Cordon Counts			
All Day Cordon Counts	Rte-Dir-Block @ Max Load Point	All	Biannual
AM Cordon Counts	Rte-Dir-Block @ Max Load Point	All	Biannual
PM Cordon Counts	Rte-Dir-Block @ Max Load Point	All	Biannual
All Day History [*]	Rte-Dir @ Max Load Point	All	Biannual
AM Peak History [*]	Rte-Dir @ Max Load Point	All	Biannual
PM Peak History [*]	Rte-Dir @ Max Load Point	All	Biannual

1. Report provides comparison to previous year's values, same quarter- boarding rides, rides per vehicle hours, net difference in boarding rides, percent change in rides per vehicle hour
2. Multiple reports generated- sorted by percent late, excess wait, and headway adherence
3. Report provides comparison to previous year's values, same quarter- on time percent
4. Multiple reports generated- sorted by rides per revenue hour, maximum load
5. Individual report sorted by load to achievable capacity ratio > 80%
6. Individual report sorted by load to achievable capacity ratio < 50%
7. Individual report sorted by maximum load factor < 50%
8. Individual report sorted by boardings per platform hour < 20%
9. Report provides comparison to previous year's values - boarding rides, rides per vehicle hours, net difference in boarding rides, percent change in rides per vehicle hour
10. Multiple reports generated- sorted by total ridership, rides per revenue hour, rides per vehicle hour

* Denotes that report provides summaries over time at level of reporting frequency

DATA AND RESEARCH METHODS

TriMet serves an area of 592 square miles with a population of 2 million people. It operates 606 vehicles on 92 routes with approximately 7,600 bus stops. There are a total of 62 million annual bus trips. TriMet has implemented its unique BDS that collects stop-level data as a part of their overall service control and management system. TriMet has shared all of its 2007 archived data with the Portland Oregon Regional Transportation Archive Listing (PORTAL), which contained about 140,000,000 records. PORTAL is the region's archived data user service (ADUS) and is a research effort in the Intelligent Transportation Systems laboratory at Portland State University (*15*). This analysis makes use of an archive of weather conditions in Portland, Oregon region, also housed in the PORTAL database. TriMet has geo-coded each stop location, which enables the use of geographic information system (GIS) mapping. Other data used in generating GIS maps were obtained from the Regional Land Information System (RLIS).

This research concentrated on new aspects of performance measures and visualizations building on previous research (*11*). The research follows a hierarchical approach, beginning with system level and ending with stop level analyses. We begin by displaying performance indicators at the system level through visualizations and concentrating on factors that may lead to higher levels of variations in system performance. These indicators concentrate on lift activity and passenger demand. Next, we focus on route level analysis, displaying various statistical analyses that we recommend to be used as performance indicators in transit agencies. Finally we focus on a stop level analysis, which will be followed by the conclusion and some final comments.

It is worth noting that the analysis of one year's worth of BDS data, even for one route, presents its own data management challenges. TriMet's Route 72 alone includes a total of 6,282,856 stop level records which represent 54,311 weekday trips made in 2007. Managing a data set in excess of 6 million rows was a challenge that required careful thought and experimentation. Ultimately, we were able to arrange the data such that complex calculations could be performed very quickly. The keys to our ultimate success were to sort the data and set up variables and scripts that optimized Matlab's powers of calculation. In short, we sorted the data by trip and then created variables that indexed the first and last occurrence of each individual trip. Because the data were sorted by trip, every record between the first and last occurrence of the trip were part of the same trip. In this way, we were able to perform trip level calculations on the entire data set in a matter of seconds.

SYSTEM LEVEL ANALYSIS

Visualizing system level performance measures in GIS can help transit planners and engineers to understand certain aspects of the entire system. Figure 2 is a 3-D map of the Portland Metropolitan region with the average number of boardings during the morning peak per day in 2007 represented in shades and heights. In addition, the coefficient of variation of passenger boarding is represented as circles that vary in size. Observing this figure, it is clear that high levels of average passenger boardings are present around major transfer points and in the downtown area (the middle of the figure). Meanwhile, high levels of variation in passenger boardings are present in the suburban routes and the routes serving non-linear streets. The routes serving the east side (grid routes) of the metropolitan region experience low variations in passenger demand. Also, high levels of passenger variation are present near the ends of some routes. Areas with high levels of variation passenger demand are generally correlated with low average passenger activity during the morning peak in 2007 (0.265 at a 99% confidence level).

Lift use is one of the major contributors to travel time variation and system disturbances. Schedulers add recovery time to account for non-recurring events such as lift activity. Each lift activity adds on average 67 seconds to dwell time or run time (*8*, *16*). Yet in many cases lift activity can be tracked through the archived BDS data. This can help to identify stops with high probabilities of lift activity. Accordingly, adequate recovery time can be added to the routes serving these stops rather than to all the routes in the system. Figure 3 is a map showing total lift activities in 2007 for the entire system. It is clear that several routes experience high levels of lift use while others are not. High levels of lift activity tend to occur in downtown locations. It is clear that some stops have high and consistent lift activities, with some stops experiencing as high as 27 lift activities per week day. Such a high level of lift usage requires great attention from transit planners and operators to ensure enough scheduled run time is assigned to the route serving this stop as compared to other routes in the system.

