RESEARCH

DEVELOPING CORRIDOR-LEVEL TRUCK TRAVEL TIME ESTIMATES AND OTHER FREIGHT PERFORMANCE MEASURES FROM ARCHIVED ITS DATA

Final Report

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16. Abstract

The objectives of this research were to retrospectively study the feasibility for using truck transponder data to produce freight corridor performance measures (travel times) and real-time traveler information. To support this analysis, weigh-in-motion data from each of the twenty-two stations in Oregon were assembled, processed, and uploaded in the WIM data archive is housed under the Portland Transportation Archive Listing (PORTAL) umbrella at Portland State University's Intelligent Transportation Systems Lab. Nearly 42,000,000 truck records were successful uploaded to the archive dating back to July 2005. Two separate algorithms necessary for this research were scripted, tested, and validated. The closest stations are 38.3 miles apart; the greatest are 258 miles apart. The first algorithm matched transponders between of all vehicles in a time window between the upstream and downstream stations. The second algorithm filtered these matches for through trucks. The filter was validated by comparing estimated travel times during a winter weather-induced delay. The analysis showed that corridor-level travel times for trucks for 2007 and 2008 could be generated from the archived data. To explore the feasibility using these same data for real-time traveler information, ground truth probe vehicle data were collected. Travel time estimates from the WIM data and the probes were used to establish a simple linear relationship between passenger car and truck performance. It was concluded that the long distances between stations was a primary challenge to directly adapting the WIM data to real-time use. Recommendations were given on increased sensor spacing and filter improvement. Finally, potential performance metrics for station level, matched trucks, and filtered matched truck data were shown
17.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	millimeters squared	mm^2
ft^2	square feet	0.093	meters squared	m^2
yd^2	square yards	0.836	meters squared	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	kilometers squared	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	ml
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	meters cubed	m^3
yd^3	cubic yards	0.765	meters cubed	m^3
	NOTE: Volumes greater than 1000 L shall be shown in m^3.			
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams	Mg
		TEMPERATURE (exact)		
°F	Fahrenheit	(F-32)/1.8	Celsius	°C

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	millimeters squared	0.0016	square inches	in^2
m^2	meters squared	10.764	square feet	ft^2
m^2	meters squared	1.196	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	kilometers squared	0.386	square miles	mi^2
		VOLUME		
ml	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	meters cubed	35.315	cubic feet	ft^3
m^3	meters cubed	1.308	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.205	pounds	lb
Mg	megagrams	1.102	short tons (2000 lb)	T
		TEMPERATURE (exact)		
°C	Celsius	1.8C+32	Fahrenheit	°F

*SI is the symbol for the International System of Measurement

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1.0 INTRODUCTION

The efficient, timely, and reliable movement of freight is a critical responsibility of the transportation system and is strategically important to the U.S. economy. The sheer amount of freight moved in 2002 by all transportation modes in the United States alone is staggering – some 11 trillion dollars of freight (*USDOT 2004*). Similarly, the transportation of freight is an important component of the Oregon economy. The Federal Highway Administration estimates that from 1998 to 2010, the total tonnage of freight shipments to, from, and within Oregon will have increased 50 percent and the value of those same shipments will have nearly doubled. While other modes are clearly important for freight transportation, trucking is the dominant mode in terms of tons and value. Forecasts suggest that the truck market share is likely to grow as shippers move towards smaller and more time sensitive shipments.

Freight planning and performance measurement is becoming more important for state agencies, cities and ports. Obtaining the necessary freight data, however, can be challenging given the complex and vast nature of good movement. The existing intelligent transportation systems (ITS) infrastructure for motor carrier weight and safety enforcement in Oregon, Green Light, provides a potential opportunity to estimate travel time for many freight corridors with little additional investment. Commercial vehicles that participate in the Green Light program are equipped with a transponder, or electronic license plate. To date, the Green Light program has enrolled approximately 3,330 trucking companies with 30,200 transponder-equipped trucks. This does not include carriers participating in other electronic screening programs from other states such as the North American Pre-Clearance and Safety System (NORPASS) or PrePASS systems, whose transponder identification data can be read and logged by the Green Light stations.

All of the Green Light stations are equipped with automatic vehicle identification (AVI) antennas, weigh-in-motion scales, and over height detection equipment. As a vehicle approaches a fixed weigh station, the transponder can be read and the vehicle uniquely identified. That information, along with the vehicle gross and axle weights is recorded and archived whether or not the station is actively open for weight enforcement. There are 22 equipped stations in Oregon where these transponders can be read.

Since a transponder-equipped truck can be uniquely identified at two stations, estimates of the vehicle's travel time can be made. Using automatic vehicle identification (AVI) to estimate corridor (link) travel times is not unique. Many metropolitan areas currently utilize electronic tolling technology to assess link performance, and many studies have offered alternate vehicle identification and tracking methods. While there has been success in using passenger vehicle AVI to predict travel times in urban areas, estimating corridor travel times using truck transponder data presents a different set of challenges:

- The market penetration of transponder tags in freight vehicles is generally lower and varies by location**;**
- the distance between weigh stations (reader locations) are relatively long;

- trucks may stop for fuel, rest and deliveries;
- and if comparisons to passenger cars is desired, truck travel speeds are different.

Thus, even if vehicle matches are made between transponder readers, accurate travel times may not be easy to predict. Because uncertainties about travel time estimates increase as the length increases, these elements combine to require a relatively large sample size to accurately predict link travel times. Long link travel estimates also heighten the issue of latency of traveler information, since incidents, delay, or weather may have developed after a vehicle has traveled the link. While this is a common problem for all time-dependent traveler information, it is heightened with long links encountered between AVI readers for motor carriers.

In this research, we explore the use of the data collected by the existing infrastructure to generate corridor level performance measures, real-time traveler information, and other freight-related metrics.

1.1 OBJECTIVES

The objectives of this research were:

- to retrospectively study truck transponder data in key corridors to determine the feasibility of producing freight corridor performance measures; and
- to study the feasibility of using transponder data from commercial vehicles to predict corridor travel times with existing infrastructure for real-time traveler information.

1.2 ORGANIZATION OF REPORT

Following this chapter, a review of the related literature is presented. The review focused on current transponder programs and technologies, tag matching algorithms, and vehicle signature matching techniques. Freight performance metrics are briefly highlighted. Chapter 3 describes the assembly, processing, and structure of the weigh-in-motion data used in this research to develop truck travel time estimates on identified freight corridors. Next, in Chapter 4, a comparison of these truck estimates are compared to ground truth probe data that were collected as part of this research. Chapter 5 describes additional freight and corridor performance measures that could be generated by the assembled data. Finally, Chapter 6 presents the conclusions and recommendations.

2.0 LITERATURE REVIEW

The objective of this literature review is to summarize the results of previous studies associated with the challenges in providing traveler information. The topics include a brief background of current transponder programs and technologies, study results on tag matching algorithms, and current vehicle signature matching techniques. Also, this review briefly highlights the work freight-related performance metrics. Accordingly, this literature review identifies related information from four areas:

- Review of electronic screening programs and truck transponders.
- Tag matching algorithms (trucks and toll tags).
- Signature matching (weight and vehicle).
- Freight performance metrics.

2.1 ELECTRONIC SCREENING PROGRAMS

Three main programs currently operate in conjunction with weigh-in-motion (WIM) stations to identify and screen vehicle safety records and classification information, these include: the Heavy Vehicle Electronic License Plate (HELP) PrePass program, the North American Pre-clearance and Safety System (NORPASS), and the Oregon Green Light Program. Each program utilizes similar transponder technology to allow qualifying motor carriers to bypass designated weigh stations. The transponder is a dedicated short range communication device which electronically identifies freight vehicles. When transponder equipped vehicles approach HELP, NORPASS, or Green Light stations, their weight and credentials are automatically reviewed and drivers are either given an in-cab green light (giving them permission to continue) or a red light (instructing them to pull in). While these programs prove very effective independently, interoperability problems exist between the for-profit HELP program and the free NORPASS and Green Light programs. As the agreement currently stands, NORPASS and Green Light transponders are read in the PrePass network, but PrePass transponders cannot be read outside of this network. While this study is not affected by this issue, interoperability problems will need to be resolved should freight AVI tags ever be used to develop tri-state (California, Oregon, and Washington) travel time estimations along major corridors.

2.2 TRUCK TRANSPONDER MATCHING

While there has been success in utilizing passenger vehicle AVI data to estimate link travel times, estimating corridor travel times using truck transponder data presents many different challenges. These challenges have been mentioned above.

2.2.1 Washington TRAC Truck Tag Project

Hallenbeck et al.*(2003)* conducted a study on deriving freight metrics from ITS data sources, including the use of truck transponders for predicting corridor travel times. Data for the analysis came from two sources within Washington: the WIM system, and the US/Canadian border system which was designed to pre-screen and track trucks. Truck transponders could be obtained in one or both directions from WIM stations on Interstate-5 at Ridgefield, Fort Lewis, Stanwood Bryant, and Bow Hill, and on Interstate-90 at Cle Elum. Tags could additionally be read at the Port of Seattle, the Port of Tacoma, and North and Southbound at the Blaine border station between Washington and British Columbia. Two major concerns became apparent upon a preliminary analysis of transponder data: a truck could exit before reaching the next reader or appear in the middle of the segment, and when traveling long distances, drivers frequently stop for a variety of reasons. To address these concerns, the algorithm developed for the Washington study excluded trucks not recorded at both readers of a link, and identified "outliers" in travel times that had similar start times on the link being monitored.

In order to remove data which may not have been representative of traffic conditions, Hallenbeck et al. determined that it was first necessary to determine which data provided accurate travel time estimations. During each 5-minute data acquisition interval, there may have been data points representing several trucks on the same freeway link. In order to convert these data points into a single value, only the data point with the fastest link speed was considered to be the representative value for the given interval. This "fastest truck" filtering step was based upon the assumption that of all trucks traveling on a link, the fastest best represents actual link conditions, and slower trucks are not representative. Once the best available travel time estimation for each 5-minute interval was determined, it was possible to determine which points should have been used as estimates of link performance and which should have been filtered out. To do this, consecutive 5-minute intervals were identified where a sudden, significant change in travel time has been observed. This filtering step was based upon the assumption that link performance generally changes in a "smooth" manner, assuming there are no blocking incidents, and therefore observed consecutive truck travel times should be relatively similar. It was possible, however, that for several consecutive intervals the fastest truck filtering step recorded trucks which made stops between reader stations, and thus a truck in question may not have appeared to have an observed travel time significantly lower than those recorded in its adjacent intervals. To ensure data of this nature was excluded from travel time estimation, a second series of comparisons was made using 10-minute consecutive intervals.

The Washington study found that the use of truck transponders to estimate travel time was limited by the challenges discussed above. However, the study concluded that the use of transponder tags to estimate corridor travel times was a promising approach. Accordingly, the Washington DOT has continued working with the Washington State Transportation Research Center (TRAC) to expand and enhance the use of truck AVI tags in the I-5 corridor in an effort to estimate travel times. They have supplemented the existing Washington Commercial Vehicle Information Systems Networks (CVISN) sites with tag readers that have been installed every 50 miles on I-5. TRAC is also working on refining the algorithms used for filtering, matching, and estimating travel times in the I-5 corridor (*Hallenbeck et al. 2003)*.

Researchers at TRAC have continued to develop the truck tag matching research effort. The main goal of this effort is through using transponder tags to calculate the freeway travel times for freight. When a truck equipped with transponder passes through the weigh station, the tag on the truck is recorded. Additional tag readers were installed on the I-5 corridor (though a recent discussion with Ed McCormack at TRAC indicated that the additional readers are not yet operational). Usually the record includes timestamp (time and date), location, direction, lane and tag number. When the same truck passes through another weigh station, a tag segment is developed. These tag segments then help to estimate travel times and speed of the segment. The project, described as the "Truck Tag Project" has developed a database architecture as shown in Figure 2.1.