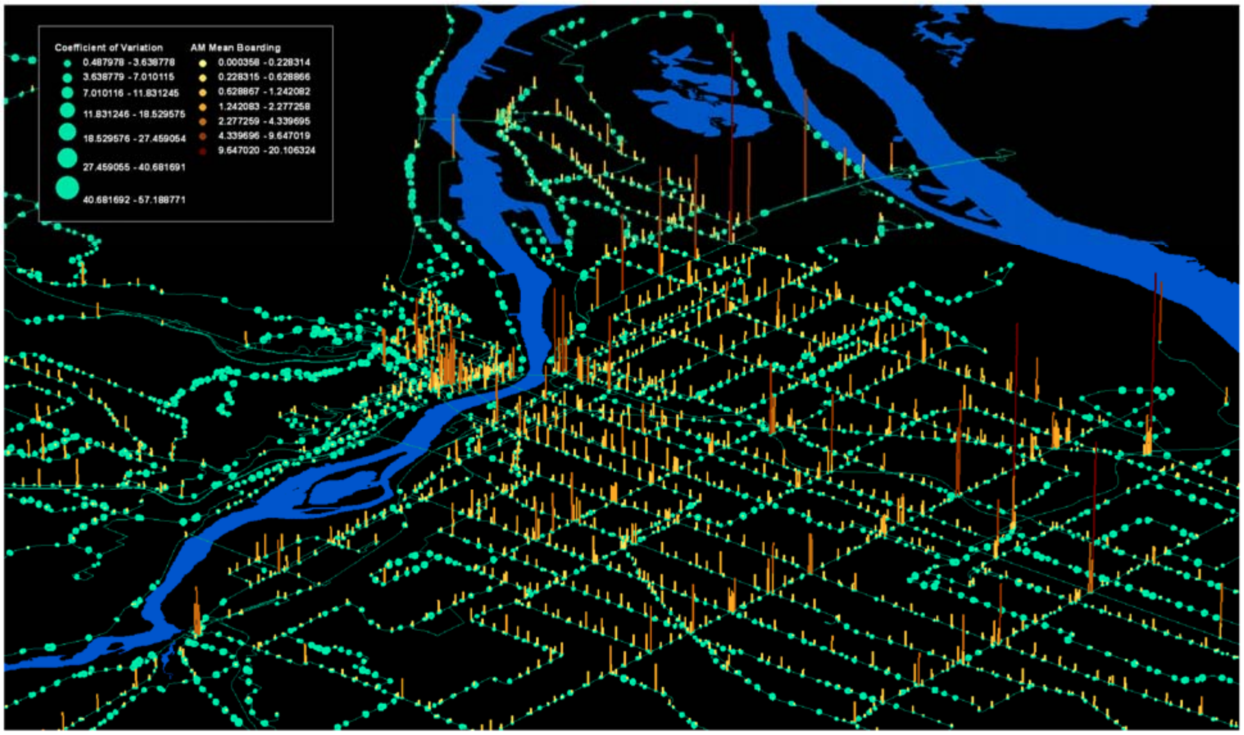


FIGURE 2 3D Passenger demand and variation.

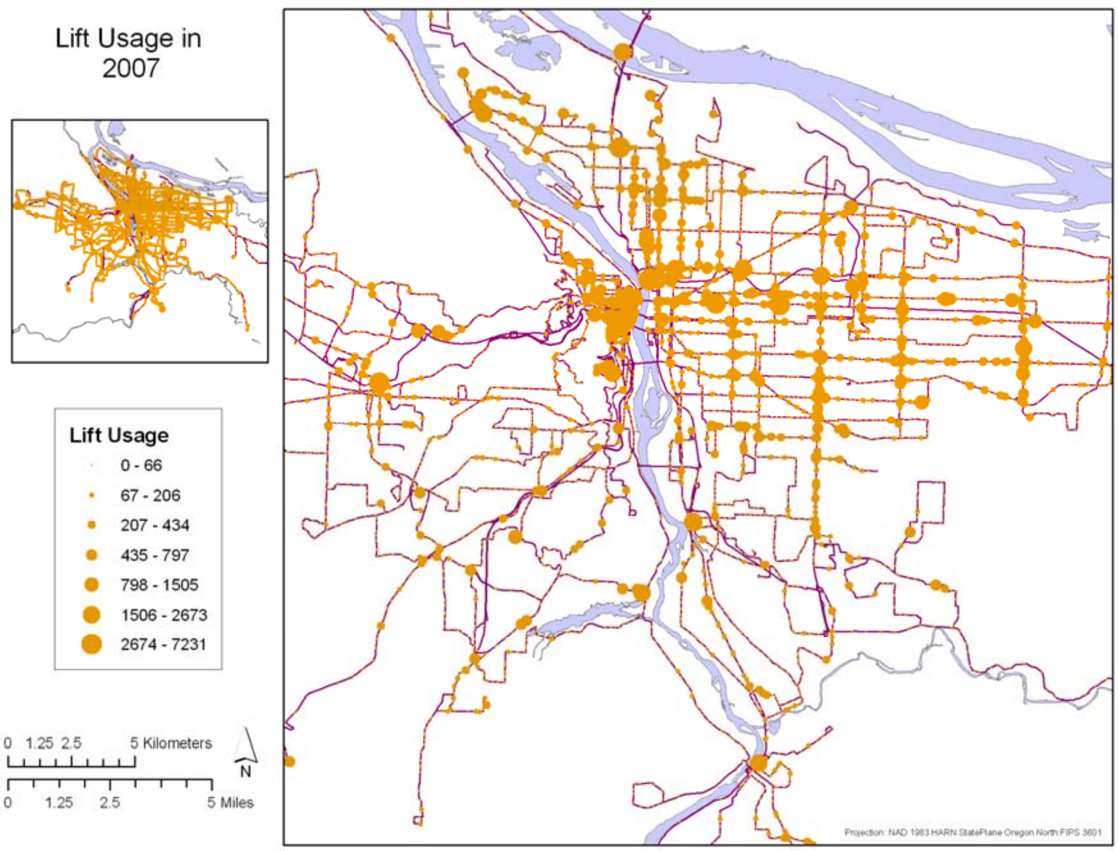
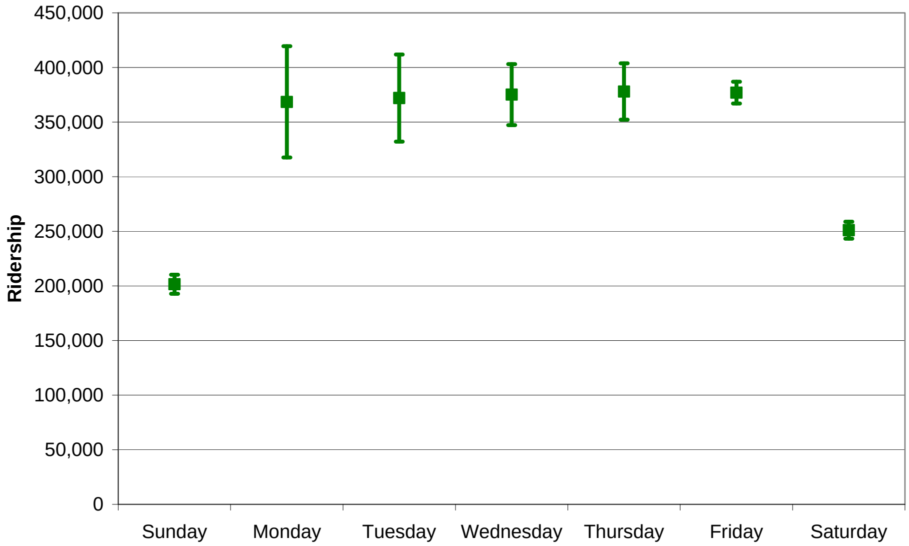
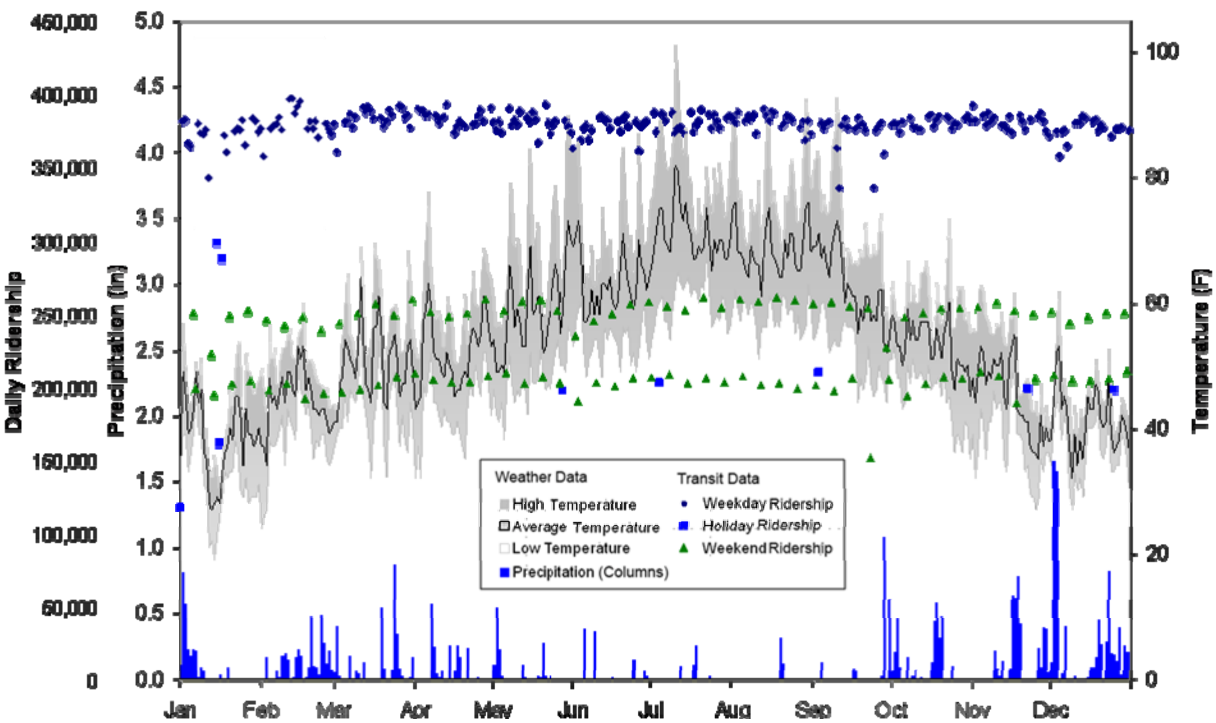


FIGURE 3 Total lift use in 2007.

In general, transit planners and engineers divide transit schedules into weekday, Saturday and Sunday services. Figure 4A shows the average ridership by day of the week plus and minus one standard deviation range for all days in 2007 (when the total ridership measured in the BDS was about 121 million riders). It is clear that Saturday and Sunday in general follow a different pattern in terms of ridership, yet the variation associated to these days is small as compared to all other days in the week. The amount of variation in transit ridership during weekdays starts at its highest levels on Mondays and ends at its lowest levels on Friday. Meanwhile the mean ridership during weekdays is almost constant. Accordingly, it is expected that TriMet usually faces system wide problems during Mondays as compared to other days of the week due to these variations in passenger demand. Variations in passenger demand are usually linked to variation in travel time and variation in headway (*10*).



A. Variation in transit ridership by day of week for 2007.



B. Relation between daily ridership, temperature and precipitation for 2007.
FIGURE 4 Daily system wide ridership in 2007.

Given the wealth of information that can be gained from an analysis of one year's worth of BDS data, it is also possible to combine data from other sources to examine correlations at the system level. For example, PORTAL archives weather data. In a city like Portland, known for its rainfall, there was a desire to explore the relationship (if any) between transit ridership and precipitation and temperature.