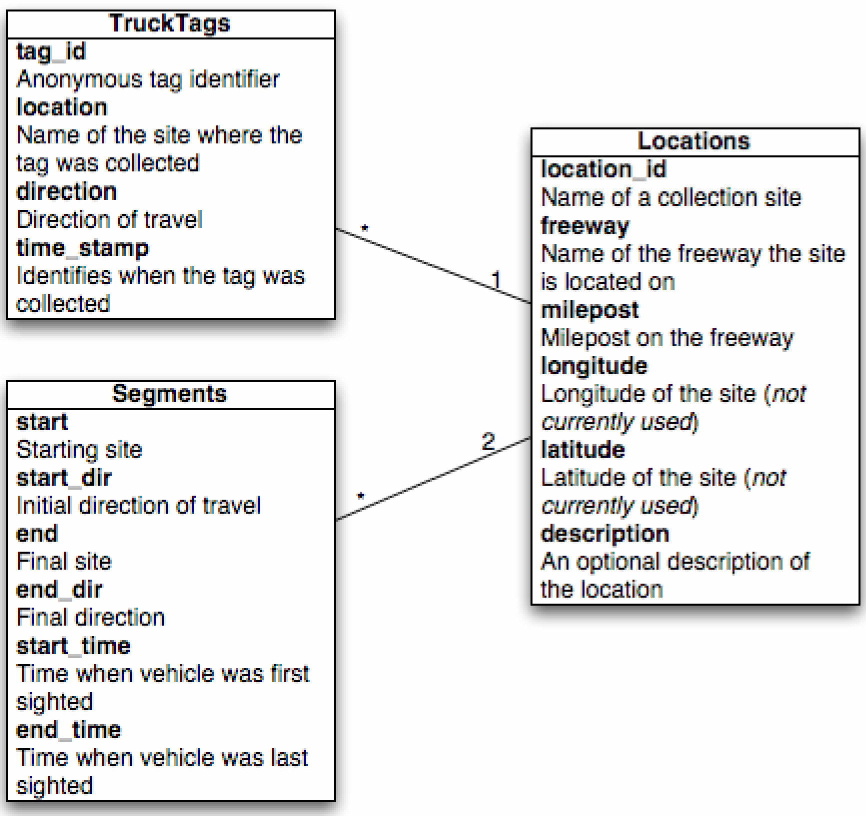


Figure 2.1: Database Schematic for TRAC Truck Tag Project

The other objective of the "Truck Tag Database" is to use it, along with High Occupancy Vehicle database (HOV) to add to the statewide data archive. The statewide archive is an integrated set of data sources which include Truck Tag data, Vehicle Occupancy data and Loop Detector data. Each component collects processes and stores data from different data sources and presents them in an appropriate manner. Finally a "TRACMap" (map-based web interface) is developed from this archive. By using TRACMap, users can select a data set and a year and get access to all available data with a summary table. Figure 2.2 exhibits the database structure of the current statewide archive.

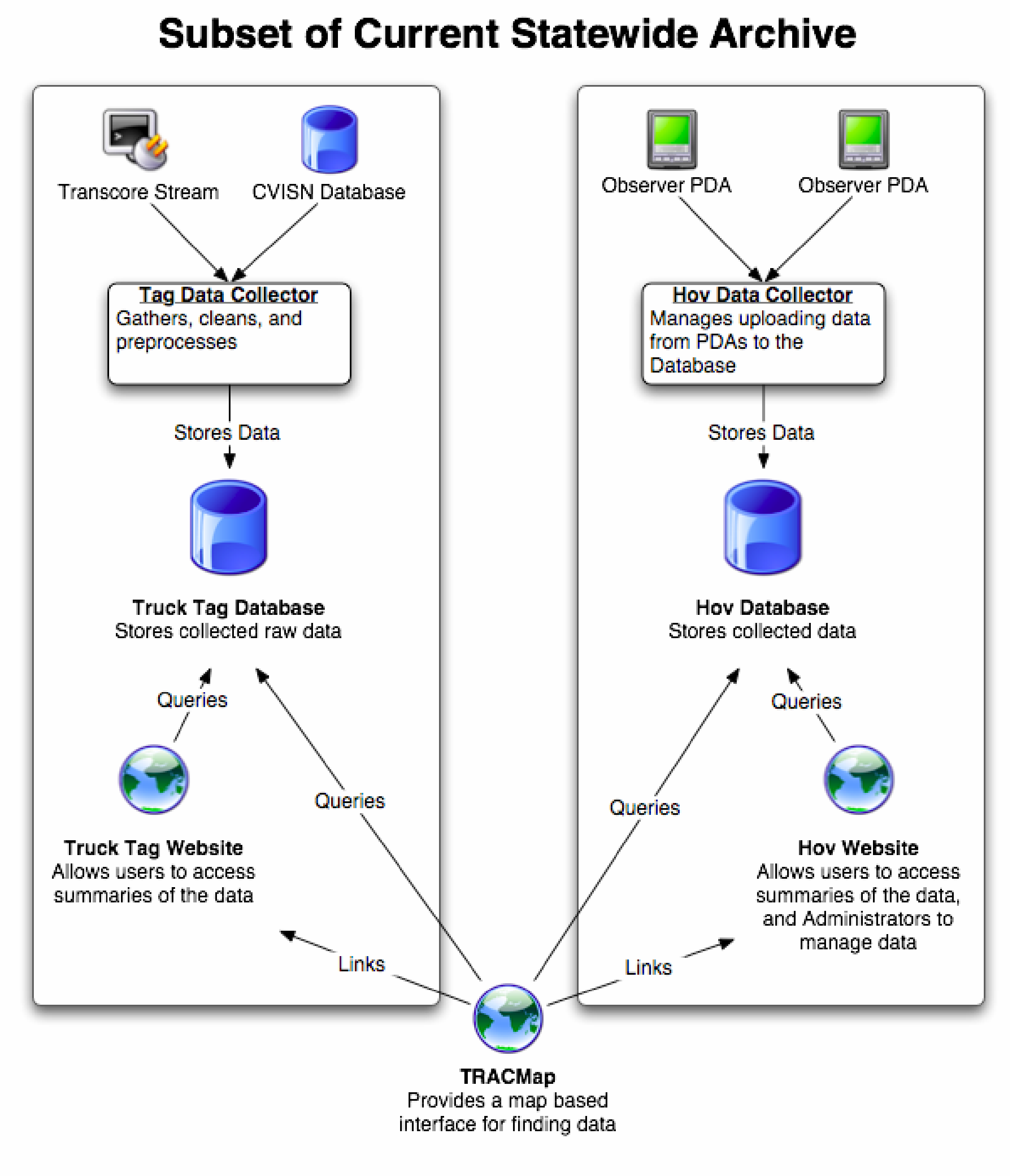


Figure 2.2: Database Schematic of Statewide Archive (TRAC).

2.3 TOLL TRANSPONDER MATCHING

AVI tags have been used around the country to assess urban corridor performance. In many metropolitan areas with electronic tolling systems, passenger vehicles are equipped with transponder technology similar to that used with Oregon motor carriers. With passenger cars in an urban freeway system, transponder market penetration is high, the spacing between reader locations is much shorter, and the possible routes are fewer. Dion and Rakha *(2003)* state that as of 2002 three traffic management systems were using AVI data to predict link travel times: TranStar in Houston, TransGuide in San Antonio, and Transmit in New York / New Jersey. The data filtering algorithms implemented by each system were described and critically evaluated.

2.3.1 TranStar Algorithm

Travel times within the TranStar system are estimated using a rolling average algorithm which automatically filters out all travel times which lie outside a user-defined link travel time. This algorithm is defined by the following equations, where Equation 1 defines the set of valid recorded travel times that is used to estimate travel time between two AVI readers and Equation 2 determines the average travel time between readers:

$$Stt_{ABt} = \{t_{Bi} - t_{Ai} | t - t_w \le t_{Bi} \le t \ \ \textbf{and} \ \ tt'_{ABt}(1 - 1_{th}) \le t_{Bi} - t_{Ai} \le tt'_{ABt}(1 + 1_{th}) \qquad \textbf{[1]}$$

$$tt_{ABt} = \frac{\sum_{i=1}^{Stt_{ABt}} (t_{Bi} - t_{Ai})}{|Stt_{ABt}|} \qquad \textbf{[2]}$$

where:

Stt_{ABt} = Set of valid recorded travel times from reader A to reader B at time t,

t_{Ai} = Detection of vehicle *i* at reader *A* (seconds),

t_{Bi} = Detection time of vehicle *i* at reader *B* (seconds),

t = Time at which travel time estimation takes place (seconds),

t_w = Rolling average window (seconds),

l_{th} = Link threshold travel time parameter (varies between 0 and 1),

tt_{ABt} = Average travel time from reader *a* to reader *B* that is estimated at time *t* (seconds), and

tt'_{ABt} = Previously estimated average travel time from reader *A* to reader *B* (seconds).

The function of the algorithm depends upon the user defined rolling average window, t_w, and the link threshold travel time parameter, l_{th}. The rolling average window designates the period of time considered when estimating average travel time (i.e. if a 30-second window is defined, only vehicles which passed the downstream reader in the last 30 seconds are considered when averaging travel time). Alternatively, the link threshold travel time is used to exclude from calculation travel times which may not be representative of traffic conditions (i.e. if the link threshold is set at .20, any estimated individual vehicle travel times between reader locations which differ by more than 20 percent from the previously estimated travel time is excluded). The TranStar algorithm uses a rolling average window of 30 seconds and a link threshold parameter of 0.20. Estimated travel times are updated each time new travel time information is obtained from an individual vehicle.

2.3.2 TransGuide Algorithm

The TransGuide algorithm is very similar to the TranStar algorithm, as it uses the same equations to predict travel times. The only major difference is that travel times are updated at periodic intervals as opposed to every time new travel time information is obtained from individual vehicles. Additionally, it is suggested that the algorithm uses a 2-minute rolling average window, and 0.20 link threshold parameter.

2.3.3 Transmit Algorithm

The methodology utilized by the Transmit algorithm is fairly similar to the other systems. However, as opposed to using a rolling average to obtain travel time estimates, they are developed using fixed 15-minute observation intervals. A sample of up to 200 individual link travel times may be recorded during each interval, and the sample is then used to estimate an average travel time using the following equation (Equation 3):

$$tt_{ABk} = \frac{\sum_{i=1}^{n_k} (t_{Bi} - t_{Ai})}{n_k} \qquad \textbf{[3]}$$

where:

tt_{ABk} = Average link trave time from readers *A* and to reader *B* in the k_{th} 15-minute interval (seconds),

t_{Ai} = Detection time of vehicle *i* at reader *A* (seconds),

t_{Bi} = Detection time of vehicle *i* at reader *B* (seconds), and

n_k = Number of observed travel times in k_{th} 15-minute interval.

Following the development of an estimation of the average travel time for the current interval, historical data and an exponential smoothing algorithm are used to “smooth” the estimation. To ensure the accuracy of the estimation during periods of non-recurring congestion, the algorithm uses a smoothing factor of 10 percent when no “incident” is detected or reported, and 0.0 percent when incidents are present. The following equation (Equation 4) describes the smoothing algorithm:

$$tth''_{ABk} = (\alpha)tth_{ABk} + (1-\alpha)tth''A_{ABk-1} \qquad \textbf{[4]}$$

where:

tt_{ABk} = Estimated average link travel time from reader A to reader B for k_{th} 15-minute interval (seconds),

tth_{ABk} = Historical smoothed travel time for k_{th} 15-minute interval (seconds),

tth''_{ABk} = Updated historical smoothed travel time for k_{th} 15-minute interval (seconds), and

α = User-specified smoothing parameter, currently set at 0.1.

Incidents within Transmit are either reported manually, or through an automatic detection algorithm. The algorithm monitors the number of vehicles which fail to pass monitoring stations within free flow expected times, and sets off an alarm when this number surpasses a user defined threshold.

2.3.4 Dion and Rakha Proposed Algorithm

Two main differences exist between the TransGuide/TranStar and Transmit systems: the method by which observed travel times are filtered, and the inherent ability of each system to reflect short term fluctuations in traffic. In the TransGuide/Transtar algorithms, assumed invalid travel times are removed before calculation, while the Transmit algorithm simply "smoothes" invalid data using historical average travel times. Because the Transmit system relies upon weights assigned to newly collected and historical averages, the system slowly adjusts to observed changes in traffic from day to day, and therefore cannot be used for real-time traffic functions. The TransGuide/Transtar systems, on the other hand, are capable of reporting current travel times fairly accurately. With rolling average windows of 30 seconds and 2-minutes, and link threshold parameters of 20 percent, TranStar and TransGuide are able to report changes in travel time that do not cause the average travel time to change by more than 20 percent every 30 seconds and 2-minutes respectively.

As both the TransGuide and TransStar systems utilize similar algorithms to track short-term changes in average link travel times, differences lie in their ability function within their respective networks. While TranStar was found to be more effective in tracking short-term changes in traffic conditions, both networks experience problems due to low rates of AVI equipment penetration. The TranStar system collects information from approximately 9 percent of passing vehicles, while TransGuide is only able to track about 1 percent.

Dion and Rakha present an algorithm which overcomes the shortcomings of the preceding systems by effectively addressing issues presented by dynamic traffic conditions and low levels of AVI tag market penetration. The algorithm first removes duplicate records frequently generated by tag reading technology, then applies a series of filters to remove invalid observations. The validity range of observed travel times is determined by the following four factors:

a) Expected average trip time and trip time variability in current interval,

b) Number of consecutive intervals without any readings since the last recorded trip time,

c) Number of consecutive data points that are either above or below the validity range, and

d) Variability in travel times within an analysis interval.