Toward this end, Figure 4B (the *x* axis represents the days of the year) shows total transit ridership each day in the year using the far left hand *y* axis. Passenger activity is shown separately for weekdays, weekends and holidays. The second left hand *y* axis is used to depict the daily measured precipitation (in inches) as a bar chart, while the right hand *y*-axis shows each day's average temperature and its variation (high and low). It is clear that transit ridership during the weekdays is nearly constant over the course of the year at about 374,000 per day. Neither changes in temperature nor precipitation seem to have a dramatic effect on total daily ridership. The phenomenon of Sundays having lower passenger demand than Saturdays, as indicated in Figure 4A, is still clear in this figure. Holidays also tend to experience even lower levels of demand than weekends. Portland, Oregon is a region that is well known for its long rainy season. Accordingly not having clear relationship between ridership and precipitation is not a surprising factor. Finally, it is clear that ridership does decline when the average temperature in a weekday is below 32^{o} F (0^{o} C).

ROUTE LEVEL ANALYSIS

It is now possible to move from the system level to the analysis of a particular route. For this research, we examined Route 72. A schematic of the 18 mile route is presented in Figure 5. For a large part of the route the bus traverses 82nd Avenue, a busy, four-lane auto oriented street that is characterized by stop and go traffic and is surrounded by strip mall style development on both sides of the street. Table 2 demonstrates some simple performance measures that can be generated from the data. Table 2 contains annual numbers for both all northbound and southbound trips as well as measures that focus only on the AM peak period.

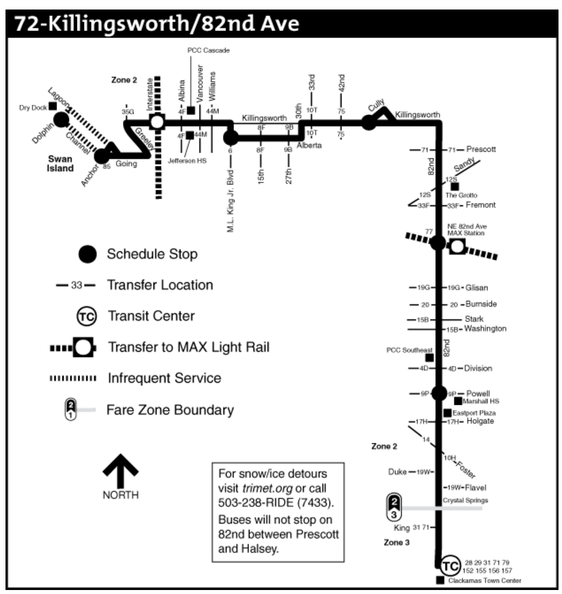


FIGURE 5 Map of TriMet Route 72 Killingsworth/82nd Ave.

When moving between different levels of analysis, it is important to note that a phenomenon noticed at the system level may not occur at the level of an individual route. This is clear in Figure 6, which shows the relationship between passenger boardings along Route 72 and mean temperature. The total number of boardings declined seasonally during periods with increased mean temperatures (especially in the summer) in the Portland region. The number of passenger boardings also declined during the last week of March. Route 72 is a suburb-to-suburb type of route (as opposed to a radial style route oriented toward downtown Portland) that serves a large number of students as well as other commuters. The effect of summer vacations, spring and winter break vacations, and other holidays is clear in the figure.

TABLE 2 2007 Annual Report for Overall Route 72 and for AM Peak Period

Total Annual Performance	Northbound	Southbound
Scheduled hours of service	34,002	32,042
Actual hours of service	36,547	32,233
Number of scheduled trips	29,464	27,432
Number of actual trips	27,436	26,875
Number of scheduled miles	491,134	442,442
Number of actual miles operated	517,856	494,345
Number of passengers carried	2,008,225	1,973,323
Total boardings and alightings	4,016,451	3,946,646
Average passenger load during each trip	16.5	16.6
Number of passengers per mile	3.9	4.0
Average scheduled speed (mi/h)	14.4	13.8
Average speed (mi/h)	14.2	15.3
Number of operators	502	487
Average trip time (min)	79.7	71.8
Trip time standard deviation (min)	13.9	13.1
AM Peak Period Performance	**Northbound**	**Southbound**
Actual trip time	3,711	3,442
Scheduled trip time	3,788	3,564
Actual Layover	19	17
Total dwell time	1,337	1,142
Total passenger boardings	240,320	200,064
Total passenger alightings	227,904	205,222
Total number of trips	2,804	2,890