An adaptive smoothing exponential technique is used to calculate average trip time and trip time variability. These parameters are calculated by Equations 5 and 6.

$$\left(tts_{AB}\right)_k = \begin{cases} e^{[(\alpha)\ln(tt_{AB})_{k-1}+(1-\alpha)\ln(tts_{AB})_{k-1}]} & if\ n_{vk} > 0 \\ (tts_{AB})_{k-1} & if\ n_{vk} = 0 \end{cases} \qquad \textbf{[5]}$$

$$\left(\sigma^2{}_{stt_{AB}}\right)_k = \begin{cases} (\alpha)(\sigma^2{}_{tt_{AB}}) + (1-\alpha)(\sigma^2{}_{stt_{AB}})_{k-1} & if\ n_{vk} > 1 \\ (\sigma^2{}_{stt_{AB}})_{k-1} & if\ n_{vk} \le 1 \end{cases} \qquad \textbf{[6]}$$

where:

$(tt_{AB})_k$ = Observed average travel time between readers A and B in the k^{th} sampling interval (seconds),

$(tts_{AB})_k$ = Expected (smoothed average travel time between readers A and B in k^{th} sampling interval (seconds),

$(\sigma^2{}_{ttAB})_k$ = Variance of observed travel times relative to observed average travel time in k^{th} sampling interval (seconds),

$(\sigma^2{}_{sttAB})k$ = Variance of observed travel times relative to expected men in k^{th} sampling interval (seconds),

n_{vk} = Number of valid travel time readings in k^{th} sampling interval, and

α = Exponential smoothing factor.

Both equations utilize a lognormal distribution to account for the fact that travel times will generally be longer than estimated free flow times due to recurring and non-recurring congestion.

The exponential smoothing factor α used in both Equations 5 and 6 accounts for periods of short sampling intervals and low sample rates by weighting current average travel time and travel time variance estimates with estimates from previous intervals. Defined by Equation 7, the value of the smoothing factor depends upon the number of samples taken in a given interval and a user defined parameter β. Confidence levels in estimated travel times are thus based upon the number of samples taken in the given interval.

$$\alpha = 1 - (1-\beta)^{n_{vk}} \qquad \textbf{[7]}$$

where:

α = Exponential smoothing factor,

β = User-defined sensitivity parameter, and

n_{vk} = Number of valid travel time readings in k^{th} sampling interval.

Values calculated for the smoothing parameter generally fall between 0 and 1. The algorithm uses a value of 0 when no valid observations have been made during a given interval, and the average travel time estimated in the previous interval is carried to the current one. A value of 1, on the other hand, means full confidence should be placed in the estimation, and this value should replace the moving average. The sensitivity of the smoothing factor β has not been assigned a fixed value, and thus must be assigned by the user.

Using an exponential smoothing factor to weight travel time estimation confidence levels on the number of observations during a given interval ensures the validity of the data; however in doing so it renders the algorithm less sensitive to short-term fluctuations in traffic. In order to track sudden changes in traffic, Dion and Rakha modified Equation 7 to account for periods when three or more consecutive data points lie outside the validity range. This modification is described by Equation 8:

$$\alpha = \begin{cases} 1-(1-\beta)^{n_{vk}} & \textit{for } n_a < 3 \textit{ and } n_b < 3 \\ \max(0.5, 1-(1-\beta)^{n_{vk}}) & \textit{for } n_a \geq 3 \textit{ or } n_b \geq 3 \end{cases} \quad \textbf{[8]}$$

where:

α = Exponential smoothing factor,

β = User-defined sensitivity parameter,

n_a = Number of consecutive observations above the limits of the validity window,

n_b = Number of consecutive observations below the limits of the validity window, and

n_{vk} = Number of valid travel time readings in k^{th} sampling interval,

The addition of a fixed smoothing factor of 0.5 each time a third consecutive data point lies either above or below the validity range ensures the algorithm is able to quickly adjust to changing traffic conditions.

To account for large variability's in observed link travel times, Dion and Rakha consider successive link arrival and departure times. Vehicles which successively enter links at similar times should be subject to similar traffic conditions, and thus should have similar observed travel times. When differences in successive vehicle travel times vary by large amounts, however, it becomes apparent that one of the observed vehicles stopped between AVI reader locations. To invalidate data collected from such vehicles, the following equation is presented:

$$Stt_{ABk} = \left\{ t_{Bi} - t_{Ai} \middle| (t_{Bi} - t_{Ai}) \leq (tB_{(i-1)} - tA_{(i-1)}) + e^{2(\sigma_{sttAB})_k} \textit{ for } t_{Bi} \geq t_{B(i-1)} \textit{ and } t_{Ai} \leq t_{A(i-1)} \right\} \quad \textbf{[9]}$$

where:

Stt_{ABk} = Set of valid recorded travel time from reader A to reader B in k^{th} interval,

t_{Ai} = Time at which vehicle i was detected at reader A (seconds),

t_{Bi} = Time at which vehicle i was detected at reader B (seconds), and

$(\sigma^2_{sttAB})_k$ = Expected standard deviation of travel times in k^{th} interval, as defined in Equation 6 (seconds).

The Dion and Rakha algorithm has successfully been implemented on freeway and arterial links around San Antonio, and it could easily be adapted to operate in other networks. Its ability to function with relatively low sampling rates proves very interesting and relevant to this study.

2.3.5 Other Tag Matching

Hellinga *(2001)* additionally discusses the complexities associated with three potential tag matching algorithms. The computational load for each algorithm was estimated for worst case scenarios, and a simulation was run to confirm assumptions.

Sequential Search Algorithm

The sequential search algorithm assumes records from the upstream tag reader are maintained in chronological order. The problem of finding a match in downstream detectors is therefore as simple as searching a single unsorted list. The computational load associated with this algorithm is based on the size of the list at the upstream detector as the sequential search algorithm must be applied for each corresponding record at the downstream detector.

Modified Sequential Search Algorithm

The modified sequential search algorithm is very similar to the sequential search algorithm; however an attempt is made to reduce the amount of data which must be examined. While the preceding algorithm requires a search of all entries recorded at the downstream reader, the modified version limits the search to only potentially valid entries by taking into account a user defined minimum travel time between readers (t_{min}). Vehicles which pass downstream readers at time t cannot have passed upstream readers any later than time t-t_{min}, and therefore only data points in the downstream list which fall outside of this time threshold are searched. The computational load associated with this algorithm is based upon the size of list A and the minimum travel time between tag readers.

Binary Search Algorithm

The binary search algorithm differs from the preceding algorithms in that records taken at the upstream reader are sorted by tag ID. Each time a new record is taken at this reader, it is inserted into the list such that all records in the list are in non-descending order by vehicle ID. The algorithm then develops tag matches by searching list A for tag number X. When searching the list, the algorithm considers a value from the middle of the list. If X is greater than this value, the lower half of the list is eliminated, and the midpoint of the upper half of the list is considered for the next search. Each time comparisons are made, half of the data is eliminated.

Worst Case Analysis

The worst case analysis for the sequential search algorithm and its modified counterpart simply relates to the number of entries recorded by the upstream tag reader (Equation 10). The maximum number of required comparisons for a single application of the algorithm with a list having n entries is n. This is the worst case scenario.

$$W_1(n) = W_2(n) = n \qquad \textbf{[10]}$$

where:

> $W_1(n)$ = maximum number of comparisons associated with the sequential search algorithm for a list with n entries and
>
> $W_2(n)$ = maximum number of comparisons associated with the modified sequential search algorithm for a list with n entries.

The worst case analysis for the binary search algorithm, on the other hand, proves slightly more complex, as half of the data is eliminated during each search. The maximum number of comparisons associated with each use of the algorithm can represented by the following equation (Equation 11):

$$W_2(n) = 1 + W_2(\frac{n}{2}) = 1 + \log_2(n) \qquad \textbf{[11]}$$

where:

> $W_2(n)$ = maximum number of comparisons associated with the binary search algorithm for a list with n entries.

Simulation Analysis and Conclusions

A simulation was run on the discussed algorithms to assess with what accuracy their worst case computational loads were estimated, and to determine their sensitivity to the following system parameters: the mean travel time between tag readers, the coefficient of variation of travel time (CVO), total traffic demand passing upstream tag readers, the probability that a vehicle generating a record at downstream reader stations also generated a record at upstream stations, and the probability that a vehicle that has generated a record at upstream stations also generates a record at downstream stations. It was determined the worst case loads predicted by Equations 10 and 11 were generally worse than those found in the simulation. This is due to the fact the equations assumed the vehicles being searched for (X) would be randomly distributed throughout the lists, while in fact they tended to fall towards the top. During the simulation, there was more than a 70 percent chance that the vehicles would fall in the top 25 percent of each list. It was additionally concluded that of the five system parameters considered, the most critical factors for influencing computational load were the number of AVI equipped vehicles, the mean travel time between tag readers, and the proportion of vehicles passing downstream tag readers that have also passed upstream readers. Both the worst case analysis and simulation results show that the binary search algorithm is much more computationally efficient that the sequential search algorithm and its modified version.

2.4 OTHER VEHICLE MATCHING TECHNIQUES

While the use of existing toll and WIM infrastructure presents an interesting and economical opportunity to identify and track vehicle progress, this opportunity is limited to areas where such technology already exists. In the interest of using AVI data to analyze corridor performance in areas absent of electronic tolling or WIM sites, many other vehicle identification and tracking methods have been proposed.

2.4.1 Weight Signature Matching

Christiansen and Hauer *(1998)* studied the possibility of using existing WIM infrastructure to assess corridor performance. Through use of axle and weight data gathered at WIM stations, an algorithm was developed to detect and track freight vehicles with "irregular" axle configurations or axle weights. While only 10 to 15 percent of vehicles were recognized from the axle data, the percentage proved high enough to obtain reliable travel time estimations. Recently, Cetin and Nichols (*2009*) explored the use of axle spacing and axle weight data to re-identify commercial trucks at two WIM stations in Indiana where commercial trucks cross both stations. They developed matching algorithms based on statistical mixture models and tested the performance of the algorithms on the data from these two WIM stations that are separated by one mile. The results showed that trucks were matched with 97 percent accuracy when both axle spacings and weights were used; and with 95 percent accuracy when only one axle spacing was used. Neither of these studies had transponder data available to analyze.

2.4.2 Vehicle Signature Matching

As nearly every major metropolitan area currently implements a loop detector network, there exists an opportunity to utilize data collected by these detectors to identify and track vehicle progress. Loop detector signature matching (re-identification) has focused primarily on passenger cars and light trucks, which typically make up the majority of traffic in urban areas where the link performance varies the most. Various techniques and technologies have been employed for the re-identification of vehicles from inductive loop sensors (*Coifman 1998; Oh and Ritchie 2002; Oh et al. 2005*).

Coifman and Ergueta *(2002)* discuss an algorithm which automatically extracts and identifies vehicles based on length measurements taken at consecutive loop detectors. The algorithm measures and successively numbers each vehicle which passes upstream and downstream detector stations, creates a vehicle match matrix (VMM) with which to extract and analyze possible matches, and eliminates "false positives" by placing these matches through a series of tests. In order to match vehicle measurements taken at downstream detector stations with corresponding measurements made upstream, the algorithm first creates a VMM. To accomplish this, the modified sequential search algorithm is initially used to generate a feasible set of upstream measurements which potentially match records taken at the downstream station. The algorithm then finds all vehicles in this set which lie in the length classification range of the downstream record, and eliminates all other vehicles. For each vehicle which passes downstream detector stations, a single row is created in the VMM. The matrix is completed when the number of vehicles detected at the downstream station exceed a user defined amount (for this study, 100 vehicle sample sets were used). The columns in the VMM are defined by the difference between the arrival numbers assigned to vehicles at upstream and downstream stations, and thus every diagonal in the VMM corresponds to all possible vehicle matches. Following the completion of the initial VMM the algorithm accounts for lane change maneuvers by searching for possible sequences in the matrix which can be linked to earlier sequences. If such "links" are found, the algorithm automatically validates these sequences by combining them; creating "modified sequences." Under the assumption that all vehicles which successively enter links at similar times should be subject to similar traffic conditions, the algorithm then determines the "best match" by locating the longest vertical sequence in the matrix.

The algorithm uses four independent tests to eliminate "false positives" and ensure the validity of travel time estimations; the filter test, the cone test, the travel time test, and the multiple lane change test. The filter and cone tests are used before lane change maneuvers are accounted for to determine the general region within the VMM where the true match is most likely located. As true matches tend to form longer sequences than "false positives," the tests develop a set of feasible matches within the VMM by statistically weighting vertical sequences based upon their length. The travel time test, on the other hand, eliminates "false positives" by first removing any possible match which has been found to be traveling at excessive velocities, and then comparing remaining matches to the median travel time of all final matches. If the travel time is within 20 seconds of the median, the match will be retained. Finally, the multiple lane change test further modifies the VMM to account for multiple lane changes which may have occurred within the link. Rather than creating a single "modified sequence," the test processes the VMM five times; allowing for up to a total of five lane change maneuvers. This test accounts for long strings of false positives which may be generated when only single lane change maneuvers are accounted for in the algorithm.

The algorithm was applied to two separate empirical data sets to assess performance; data collected for an hour, collected from a single lane between two separate stations 0.55 km apart with no ramps between them, and data collected for two hours collected from all lanes at two detector stations also 0.55 km apart, however with an off ramp between them. For the first data set, the algorithm was able to match 86 percent of vehicles, while for the second it recognized between 35 and 65 percent depending upon the lane.

2.4.3 Cell Phone Matching

The use of cell phones as real-time traffic probes has also been evaluated. Work by Wunnava et al (*2007*) examined the reliability, accuracy, and reproducibility of travel time and speed estimation based on data collected and tracked by cell networks. As current cell network technology requires cell companies to continually probe cell phones, it appears data collected by carriers could readily be used to calculate travel times on roadways. To communicate with cell phones and select proper transmitting stations, the carrier must know which area the cell user is in. Additionally, as the user moves from one area to another, the call must be handed between stations, and therefore the network is continually identifying and tracking cell phones. As cell phone market penetration is very high, it would appear that sufficient data is available to accurately estimate corridor travel times.

Despite the seeming simplicity in using cell carriers as real time traffic probes, many problems including data accuracy and privacy concerns were cited in the study. As cell phone companies are not interested in the exact location of their customers, it was found that location procedures for handing calls between stations are not very precise. Additionally, differing strengths of cell signals and competitive cell networks resulted in large errors in location computations. Finally, service providers already encounter problems of protecting the private information of their users, and, as these concerns are expected to increase, providers have begun to implement strict security measures which may limit the use of cell phones as traffic probes. It was eventually concluded that the technology provided reliable information only under free flow traffic conditions, and further research is necessary to determine practical applications of the technology.

2.4.4 License Plate Image Matching

License plate imaging has additionally been assessed as a method to automatically identify vehicles and evaluate corridor performance. Shuldiner and Upchurch (*2001*) successfully implemented such a system on a 3.9 mile segment of Highway 9 in Western Massachusetts. Video cameras view license plates on the upstream and downstream end of the segment, and video imaging software is used to extract and match plate numbers. Travel time information is continually updated by a license plate matching algorithm.

Bertini et al (*2005*) evaluated the Frontier Travel Time project. As part of the Frontier project, the Oregon Department of Transportation deployed a video image processing system with license plate recognition and privacy-protecting data encryption, a central server, and proprietary algorithms to predict corridor travel times on a 25 mile section of rural highway in northwest Oregon. The Frontier Travel Time system consisted of six license plate recognition cameras mounted on poles above the roadway placed at two locations on OR-18 and one location on US-101, just north of Lincoln City. The license plate numbers were privacy-protected with encryption and time-stamped tags, which were sent via telephone communications network to the central server. The server matched the time-stamped tags collected at different checkpoints to identify vehicles that passed between two or more locations. The system predicted travel times were compared to data independently collected by probe vehicles equipped with Global Positioning System (GPS) devices. The comparison shows that the predicted travel times were not statistically different than the travel times observed by the probe vehicles. Despite attempts to validate the system under congested conditions, all comparisons were made under essentially free flow travel.

2.5 FREIGHT PERFORMANCE METRICS

Performance measurement of government transportation agencies is becoming more common, particularly at the state level. Performance measures can be used to communicate with both internal (i.e., decision makers) and external (i.e., public stakeholders) customers and can be based on either quantitative (i.e., crash data) or qualitative (i.e., surveys such as customer orientation) data. Without going into significant detail about performance measurement, it is essential that performance measures clearly relate to identified agency or program goals so that decision makers and public constituents can follow investment decisions (*Meyer 2002*). NCHRP Report 446 (*2000*) summarized the state-of-the practice in transportation performance measurement. Meyer (*2002*) suggests that following performance measures seem to be most important for system users (in Meyer's order and words):

1. System reliability; measured in changes in average travel time for specific origin-destination pairs

2. "Reasonable" travel time (or speed); measured for specific origin-destination pairs, possibly by route and by time of day; or other measures such as average minutes per mile, and average minutes of delay
3. Safety; measured in number of crash or possibly economic costs of crashes
4. Average delay at top "x" bottleneck points in transportation system
5. Traveler costs
6. Physical condition of the transportation system
7. Customer satisfaction measures

As an example, the New Jersey Transportation Planning Authority, Inc, which serves as a metropolitan planning organization for 13 counties in northern New Jersey, sponsored a study in 2003 to identify long-range freight performance measures. Like many agencies developing performance measures, one of the first tasks was to identify available indicators of performance in the state and identify data collection that is currently undertaken but unused (*Harrison et al. 2006*). The recommended indicators fall mostly into five categories (similar to Meyer's):

1. Average travel time measures—congestion delay;
2. Private sector cost measures—fuel costs per mile, insurance costs;
3. Public impact measures—freight-related crash rates, emissions;
4. Economic impact measures—value of transportation goods, impact of transportation investments to regional economy; and
5. Transportation industry productivity measures—vehicle miles traveled, system performance (by survey), average haul length

Most agencies that are using performance measures on a broad scale provide targeted information on mobility and accessibility to decision makers, program cost-effectiveness, and annual "report cards." Primary goals for freight are to ensure that the transportation system allows freight carriers to transport goods efficiently and reduce the negative impacts associated with freight movement. These goals form a framework and vision for the agencies to determine the planned objectives. These objectives categorize performance measure in terms of mobility, reliability, economic issues, safety and environmental impact, and infrastructure concern. The USDOT identified general transportation performance measures that are often used to evaluate intermodal freight performance (see).

Table 2.1: General Transportation Performance Measures Often Used to Evaluate Intermodal Freight Performance

Indicators	Measures	Strengths/Weaknesses
Travel time	• Average travel time in peak period • Crossing time at Borders, weigh stations, toll plazas • Hours of delay per 1,000 vehicle mile	• Data often not readily available • Focuses on one point of network • Delay associated with commuter traffic
Reliability	• Hours of incident based delay • Percent of on-time arrivals • Ratio or variance to average minute per trip in peak periods in metro areas	• Need to disaggregate recurrent versus incident-based congestion • "On-time" is a subjective measure and a moving target. Data held privately and difficult to access • Reflects seasonal fluctuations as well as unexpected incident delay
Cost Measures	• Cost of highway freight per ton-mile • Fuel consumption per ton mile • Maintenance cost of connector links	• Can be skewed by other exogenous factors • Good reflection of highway condition • Maintenance spending can be negative and positive—does not indicate an improvement in highway condition—could be wasteful spending
Safety/Damage	• Accident rates • Fatality rates • Insurance cost	• Data is limited on costs associated with these measures • Can reflect other conditions e.g., driver experience and theft levels
Highway Condition	• Lane-miles of high level highway requiring rehabilitation • NHS intermodal connectors condition • % of roads/bridges with surface/condition classified as good • Number of at-grade railroad crossings • Overpasses with vertical clearance restrictions • Weight restricted bridges • Intersections with inadequate turning radii	• Quality measures that don't accurately reflect effect with any specificity for freight and applies to all users • These are impedances to freight but may be on segments not used by the freight industry
Economic Impact	• Contribution of investment to GDP • Net present value of improvements/ Benefit-cost ratio of highway improvements	• Difficult to separate passenger travel effects • Most of these benefits are associated with passenger travel and do not disaggregate the freight element.
Industry Productivity	• Average length of haul/average load/ percent of VMT empty • Annual miles per truck	• All measure output per unit of input and capture productivity of industry but not the relationship to highway system

Source: *USDOT 2000*

In support of identifying freight performance measures that might be generated using the data available for this research, a review of various state-level performance measures was conducted. The Oregon DOT's Annual Performance Progress Report, published for fiscal year 2006-07 (July 1, 2006 to June 30, 2007), identified 27 key performance measures for agency. These metrics are shown in Figure 2.3. Freight-related safety measures (large truck crashes, rail crossing incidents, and derailments) are included; however, there are no other direct freight-related performance metrics reported annually. The travel delay metric is only reported for metropolitan areas and even then, is only estimated from the Texas Transportation Institute mobility report (which does not use actual operational-level data).

Goal 1: Improve Travel Safety in Oregon * ▪ Traffic Fatalities (#1) ▪ Traffic Injuries (#2) ▪ Safe Drivers (#3) ▪ Impaired Driving-Related Traffic Fatalities (#4) ▪ Use of Safety Belts (#5) ▪ Large Truck At-Fault Crashes (#6) ▪ Rail Crossing Incidents (#7) ▪ Derailment Incidents (#8) ▪ Travelers Feel Safe (#9)	**Goal 2: Move People and Goods Efficiently** ▪ Special Transit Rides (#10) ▪ Travel Delay (#11) ▪ Passenger Rail Ridership (#12) ▪ Alternatives to One-Person Commuting (#13) ▪ Traffic Volume (#14) ▪ Pavement Condition (#15) ▪ Bridge Condition (#16)
Goal 3: Provide a Transportation System that Supports Livability and Economic Prosperity ▪ Fish Passage at State Culverts (#17) ▪ Intercity Passenger Service (#18) ▪ Bike Lanes and Sidewalks (#19) ▪ Jobs from Construction Spending (#20) ▪ Timeliness of Projects Going to Construction Phase (#21) ▪ Construction Project Completion Timeliness (#22) ▪ Construction Projects On Budget (#23) ▪ Certified Businesses (DMWESB) (#24)	**Goal 4: Provide Excellent Customer Services** ▪ Customer Service Satisfaction (#25) ▪ DMV Customer Services (#26) -- DMV Field Office Wait Time (#26a), DMV Phone Wait Time (#26b), and DMV Title Wait Time (#26c) ▪ Economic Recovery Team Customer Satisfaction (#27)

Figure 2.3: Oregon DOT Key Performance Metrics, 2007

The California Department of Transportation's (CalTrans) Division of Transportation Systems Information has led the state's effort in transportation performance measures. The primary goal of this effort was to establish measures that would monitor the state transportation system, help transportation planners make informed decisions and lead to ongoing performance measurement (*CalTrans 2000*). Within these efforts, performance measures for freight systems have been defined for all freight modes and for the following objectives: safety, reliability, mobility/accessibility, equity, economic well-being, and environmental quality. Most of the measures are compared against established baselines (*Harrison et al. 2006*) . The measures for each policy objective are shown in. Table 2.3 presents measures from Minnesota.

Table 2.2: Freight Performance Metrics from California

Policy Objective	Performance Measure
Safety	# of crashes x 1,000,000 / truck vehicle miles traveled
Reliability	Standard Deviation of Travel Time
Mobility	Travel time, Delay
Accessibility	Access to intermodal facilities
Equity	Regional share of mobility benefits
Economic Well Being	Final demand
Environmental Quality	Emission quantities in lbs per year

Source: California Department of Transportation, 2000

Table 2.3: Freight-Oriented Performance Measures From Minnesota

Performance Concept	Performance Measures
Predictable, competitive Twin Cities' travel time	• Metro freeway travel time by route and time of day • Ave. speed on metro freeways by route and time of day • Congestion ranking of metro freeways, by route • Congestion level compared to other major metro areas
Economic benefit/cost	• Benefit/cost ratio of major state transportation projects
Transportation investment	• State's transportation investment and spending as % of gross state product
Intercity travel time	• Peak hour ave. travel speeds on major routes between 27 state regional centers • Shipper point-to-point travel time
Freight travel time to global markets	• Travel time to major regional, national and global markets—by rail, air, water, and truck
Competitiveness of shipping rates	• Shipment cost per mile—by ton or value, by mode for major commodities
Crash rate and cost comparison	• Dollar of crashes and crash cost comparison by mode • Crash rate per mile traveled by freight mode
Bottlenecks and impediments	• Number of design impediments to freight traffic, by mode, by type
Timely access to intermodal terminals	• Number of design impediments slowing access to truck, rail, air, and waterways terminals

Source: *Larson, 2000*

Austroad, the association of Australian and New Zealand road transport and traffic authorities has indicated that in the last 20 years Australian road freight has increased from 20 to 34 percent of the yearly total for all freight modes and the annual cost of road freight in Australia was about $30 billion. In order to support improved freight/trade planning activities and regulation, they developed a performance management framework within which road system and agency performance could be reported. As a part of this effort they selected a series of national indicators to deliver objectives for reporting purpose. One of these indicators is "Lane

Occupancy Rate" for freight which could be defined as the average number of freight tons per lane per hour during a specific time (*Koniditsiotis 2000*).