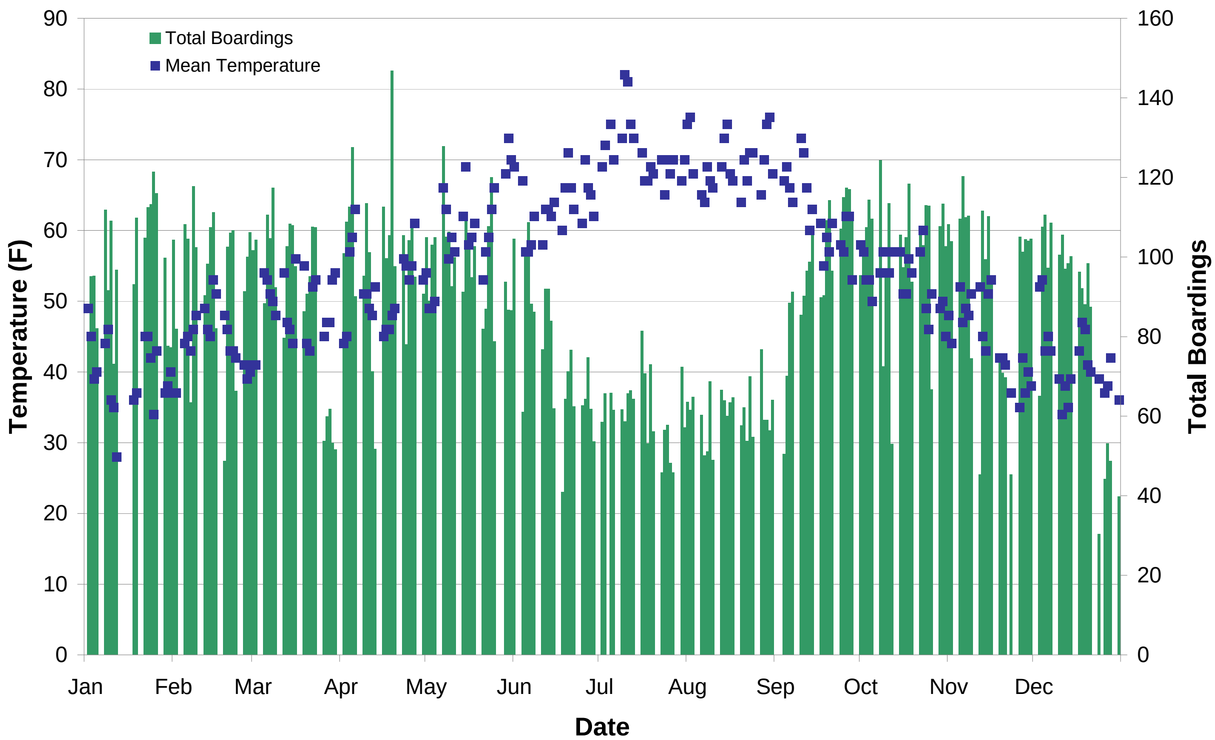


FIGURE 6 Seasonal effect on transit ridership along route 72.

Run Time Model

Run time refers to the amount of time that it takes a bus to traverse its route. Previous research (*17*) has found route length, passenger activity and the number of signalized intersections to be factors influencing mean run time. Most research agrees on these basic factors. Transit agencies, when attempting to optimize run times, face the conflicting forces of operating cost and service reliability (*2,18-21, 24*).

The variables used in generating a run time model are already present in current performance measure reporting. These variables are also present in TriMet's stop level database. Accordingly, run time models can easily be generated on a systematic basis. The major advantage of using a run time model is that it can be a useful tool when generating scenarios to measure and test the impacts of different planning and operations strategies. Most research attempting to quantify effects of certain strategies or policies in transit operations on run time use run time models to quantify these effects. A run time model can be formulated as a linear regression model:

$$Y = Ax_1 + Bx_2 + Cx_3 + \text{Constant}$$

where Y is the run time, x_1, x_2, and x_3 are variables influencing the run time, and A, B, and C are the strength of the effects of x_1, x_2 and x_3 on run time. A run time model provides the researcher with values for A, B, and C and an average run time can be obtained by multiplying A, B, and C by the mean values of x_1, x_2 and x_3 respectively.

As an example, consider a researcher that would like to test the effects of a particular strategy such as the implementation of TSP on run time in a region where TSP is partially implemented. To do so, the researcher would include a dummy variable in the model which would equal one if the data is obtained from a route with TSP and zero if the data is obtained from a non-TSP route. Calculating the average effect of TSP on run time can be easily done by inserting the mean values for all the variables in the model, with the exception of the TSP coefficient, and multiplying them by the coefficients and adding them. The output of this addition is the average mean travel time without TSP. Meanwhile average mean travel time with TSP can be calculated by adding the TSP coefficient to generate a new average run time value. Numerous run time models were tested using the 2007 BDS data for Route 72. Table 3 includes the output of one of these run time models as a sample.

TABLE 3 Run Time Model for TriMet Route 72

Variable	Coefficient	*t*-statistic	Mean
Distance (miles)	93.90	71.69	17.63
Scheduled Number of Stops	12.20	60.65	105.12
Southbound	−134.52	−31.18	0.49
AM Peak	−90.02	−13.78	0.10
PM Peak	399.42	68.90	0.14
Actual Number of Stops	5.82	24.20	50.60
Total Dwell Time	0.52	93.45	908.54
Boardings + Alightings	1.29	12.82	144.11
$(\text{Boardings + Alightings})^2$	0.01	4.85	25,769.44
Lift Use	30.43	16.14	0.56
Average Passenger Load	−0.84	4.90	16.66
Precipitation	90.23	7.91	0.08
Average Temperature	−2.28	−9.52	54.23
Summer (dummy variable if month = June through August)	62.46	9.86	0.25
Intercept (seconds)	665.93		
R^2	0.67		
N	53,130		

First we will start with interpretations of the model then will follow that with a scenario building methodology. All variables in the run time model are statistically significant at the 99% level of confidence. The run time model has an R^2 of 0.67. In addition, all variables in the model follow the transit operating theory in terms of direction. For example, the distance traveled along the Route 72 is found to be statistically significant with a positive effect on run time. Run time increases by 93 seconds for every mile traveled by the bus. This can be translated to an average speed of 38 miles/hour (60 km/hour) when all of the other variables in the equation are held at their mean values. Each scheduled stop adds 12.2 seconds to the travel time, regardless of whether the bus stops. Buses traveling in the southbound direction are faster than the ones traveling northbound by 134 seconds. This can be attributed to street characteristics and congestion levels in the particular direction. Other aspects that can be related to the level of congestion along the Route 72 corridor are the variables differentiating the time of day the data was collected. Morning peak trips are faster than off peak trips by 90 seconds, while evening peak trips are slower than midday by 399 seconds. This indicates a difference of 489 seconds in run time between the morning peak and the evening peak.

For each actual stop being made along this route, 5 seconds is added to the run time. On the other hand, for each second of dwell time, 0.52 second is added to the total run time. Each passenger activity (boarding or alighting) adds 1.29 seconds to the run time. The squared term for passenger activity (boardings + alightings) indicates that the time associated with each passenger activity increases with each additional passenger by 0.01 seconds. Using the lift during a trip adds 30 seconds, while keeping all other variables at their mean values. This value is different from other variables observed in previous research.