After reviewing the general freight performance measures, it is clear that transponder tag matching combined with weigh-in-motion information will assist in generating travel time measures and industry productivity related measures.

2.5.1 Travel Time Measures

Perhaps the only true measure of travel time currently used on a corridor wide basis is data from a joint project between the Federal Highway Administration (FHWA) and the American Transportation Research Institute (ATRI). The data was used to determine whether, and how to, use the information derived from communications technologies used by the freight industry. During this effort ATRI measured average travel rates for five freight-significant corridors—I-5, I-10, I-45, I-65, and I-70. These data were used to derive average travel rates, a Travel Time Index (TTI) and a Buffer Index (BI). TTI is defined as a measure of mobility, the ratio of observed average travel time to free flow travel time (estimated at 60 miles per hour), whereas BI is a measure of reliability and variability, and measures how much extra time one should allow to account for variations in the system (*Jones et al. 2005a*).

The system is capable of contacting vehicles at regular, predetermined time intervals by using latitude/longitude (lat/long) positioning in order to determine the specific location of the asset using the trucking companies' satellite dispatch provider. The locations are stamped with a time, date, and vehicle tracking number. Thus, the average speed of a vehicle between two or more points could be defined by dividing the distance traveled from one position to another by the time between each position recording. The average speed for a particular corridor or corridor segment can be reported on an aggregated basis. Thus the speed calculation of a corridor segment in the beta-test demonstrates the system's ability to convert speed and time calculations into average speeds per corridor segment, which helps to identify the possible infrastructure bottlenecks. (*Jones et al., 2005b*)

The Missouri DOT has used these same data to produce monthly average travel times on I-70, a key corridor in Missouri (*2007*). The measure of average travel speeds for trucks on selected roadway sections was produced from the American Transportation Research Institute (ATRI) data. Additional Missouri routes may be added in the future, including Interstates 55, 57, and 35. Samples of the Missouri travel time performance measurement are shown in the charts in Figure 2.4.

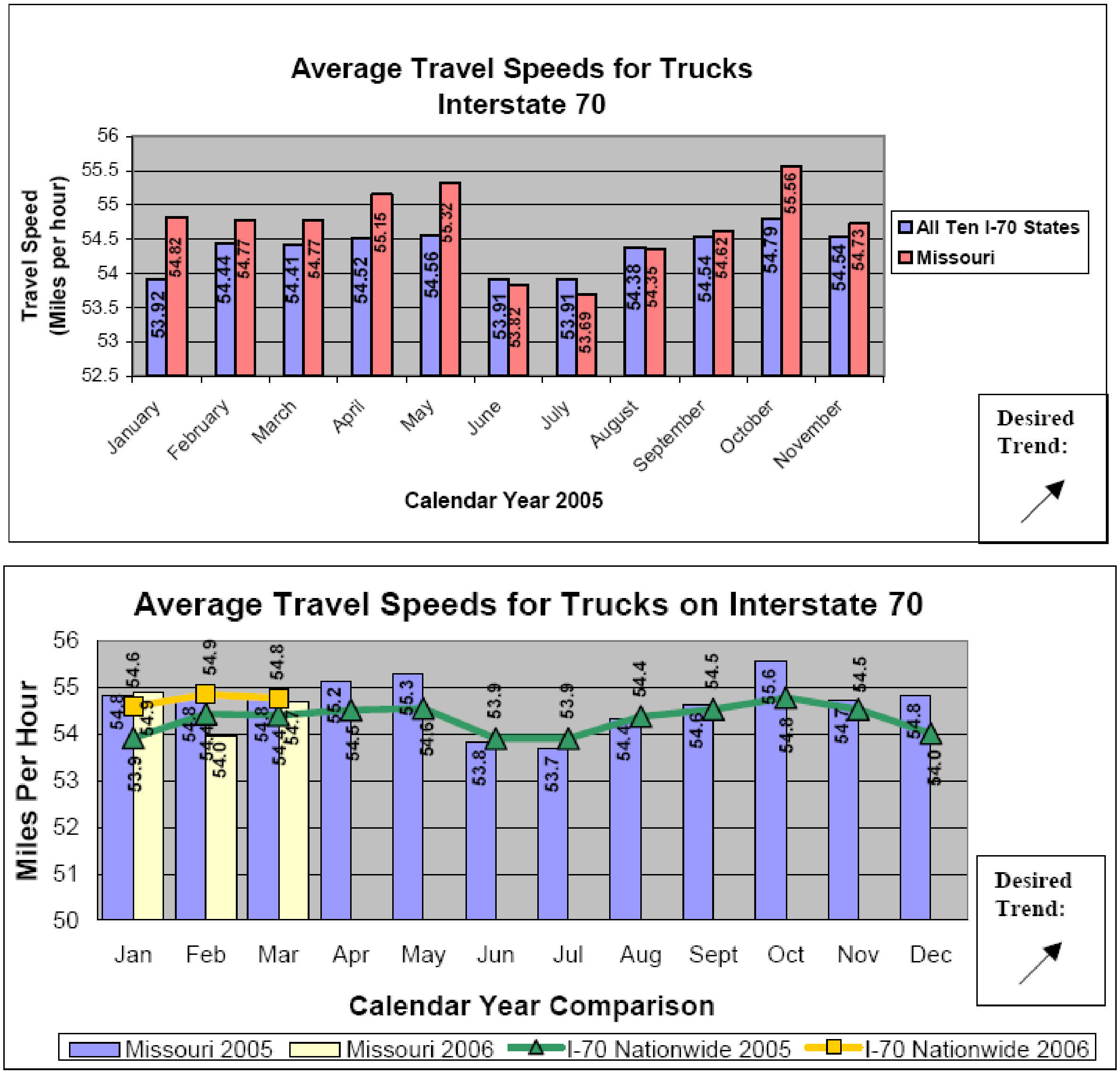


Figure 2.4: Sample Missouri Travel Time Performance Measurement

In a recent report for the Oregon Department of Transportation (ODOT), Reiff and Gregor (*2005*) aggregated performance measures in 12 categories: economic vitality, balanced transportation system, sustainability, adaptability, mobility, quality of life, environmental justice, system preservation, land use compatibility, affordability, and safety and security (*Reiff and Gregor 2005*). Due to the lack of a performance indicator, like economic vitality, they introduced new metrics as “Freight Delay Costs” which were used for evaluating the changes in economic vitality. This measure requires that truck trips be tracked throughout the network and that both nonrecurring delay and recurring truck delay be modeled or directly measured for the truck trips. The methodology used for this new metric is from the Texas Transportation Institute Urban Mobility Report, with slight variations in establishing the quantity of truck vehicle miles traveled. The Oregon II statewide model is then used to determine freight delay cost. This model is capable of determining hourly delay costs for different trucks and different commodities and includes vehicle operating costs, driver costs, and average costs of commodity delay (*Reiff and*

Gregor 2005). The major advantage of this measure is that it could be applied successfully to a variety of transportation planning jurisdictions including small MPOs, the Portland Metro model, and statewide models, as well as being easily understandable to public.

2.5.2 Other Freight Measures

The Washington Department of Transportation (WSDOT) has developed an extensive Commercial Vehicle Information Systems and Networks (CVISN) program. The main components of the system are weigh-in-motion scales which can weigh vehicles at highway speeds and transponder readers. If transponder-equipped vehicle's weight, size, registration, and safety record of a truck's are in order the vehicle can bypass the weigh stations. According to the WSDOT Gray Notebook, in 2006, 948,000 trucks equipped with CVISN transponders were pre-screened and received bypasses weigh station, which was up 11.5 percent from 2005 (*WSDOT 2007*). These data are shown in Table 2.4.

Table 2.4: Sample Performance Measure from ITS/CVO

Percent of Trucks With Transponders and Percent of Transponder-Equipped Trucks Bypassing Weigh Stations, 2004-2006

	Total Number of Trucks with Transponders	Percent With Transponders	Percent Bypassed
2004	915,486	13.33%	85.96%
2005	1,058,843	18.72%	81.83%
2006	1,155,255	20.24%	82.12%

Data Source: WSDOT CVISN Office

Another effort of WSDOT is the Freight and Goods Transportation System (FGTS). This effort introduces the classification of state highways, county roads and city streets according to the average annual gross truck tonnage. According to the FGTS (*2005*) the estimates of this truck tonnage percentage from single, double and triple unit trucks were derived from field counts through WSDOT Automatic Data Collection (ADC), Weigh-In-Motion site data (WIM), Commercial Vehicle Information System and Networks (CVISN) data, and Strategic Freight Transportation Analysis (SFTA) data. The CVISN and SFTA data were collected at weight stations; however, these data do not cover the total range of single unit trucks because trucks only weighing 26,000 pounds or more need to enter the weigh stations. The data show that average weight of a single unit truck is 14 tons, which is double the average weight of all single unit trucks. Due to calibration difficulties of WIM sites, it is assumed that the CVISN and SFTA data are more accurate than WIM data for double and triple unit trucks and almost all state highways have relatively constant vehicle weight by truck class. These values are shown in Table 2.5.

Table 2.5: WSDOT WIM-Based Truck Weights

	WIM-based Average Weight (Tons)
Single Unit Trucks	7
Double Unit Trucks	27
Triple Unit Trucks	37

The Missouri DOT has used their PrePass data to track the percent of trucks using advanced technology at Missouri weigh stations. The Missouri DOT assumes that this measure "indicates motor carriers' acceptance of tools designed to improve the flow of freight traffic on Missouri highways" (*MoDOT 2007*). Data are collected by HELP, Inc.'s PrePass system at 19 Missouri weigh stations. They also compare their participation to the State of Illinois which has similar rural interstate volumes and weigh stations *(MoDOT 2007)*. A sample of these metrics from the Missouri Tracker system is shown in Figure 2.5.

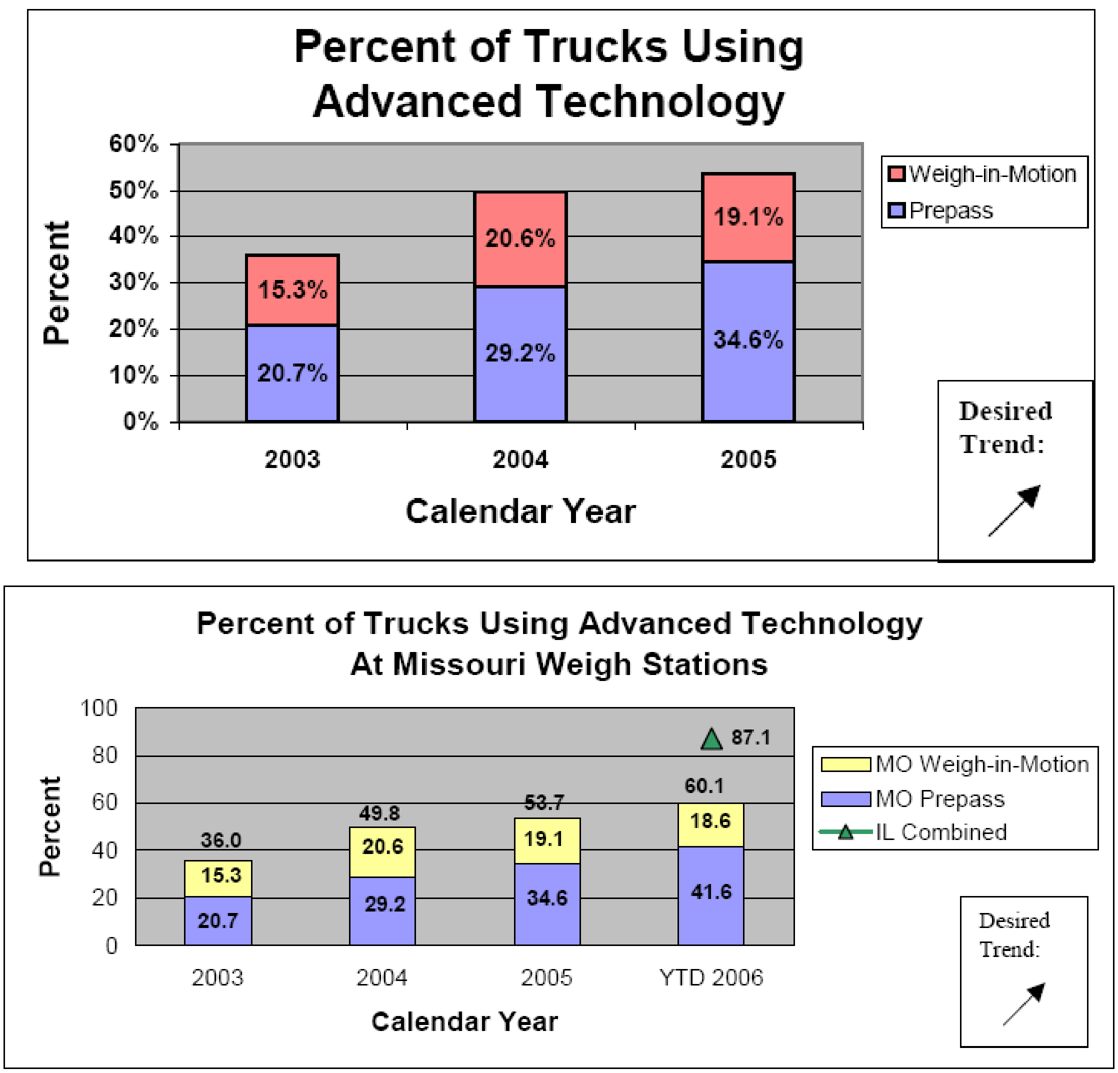


Figure 2.5: Sample Missouri ITS/CVO Technology Uses

Finally, although AVI data has frequently been used in the development of travel time and speed information, the potential exists to use the data to sample travel patterns. Dixon and Rilett (*2005*) proposed a methodology to develop origin-destination matrices based upon AVI information. Two algorithms were proposed for estimating the volume matrices – the volume proportional algorithm and the multi-proportional algorithm. A simulation ran using data from around the Houston area suggested it would be extremely beneficial to incorporate AVI information into the origin-destination estimation process.