The average passenger load on the bus decreases the travel time by 0.84 seconds. In other words, it appears that the bus travels faster when there are more passengers onboard. For each inch of rain the travel time is expected to increase by 90 seconds, while each degree of temperature increase leads to a decline in run time of 2 seconds. Since a pattern of declining passenger activity during the summer seasons was noticed earlier, a dummy variable was added to represent the summer season. Surprisingly this variable shows that although passenger demand declines in the summer along this route, the amount of time need for a bus to travel along this route increased by 62 seconds in the summer while keeping all other variables at their mean values. This result is an example of where the model can reveal an unusual result and opens up an avenue for further research.

As an example of scenario testing with this model, consider the total number of stops served by this route. The total mean number of stops being served along the route is 105. The model predicts an average run time of 78.29 minutes. On the other hand, implementing a stop consolidation policy by removing 20% of the total number of stops would reduce the average number of stops to 84. This would results in 4.27 minutes of savings in run time with the new mean run time being 74.02 minutes. A variety of similar scenarios can be generated to help in the decision making process at a transit agency.

Dwell Time Model

It is also possible to focus on the details of what occurs at stops serving passengers on Route 72 by examining the dwell time. Dwell models were generated from the entire year's worth of data for Route 72. First, stops with only boarding passengers were examined (737,614 cases in 2007). The resulting model shows a fixed 5.29 seconds for stopping plus 2.99 seconds for each boarding passenger:

- Dwell = 5.29 + (2.99 × Boardings)
- R^2 = .409

This second model was performed using only records where a dwell of less than one minute occurred and passengers alighted only (876, 802 cases). The result is 6.54 seconds of fixed dwell time required to stop plus 1.38 seconds for each passenger alighting:

- Dwell = 6.54 + (1.38 × Alightings)
- R^2 = .189

Because boarding passengers have to pay their fare, passenger boardings tend to take longer than passenger alightings. The final model was performed on records where a dwell of less than one minute occurred and passengers both boarded and alighted (634,402 cases). The result is 9.60 seconds of base dwell time plus 2.20 seconds for each passenger boarding and 0.92 seconds for each passenger alighting:.

- Dwell = 9.60 + (2.20 × Boardings) + (0.92 × Alightings)
- R^2 = .410

Table 4 expands on the simple dwell models presented above by introducing other variables present in the AVL data to determine their impact on dwell time. We can interpret this dwell time model in a similar fashion to the way we discussed the run time model presented in Table 3. The intercept value suggests a base dwell time of 7.95 seconds. For each passenger boarding, the dwell time increases by 2.41 seconds while each passenger alighting adds 1.16 seconds. This relationship where boardings add more time to dwell than alightings is logical and consistent with previous studies (*8*). Each minute that a bus is late increases the average dwell by .09 seconds. The likely explanation is that passengers tend to accumulate at stops when buses are running behind schedule. Buses tend to dwell 2.04 seconds longer at stops that TriMet classifies as time points, which are stops where buses wait to get back on schedule, which leads to longer dwell times. For every inch of precipitation, dwells are 0.24 seconds longer while for every extra degree of temperature, dwell time increases 0.02 seconds. The squared term for boardings, which is negative, signifies that the amount of time taken by a passenger to board decreases with an increase in the number of passengers boarding. So this model would predict an average of 2.41 seconds for the first passenger, 2.40 for the second, 2.39 second for the third and so on. Finally, the low floor variable indicates that the low floor feature on a bus reduces dwell time by 0.66 seconds on average.

TABLE 4 Dwell Time Model for TriMet Route 72

Variable	**Coefficient**	***t*-statistic**
Boardings	2.41	521.96
Alightings	1.16	166.86
Late	0.09	26.67
Time Point (dummy)	2.04	60.37
Precipitation	0.24	3.81
Average Temperature	0.02	19.00
Boardings^2	−0.01	−102.34
Alightings^2	−0.02	−59.41
Low Floor Vehicle (dummy)	−0.66	−7.08
Intercept (seconds)	7.95	
R^2	0.443	
N	627,022	

SEGMENT LEVEL ANALYSIS

Finally we turn to the segment level of analysis. In transit planning and operations headways are a critical element and are key performance measures for transit service reliability. Headway variation results in excess passenger waiting time for passengers (*22*). This is particularly important as research suggests that passengers value waiting time 2 to 3 times more than they value in-vehicle time (*23*). For agencies, headways relate to system productivity and efficiency and headway variation translates to lost time. Headways are usually dealt with at the segment level since transit agencies try to adjust headways in the middle of the route to avoid excess waiting time for passengers waiting downstream.

Figure 7 shows the mean headway measured at a sample of stops along Route 72, and plus/minus one standard deviation of headway is shown in the same figure. It is clear from the figure that headway variation increases with distance traveled along the route until a particular stop where headway variation declines sharply before starting to increase again. At stop 50 (NE 82nd Ave. & MAX Overpass), some factor is leading to a decline in the variation of the headway along the route. First of all this bus stop is both a time point and a transfer point to the MAX light rail system. Observing the passenger activity that is also shown in Figure 7 using the right hand *y*-axis it is clear that the passenger load declines at a higher rate compared to all other stops when the bus reaches this stop.

Yet the large number of passengers alighting at this stop is not the only cause of the improvement in headway variation. Being a time point, NE 82nd & Max Overpass is a location where buses attempt to get themselves back on schedule. However, the figure indicates that this stop is one of several time points. Other time points do not appear to be experiencing the same dramatic improvement in headway variation. Shifting down to a point level analysis will shed even further light on the situation.

POINT LEVEL ANALYSIS

Figure 8A is a histogram illustrating the difference in dwell times between the NE 82nd Ave & MAX Overpass stop and the previous time point at stop 31 (SE 82nd & Powell). Most dwells at SE 82nd & Powell, which are represented as blue vertical bars in the figure, are less than 1 minute long. The NE 82nd & MAX Overpass stop, by contrast, has a much wider distribution of dwell times. This suggests that buses are taking more time at this stop to right its schedule. Figure 8B, which shows a histogram of late/early status, sheds further light on this question. In

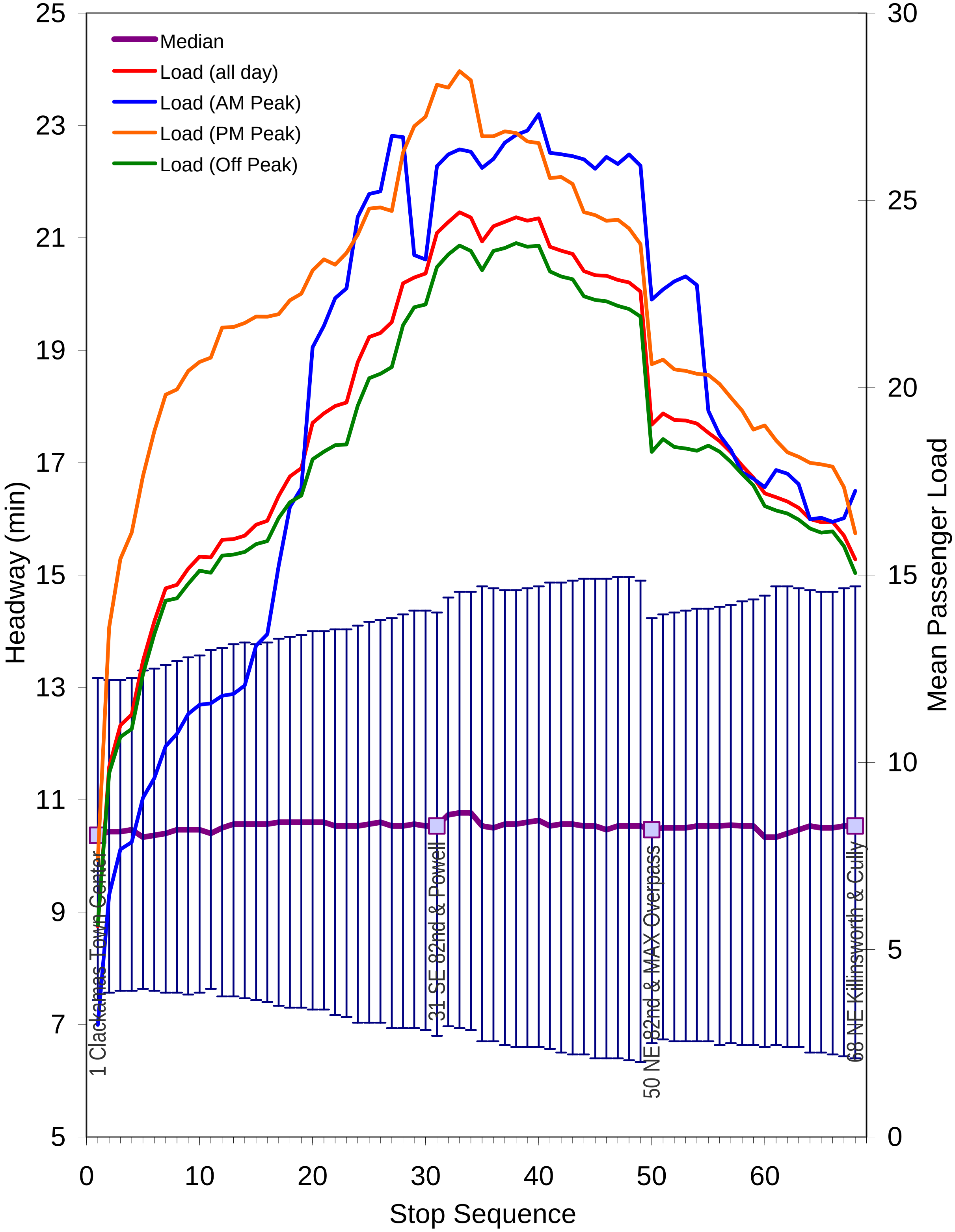
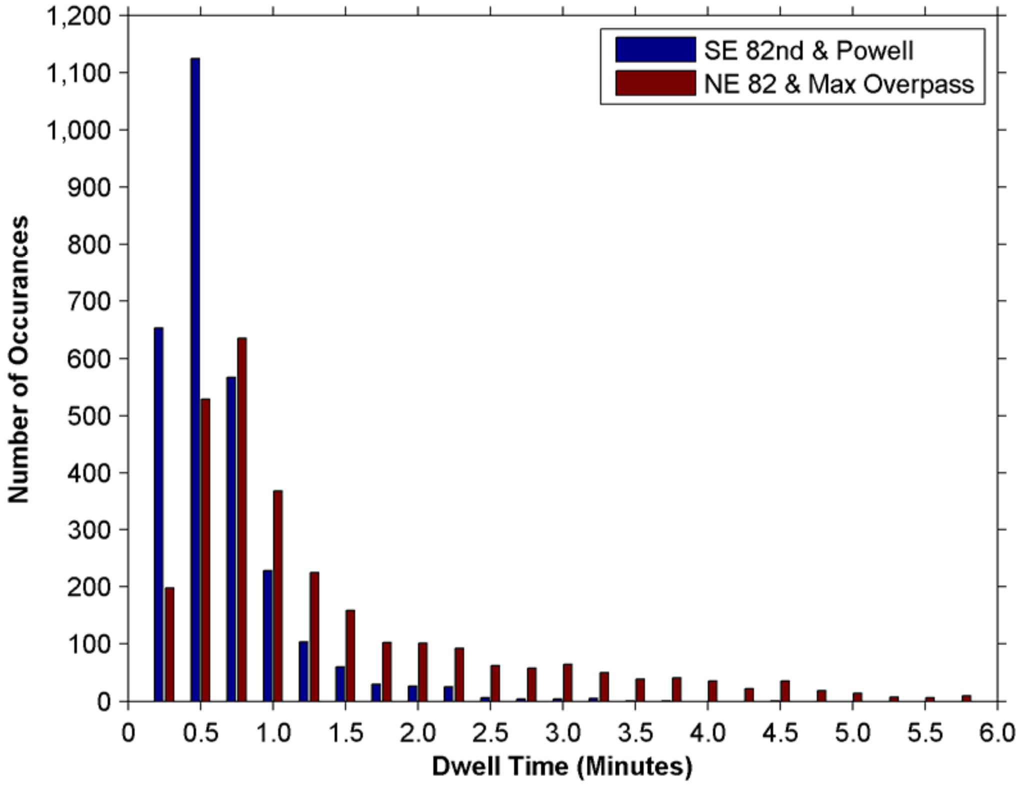
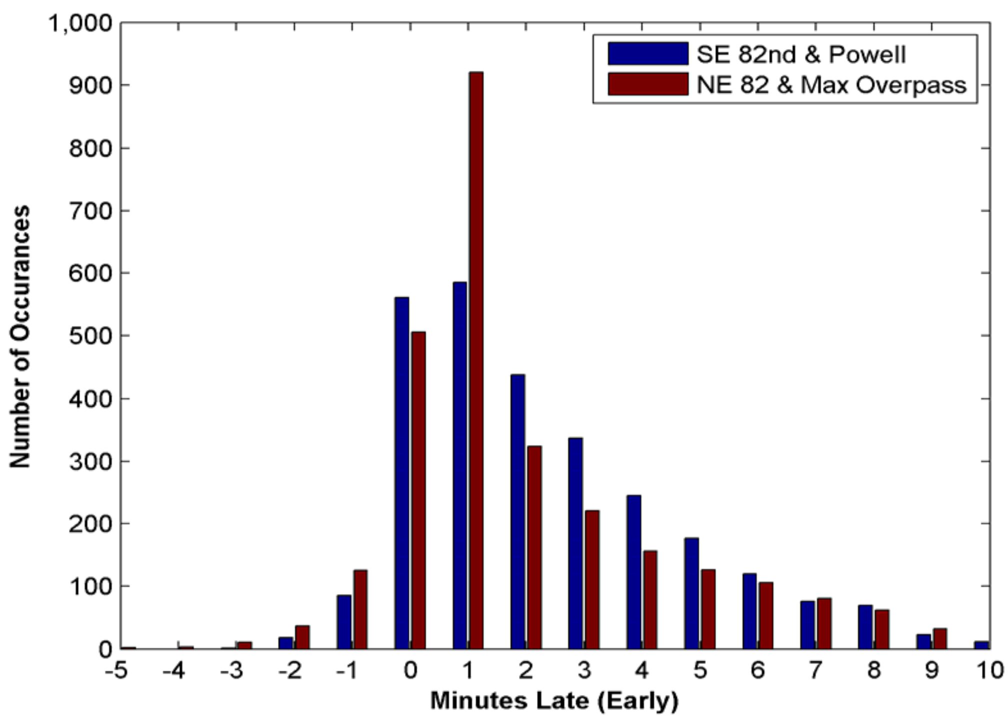