2.6 CONCLUSIONS

The literature review highlights some key issues to consider in the development of the transponder matching algorithm for freight performance. First, the issue of privacy should be considered in any public release of the data. Another significant issue is the spacing of WIM stations, which was identified as a challenge as part of the TRAC work. Identifying trucks that leave the corridor between stations will be critical. Research suggests that it may be feasible to match vehicles using the weight signatures (but perhaps not in real-time and certainly not without significant additional research). Existing algorithms for toll tag matching suggest that calibration parameters of interest might include the link threshold travel time parameter, the average travel time from reader to reader, and previously estimated average travel time from reader to reader.

Promising freight performance measures to explore for the transponder-linked WIM data included: average travel times on key corridors; ton-miles on each corridor by various temporal considerations; overweight vehicles on corridors by temporal variation (measuring change); empty vehicles; seasonal variability in loading, routes, and volumes; percent trucks with tags on each corridor; potentially estimating an origin-destination matrix; and average weight for various configurations.

3.0 WEIGH-IN-MOTION DATA

In this chapter, the assembly, processing, and storage of the weigh-in-motion data is described. At each of the Green Light stations, approaching trucks are directed into the appropriate lane on the mainline highway. At a location upstream from the static weigh station, if a truck is equipped with a transponder, it is identified by the reader. The unique aspect of Oregon's system is that this unique transponder identification and subsequent data are recoded together. At this same location, the vehicles are weighed in motion by load cells in the pavement. The observation consists of left and right axle weights as well as the spacing of these axles. The data also include speed, a timestamp and the lane of observation (some stations are multilane), length, gross vehicle weight, and a count of the number of axles. As part of the proprietary control program by International Road Dynamics (IRD), a sieved-based classification algorithm uses the axle spacing parameters to classify vehicles. An example of the transponder reader, over-height detection, and load and axle sensors is shown in Figure 3.1. A good description of the WIM system is provided by Elkins and Higgins (*2008*) in the publication *Calibration of LRFR Live Load Factors Using Weigh-In-Motion Data*.

As mentioned in the introduction, there are 22 green-light equipped stations on the Oregon highway system. These locations are shown in Figure 3.2 with a corresponding list of stations shown in Table 3.1. Data were assembled by month for operating stations staring in July 2005. The data collection is ongoing but presently data are available to February 2009 (approximately 42,000,000 observations). The research data set assembled did not include data from stations 21 (Umatilla POE) and 22 (Rocky Point) until February 2009 (due to the structure of a historical request). For the research, only data from 2007 and 2008 were used.

In addition to the Oregon data, one month (March 2008) data from the first downstream stations in Washington state was obtained from UW-TRAC. The original intent of this research was to explore bi-state corridor measures, however, the manner in which the transponder identification is logged in the Washington data in a different format than the Oregon data (Washington is alpha-numeric, Oregon is numeric). As such, the remainder of this work focuses on Oregon data only.

Figure 3.1: A Green Light RFID Transponder and Station Pre-clearance Arrangement

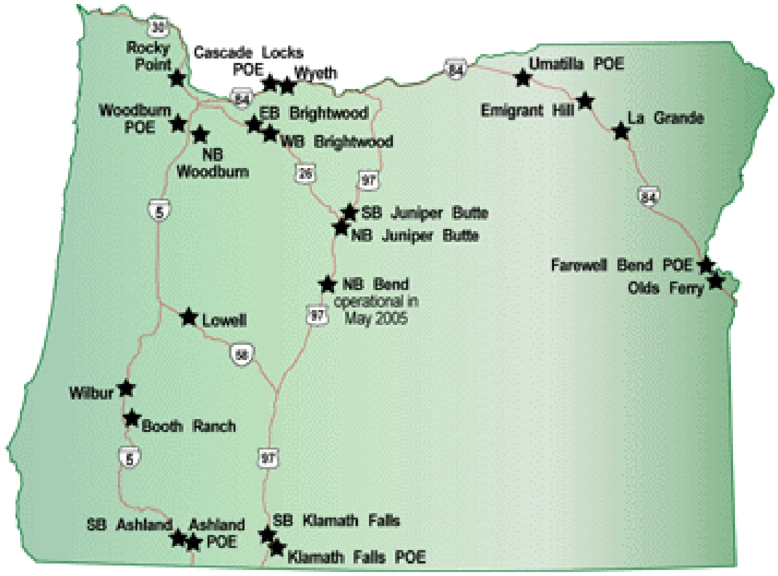


Figure 3.2: Oregon Green Light Locations

Table 3.1: List of Stations

Number	Code	Name	Route	Direction	MP
1	FWB	Farewell Bend POE	I-84	WB	353.31
2	EMH	Emigrant Hill	I-84	WB	226.95
3	WYT	Wyeth	I-84	WB	54.3
4	CSL	Cascade Locks POE	I-84	EB	44.93
5	LGR	LaGrande	I-84	EB	258.52
6	ODF	Olds Ferry	I-84	EB	354.38
7	ASP	Ashland POE	I-5	NB	18.08
8	BOR	Booth Ranch	I-5	NB	111.07
9	WDN	Woodburn, NB	I-5	NB	274.15
10	WDS	Woodburn, SB	I-5	SB	274.18
11	BRE	Brightwood, EB	US-26	EB	36.51
12	BRW	Brightwood, WB	US-26	WB	36.31
13	JBS	Juniper Butte	US-97	SB	108.2
14	LWL	Lowell	US-58	WB	17.17
15	WLB	Wilbur	I-5	SB	130
16	ASH	Ashland, SB	I-5	SB	18.08
17	KFP	Klamath Falls POE	US-97	NB	271.73
18	BND	Bend	US-97	NB	145.5
19	JBN	Juniper Butte	US-97	NB	106.9
20	KFS	Klamath Falls, SB	US-97	SB	271.41
21	UMT	Umatilla POE	I-82	EB	183.8
22	RPT	Rocky Point	US-30	WB	16.53

3.1 DATA ARCHIVE

To manage the vast amounts of data used in this research, a WIM data archive was created. This archive is housed under the Portland Transportation Archive Listing (PORTAL) umbrella at Portland State University's Intelligent Transportation Systems Lab. PORTAL is the official Archived Data User Service (ADUS) for the Portland Metropolitan region as specified in the Regional ITS Architecture. PORTAL provides a centralized, electronic database that facilitates the collection, archiving, and sharing of information/data for public agencies within the region. The creation of the PORTAL data archive was supported by a CAREER grant from the National Science Foundation (NSF). In addition, the FHWA (through ODOT) has supported the purchase of hard disc storage and the Portland metropolitan regional government (Metro) has invested in the ongoing support of the archive.

The archive stores data in a PostgreSQL relational database management system (RDBMS). This archive implements a data warehousing strategy in that it retains large amounts of raw operational data for analysis and decision making processes, and in that these data are stored independently of their operational sources, allowing the execution of time-consuming queries with no impact on critical operations uses. The database server is a Dell Server with two Quad Core Intel Xeon Processors running at 2.33 GHz with 8GB of memory. The database server runs Red Hat Linux. The RDBMS stores data physically on a 3.2 Terabyte redundant array of independent disks (RAID) providing both high-speed access and increased reliability through redundancy in the event of hardware failure. Offsite backups of the raw data are done once a week.

3.2 DATA PROCESSING

Prior to August 2008, data were sent on a monthly basis to Portland State University from ODOT Motor Carrier via the ODOT FTP site. The format of this data was formatted report in text format. A FORTRAN program written by OSU students, under the direction of Dr. Chris Higgins, stripped the data in these text-report files into a comma-separated file suitable for loading in a database. The OSU script did not extract the transponder number from these text-report files (because it was not needed in their work). A PHP script, written by PSU, extracted the transponder numbers from the same text-report file. These two files were then joined and loaded into the archive. This process was inefficient and resulted in time consuming. After some discussions with Motor Carrier in July 2008, the raw data was revised and sent to PSU in a comma separated file. These files, transferred monthly by FTP, could be easily loaded directly into the database with all data elements and no post processing. This data format included new data elements (left and right axle weights) but is otherwise identical.

For various reasons (construction, sensor maintenance, communication issues, others) some stations are missing full or partial months of data. For summary purposes, Table 3.2 presents the data availability by month for all stations for the years 2007 and 2008. This table only presents the availability of the raw station-level data. As will be shown in the following chapter, processing of the data for matched tags resulted in additional missing data for analysis.

Table 3.2: Stations, Missing Data by Month 2007 and 2008

Stations Missing Data, 2007

Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1 FWB												
2 EMH												
3 WYT					M							
4 CSL												
5 LGR												
6 ODF												
7 ASP												
8 BOR												M
9 WDN												
10 WDS												
11 BRE	M	M	M	M	M							
12 BRW				M								
13 JBS												
14 LWL												
15 WLB	M	M	M	M	M	M	M	M	M	M	M	M
16 ASH												
17 KFP												
18 BND			M					M	M			
19 JBN												
20 KFS												
21 UMT	M	M	M	M	M	M	M	M	M	M	M	M
22 ROC	M	M	M	M	M	M	M	M	M	M	M	M

Stations, Missing Data, 2008

Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1 FWB				P		P	P					
2 EMH				P			M					
3 WYT				P		P		M	M	M	P	
4 CSL				P								
5 LGR				P								
6 ODF				P			P					
7 ASP				P		P						
8 BOR	M	M	M	P		P						
9 WDN				P								
10 WDS				P			P					
11 BRE				M								
12 BRW				M								P
13 JBS				P			P					
14 LWL				P							P	
15 WLB	M	M	M	M	M	M	M	M	M	M	M	M
16 ASH				P								
17 KFP				P								
18 BND				P							M	M
19 JBN				P								
20 KFS	M	M	M	M	M	M	M	M	M			
21 UMT	M	M	M	M	M	M	M	M	M	M	M	M
22 ROC	M	M	M	M	M	M	M	M	M	M	M	

M = Missing Data, P = Partial Month Missing

3.3 DATA STRUCTURE

There are four primary tables that were created in the WIM data archive for this research. A schematic of the database is shown in Figure 3.3. The truck-level observations are loaded in a table called *wimdata*. Researchers at PSU have written a program to upload the data in an automated manner. A table *stations* includes the identifying information about each station. Two additional tables are created by the methods and algorithms developed in this research. The methods are described in Chapter 4. The table *stationmap* is a list of all possible routes (i.e. upstream to downstream stations station pairs) which defines the free flow travel time, distance, and a parameter called upper time (currently time to travel between stations at 50 mph). A table of all trucks matched by transponder identification number between stations, (*linktraveltime)* contains the upstream and downstream station numbers, tag number, and timestamps of each observation.

WIMDATA
timestamp timestamp with time zone
type integer
lane integer
speed integer
gvw real
sumlen real
length integer
numaxles integer
esal real
axl1 real
axl2 real
axl3 real
axl4 real
axl5 real
axl6 real
axl7 real
axl8 real
axl9 real
axl10 real
axl11 real
axl12 real
axl13 real
spc1 real
spc2 real
spc3 real
spc4 real
spc5 real
spc6 real
spc7 real
spc8 real
spc9 real
spc10 real
spc11 real
spc12 real
trucknum integer
stationnum integer
tag text
timestamp_nomil timestamp with time zone
year integer
month integer
day integer
hour integer
minute integer
seconds integer

STATIONS
stationnum integer
station_code character(3)
longname text
name text
route character(5)
direction character(2)
hwy_no integer
roadbed integer
mp double precision
lrs character varying(15)
lat double precision
long double precision

STATION MAP
linkid integer
up_station integer
up_stationname character(3)
dwn_station integer
dwn_stationname character(3)
freeflow real
distance real
uppertime real

LINKTRAVELTIME
linkid integer
up_station integer
up_tag text
up_timestamp timestamp with time zone
dwn_station integer
dwn_tag text
dwn_timestamp timestamp with time zone
rowid integer

Figure 3.3: Database Schematic for PSU PORTAL WIM Archive

3.4 PRIVACY ISSUES

As with any system that uniquely identifies a vehicle, privacy is paramount. ODOT Motor Carrier's policy is to protect the identity of any individual truck or carriers. The data used in this research contains a transponder number which can be uniquely associated with a registered truck and company. The data that associates a transponder with a particular truck or trucking company is not available to the research team nor has any request been made. However, because the possibility exists that an individual truck could be identified by those with such records the research team has taken strong steps to preserve the integrity and privacy of the data archive. All data are stored on secure PSU computer systems requiring a username and password to access. In addition, in this research report or subsequent publication no complete or partial tag numbers will be presented. Any unique identifying number in any text or table is fictitious and is used to represent a unique truck.

4.0 ESTIMATING TRUCK TRAVEL TIMES

This chapter describes the methods used to identify matched transponders between stations and filter these matches to identify through trucks. This filter was validated by comparing how well it identified delays during a period of known inclement weather. A brief sensitivity analysis is then presented by changing the variable parameters of the filter. Then the estimated average travel times between stations are presented. A discussion of the results concludes the chapter.

4.1 TAG MATCHING ALGORITHM

Identifying trucks traveling between two stations was done in two steps. First, a table of all possible matches within a specified time window was created. For this task, the time window was defined to be 0.75*free flow time to 2*free flow. Free-flow time was defined as the time to traverse the route between stations at 55 mph. This large time window will clearly include trucks that did not take a direct path between stations. The second step is to identify only the through trucks (which is described in the next section).

The logic for developing a match can be summarized as such:

1. Determine the set of all possible upstream and downstream stations. Each of these station pairs are referred to as links.
2. For each link, select all trucks from the upstream station with a tag.
3. For each truck with a tag at the upstream station, search for a match within the time window of 0.75*free flow time to 2*free flow time at the downstream station.
4. Create a unique record for each match.
5. Repeat for each truck with a tag until complete; move to next link.

The tag matching algorithm was developed in R with an ODBC connection to the postgreSQL database. A copy of this script is in the Appendix. The above algorithm developed was not optimized for computational efficiency; to complete a search of all trucks with tags in 2007 (4,705,702 trucks) required approximately 40 computation hours. Improvements to the code reduced the processing time for 2008 data (3,779,900 trucks) to approximately 30 hours.

4.1.1 Developing the Link Data

One input for the tag matching algorithm is the possible stations that a truck can be observed downstream from an observation point. In reality, there are many alternatives for trucks traveling between stations and the "true" route of a truck cannot be known. To simplify, it was assumed that a truck traveled between two stations on the fastest available path. For most pairs, this assumption was very reasonable. All WIM stations were located in Google Earth and all logical potential downstream stations were identified by inspection. The distance between these stations was calculated using Google's default routing algorithm maps for the quickest path between two points. Visual confirmation was made that these path were logical truck routes. The distance (in miles) was recorded. Assuming trucks traveled at the posted speed limit, 55 mph was assumed to be the free flow speed. This was converted to a time based on the distance between paths.

These links (unique station pairs) and associated data are shown in Table 4.1. The links were placed in one of three groups: primary, secondary, and tertiary. The primary links were those where the path of the through trucks was very certain. These routes included all of the interstates and primary highways monitored by WIM stations. For example, a truck on I-84WB that was observed at Farewell Bend and later downstream at Emigrant Hill almost certainly traveled on I-84. Secondary links generally involved more than one highway, a path of the truck between stations was less certain. The final grouping, tertiary, was links where there were alternative routes between stations. Because the truck's travel time could not be assigned to a specific corridor these station pairs are not of interest for travel time performance measures. However, it is still useful for determining freight patterns.

4.1.2 Trucks with Transponders at Each Station

The proportion of trucks with transponders at each station is relatively high. Figure 4.1 and Figure 4.2 show the number of trucks with tags and those without tags observed at each station. About 40 percent of all observed trucks have transponders, though there is substantial station-to-station variation. A monthly time series of transponder percentages is shown in Figure 6.3 for 2007 stations.

4.1.3 Matched Trucks with Transponders Per Link

Clearly, the number of matched transponders on each link is proportional to the number of trucks with transponders at each station. The numbers of trucks matched by the tag match algorithm are shown in Figure 4.3 and Figure 4.4 for 2007 and 2008, respectively. The number of trucks matched decreased from 2007 to 2008, partially due to missing data at key stations, issues with timestamp data at select stations, and a general decline in trucking activity due to the economic climate. The links with the most observations included:

- 201-I-84 WB Farewell Bend to Emigrant Hill,
- 202- Emigrant Hill to Wyeth;
- 210-I-84EB LaGrande to Olds Ferry;
- I-5 NB Ashland POE to Booth Ranch;
- 214- Booth Ranch to Woodburn NB; and
- 220 – I-5 SB Woodburn South – Ashland.

Data from the Wilbur Station (I-5SB) was not available for 2007 and 2008 because of construction activity. The remaining matches either reflect the low volumes using the link or data outages that kept the matches relatively low. Link 237 (Juniper Butte North to Brightwood West) and 223 (Brightwood East to Juniper Butte South) would have been useful stations for identifying travel over Mt. Hood on US-26, however, data problems at the Brightwood stations kept the number of matched trucks low.

Table 4.1: Links - Upstream and Downstream Stations

Link	Route	Upstream #	Upstream Name	Downstream #	Downstream Name	Free-flow (hrs)	Distance (miles)	Upper time (hrs)
PRIMARY								
201	I-84WB	1	FWB	2	EMH	2.3	126.4	2.528
202	I-84WB	2	EMH	3	WYT	3.14	172.7	3.454
208	I-84EB	4	CSL	5	LGR	3.89	214	4.28
210	I-84EB	5	LGR	6	ODF	1.75	96.1	1.922
211	I-5NB	7	ASP	8	BOR	1.7	93.4	1.868
214	I-5NB	8	BOR	9	WDN	3	165	3.3
219	I-5SB	10	WDS	15	WLB	2.62	144.2	2.884
230	I-5SB	15	WLB	16	ASH	2.03	111.9	2.238
220*	I-5SB	10	WDS	16	ASH	4.65	256	5.12
227	US-97SB	13	JBS	20	KFS	2.97	163.2	3.264
231	US-97NB	17	KFP	18	BND	2.27	125	2.5
235	US-97NB	18	BND	19	JBN	0.7	38.3	0.766
SECONDARY								
204	I-84WB/US-97	2	EMH	13	JBS	4.24	233	4.66
205	I-84WB/I-205SB/I-5SB	3	WYT	10	WDS	1.43	78.9	1.578
209	I-84EB/US-97SB	4	CSL	13	JBS	2.4	132	2.64
217	I-5NB/I-205NB/& I-84EB	9	WDN	4	CSL	1.27	69.8	1.396
221	I-5SB/OR-58/US-97SB	10	WDS	20	KFS	4.51	248	4.96
223	US26EB/US-97SB	11	BRE	13	JBS	1.64	90	1.8
226	US-97SB/OR-58WB	13	JBS	14	LWL	2.53	139	2.78
228	OR-58WB/I-5SB	14	LWL	15	WLB	1.38	75.7	1.514
229	OR-58WB/I-5NB	14	LWL	9	WDN	1.87	103	2.06
234	US-97NB/OR-58	17	KFP	14	LWL	2.64	145	2.9
236	US-97NB/OR-22/I-5NB	18	BND	9	WDN	2.82	155	3.1
237	US-97NB/US-26	19	JBN	12	BRW	1.63	89.8	1.796
238	US-97NB/I-84WB	19	JBN	3	WYT	2.2	121	2.42
239	US-97NB/I-84EB	19	JBN	5	LGR	4.69	258	5.16
TERTIARY								
206	I-84WB/US-26EB	3	WYT	11	BRE	1.18	64.7	1.294
212	I-5NB/OR-138/& US-97NB	7	ASP	19	JBN	3.89	214	4.28
213	I-5NB/OR-138/& US-97NB	7	ASP	18	BND	3.18	175	3.5
215	I-5NB/US-20EB/US-97NB	8	BOR	19	JBN	3.82	210	4.2
218	I-5NB/I-205NB/OR-224/US-26	9	WDN	11	BRE	1	55	1.1
222	US26EB/OR-35NB/I-84EB	11	BRE	5	LGR	4.42	243	4.86
224	US-26WB/OR-224WB/I-205/5SB	12	BRW	10	WDS	0.99	54.7	1.094
232	US-97NB/OR 66 WB	17	KFP	8	BOR	2.91	160	3.2
233	US-97NB/OR 140 WB	17	KFP	16	ASH	1.23	67.6	1.352