FIGURE 7 Mean and variation of headway and passenger load along route 72 (2007).



A. **Dwell time histogram.**



B. Late/early status histogram.

FIGURE 8 Point level analysis at successive time points.

general, the bus tends to be running more behind schedule at SE 82nd & Powell (blue) as compared with NE 82nd & MAX Overpass (red). The likely explanation is that TriMet has inserted extra time into the schedule for the bus at NE 82nd & MAX Overpass, where there is more physical space available for the bus to pull out of traffic to right its schedule. Thus, despite longer dwell times, the bus tends to be late leaving this stop less often than at the previous time point.

CONCLUSION

Measuring the performance of a transit system is the first step toward efficient and proactive management. In this research we move beyond the generation of regular performance measures to introduce a set of visualization tools with a concentration on generation of performance measures related to variability of service. We also introduced a set of statistical analyses that can be easily conducted to be used in measuring various performance measures and strategies. TriMet does generate several performance measures that are considered to be at the leading edge in the transit industry, yet several opportunities do exist to build on existing efforts. The run time model introduced here can be easily used to track benefits of individual service improvements or strategies being implemented.

This experiment has shown that by using real archived data from a BDS it is possible to obtain valuable information and highlight the variation in the transit service. These direct performance measures can be used to compare performance by route, day and ultimately even by month or year. It is significant that TriMet had the foresight to archive all of its stop-level data, thereby making it possible to analyze useful measures of transit performance. This paper has demonstrated the powerful ways that BDS data can be converted into powerful TPMs) Using such measures in a regular, systematic manner can greatly aid transit providers in improving both the quality and reliability of their service.

The value of utilizing the vast amount of data collected by the BDS is that it eliminates the need to make estimates and assumptions about time-varying behavior that tend to be found in aggregate measures of performance. Because TriMet archives their data each day, measures can be generated automatically on a daily, weekly, monthly and annual basis. These measures can be introduced to transit providers to test their usefulness for planning and day to day operations. By demonstrating further applications of this data source, it is hoped that more transit employees can be equipped with performance information and the tools to perform their jobs more effectively, ultimately leading to measurable improvements in transit service in the future.

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