* WLB not reporting 2007

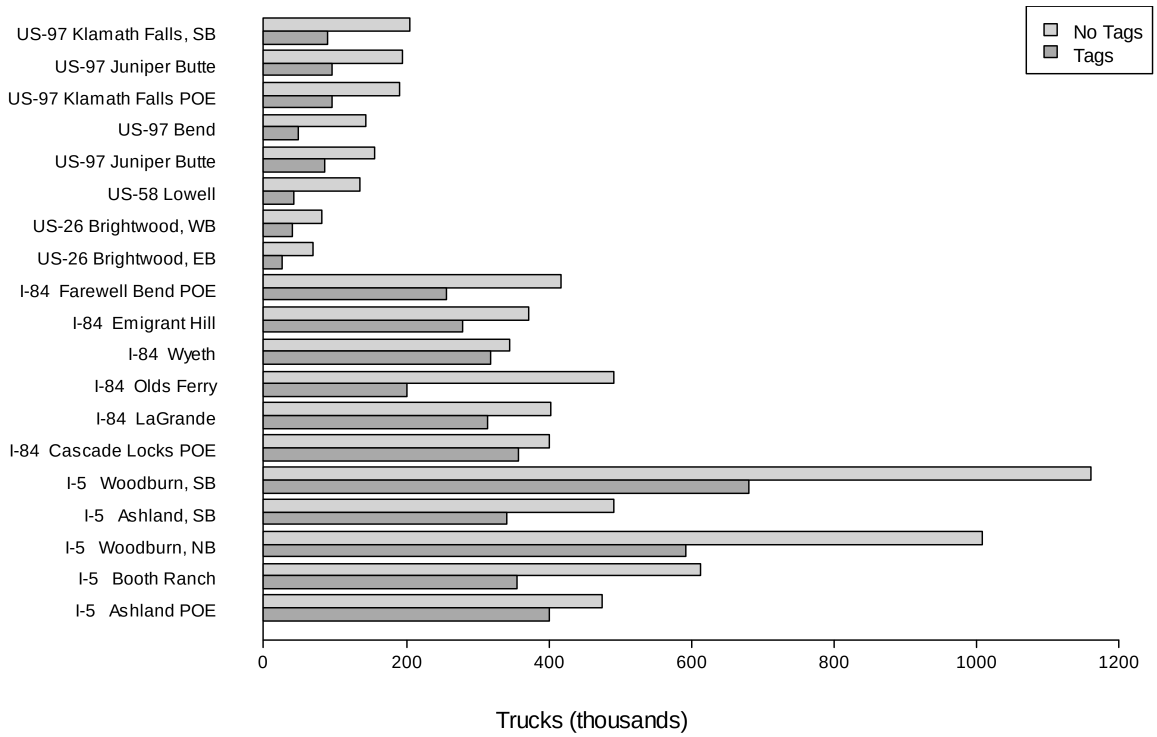


Figure 4.1: Observed Trucks by Station, 2007

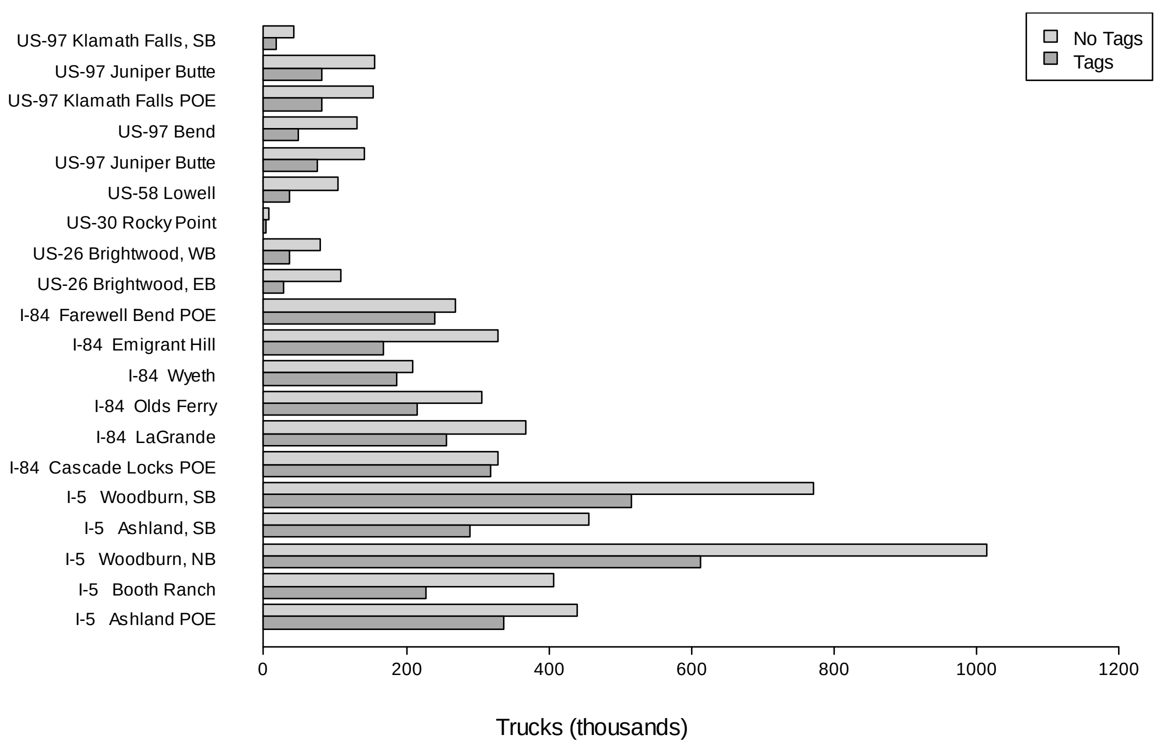


Figure 4.2: Observed Trucks by Station, 2008

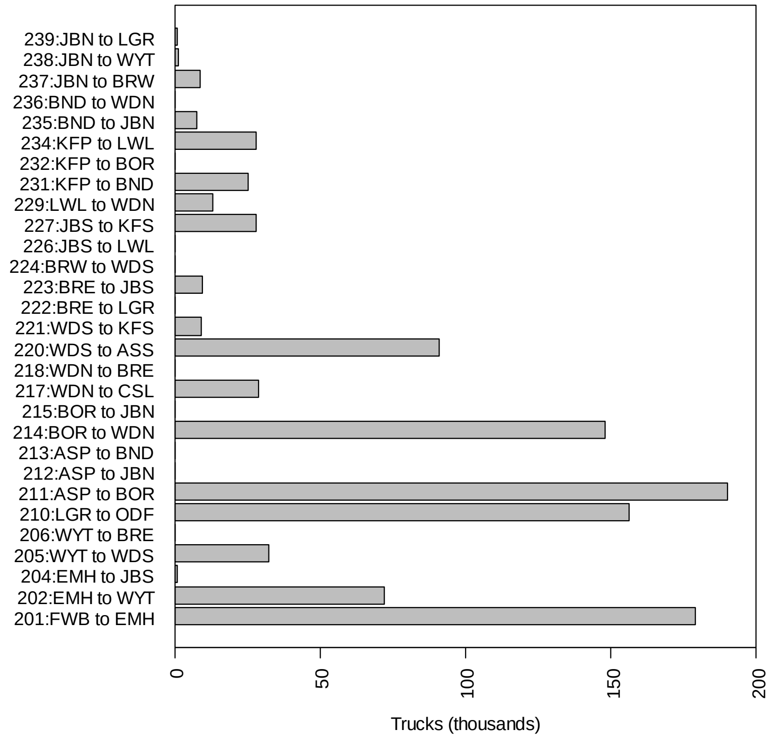


Figure 4.3: Number of Matched Trucks Per Link, 2007

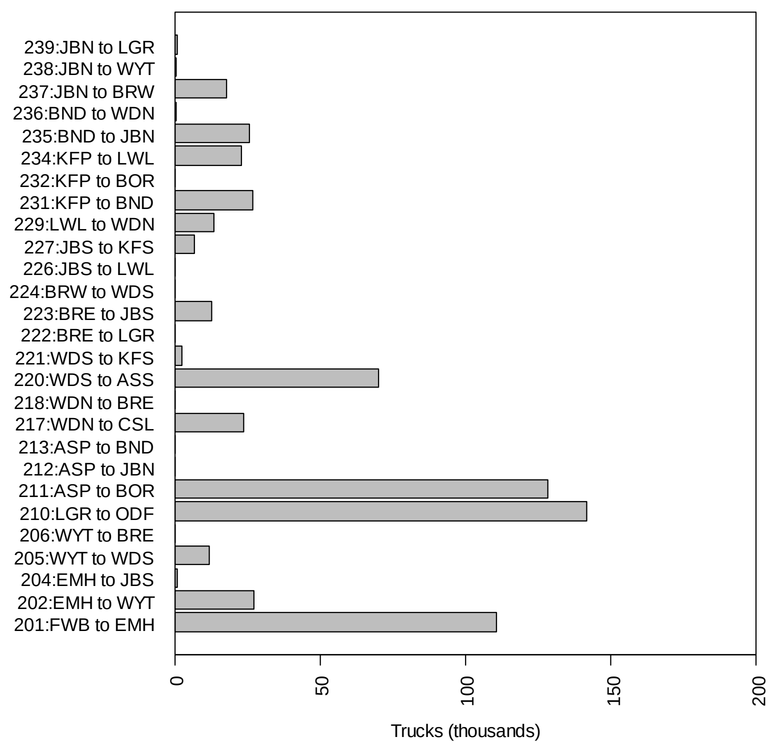


Figure 4.4: Number of Matched Trucks Per Link, 2008

4.2 THROUGH TRUCK FILTER

After trucks with the same tag were matched, the next step was to apply a filter to identify which of the matched trucks were actually through trucks (traveling from station to station without stopping). From a traveler information and corridor performance measure perspective, these are the vehicles of interest.

The algorithm was built using historical data but could be adapted to real time application with some modifications. Unlike most tag matching applications, the time between subsequent observations was very long (the closest station was approximately 1 hour apart). This gap introduced some uncertainty when attempting to establish which trucks traveled from station to station without stopping. Under normal travel conditions, the majority of trucks that traveled between stations without stopping should arrive at the downstream station in a small time window. Trucks that exceeded this time window would have likely stopped for some activity between stations. However, if a delay-causing event (e.g. weather, construction, or an incident) occurred between stations, it is reasonable to expect that travel times of through trucks would exceed the normal time window. These actual delays to though trucks needed to be identified if any meaningful travel time measure on a corridor is to be established.

Thus, the primary objective of this filter was to identify trucks that encountered some sort of delay-causing event. Unfortunately many of the algorithms found in the literature were not directly applicable to the long distances and nature of truck travel. Nonetheless, the conceptual approaches of those algorithms were adapted to our filter. If the assumption can be made that a delay-causing event affects all trucks between stations, then all that needs to be done is to identify the conditions that define trucks that have been delayed. The method used in this filter assumed that if a number of consecutive trucks had similar (long) travel times, then a delay occurred.

The logic can be described as follows (assumed that records are in sequential time order). One method for identifying a through truck in real-time is to look at the properties of a sample of previous trucks. First, trucks that exceed some minimum travel time based on average through speeds are very likely though trucks. For the remaining trucks, if an assumption is made that most (i.e., more than half) of all trucks detected are through trucks, then it follows that the median truck travel time between two stations is a through travel time. Further, the median travel time will not represent unduly fast nor slow trucks, and all of the non-through trucks will be at the tail of the distribution of travel times. Thus, through trucks are identified as those trucks that have travel times less than the median travel time of a sample (of size X) of previous trucks, plus some threshold (Y). X and Y are configurable parameters, and changing them affects the method's accuracy, sensitivity, and lag time in identifying traffic disruptions.

Schematically, the method is described as follows:

1. For each truck j traveling on link i identified by the matching algorithm, subtract the time of observation at the downstream station from the upstream station to determine the estimated travel time, $t_{j,i}$.
2. A series of logical tests are used to determine if the observed travel time can be considered a through truck:

a. If the travel time $t_{j,i}$ is less than the free-flow time $ff_{j,i}$ denote this truck as a through truck.

b. If the travel time $t_{j,i}$ is less than the upper travel time $ut_{j,i}$ (defined as an average travel time of 50 mph).

c. Find the median travel time $mt_{j,i}$ in the sample of X previous truck observations and compare that to $t_{j,i}$. If $t_{j,i}$ does not exceed $mt_{j,i}$ by a threshold of Y, truck j is assumed to be a through vehicle.

3. If none of the above criteria are met, the $t_{j,i}$ is excluded (i.e., j is not a through truck).

4.2.1 Validation

Data sets of known through trucks were not available for validation. In addition, the distribution of through truck travel times is also not known nor is how that might vary by other parameters (e.g., heavily loaded trucks may take longer over mountainous terrain). In order to validate this method for identifying through trucks, periods of known delay were identified on highway segments for which data were available to see if the filter could accurately identify periods of delay.

The types of delay that were examined included incident and weather-induced delay. To examine the effects of incident induced delay, the times and locations of incidents were taken from the Oregon State Police statewide dispatch database for the year 2007. This database was not particularly clean (i.e., the incident descriptions were not systematic and location information was challenging). Because of the long distances between stations and the large variation in truck travel times, minor incidents were not detectable in the data. Thus, significant fatal incidents on links with a suitable number of matched trucks were examined. For the incidents examined, no evident disruption in travel times was discernable that merited further investigation.

Weather-induced delay was examined next. Link 201 (Farewell Bend to Emigrant Hill on I-84WB) was selected. This 126 mile long segment crosses the Blue Mountains in Eastern Oregon, with the stretches of roadway at elevations susceptible to accumulation of snow and ice. As identified from ODOT bulletins posted to the freight list serve, the period in January and February of 2008 was known to have had several disruptions to traffic in this area. Between mileposts 216 and 265 starting at Thursday, Jan. 31, 9:40 am there were intermittent closures dues to weather.

So that the weather could be specifically quantified, data was taken from Road Weather Information Systems (RWIS) automatic weather stations at Ladd Summit, Ladd Canyon, North Powder, Meacham, and Lorenzen Road. Most of these stations collected only temperature data, but some provided more complete data, including precipitation level, barometric pressure, and humidity. This data was supplemented by data collected for National Oceanic and Atmospheric Administration (NOAA) at Pendleton, OR, though this was 20 miles away from the segment, and at a much lower elevation than the Blue Mountain portions.

Figure 4.5 presents a time-series plot of the travel time differences in the matched truck identified by the tag matching algorithm. Each point in the plot region represents the time of the upstream observation (*x*-axis) and the difference between the downstream and upstream timestamp (*y*-axis). The red dashed horizontal line represents the free flow time between these station pairs (2.3 hours). The points are plotted with a transparent fill. With this plotting technique, point observations that overlap in the plot region becomes darker. Darker colored regions indicate a concentration of observations. As shown by the first arrow from the left, many observations are clustered around the free flow travel time (as one would expect with the absence of delay). The second arrow represents a clear increase in the cluster of time differences. If this increase is the result of a weather-based delay experienced by all vehicles, the filter should identify these trucks as through trucks. A histogram of these same data is shown in Figure 4.6. The vertical dashed black line is the median value of the distribution. Note that the right tail of this distribution (and the *y*-axis of Figure 4.5) is constrained by the parameters of the tag match algorithm (no matches that are less than 0.75 or greater than 2 times the free flow travel time are in the data).

To establish that these delays are likely weather-related and not normal patterns visible in the data, similar plots for the same link during the summer months are presented. As can be seen in Figure 4.7 and Figure 4.8, the periods of increased travel time that were evident in the winter months are not present in the summer (the majority of observations are clustered around the free flow travel times). Likewise the distribution of these unfiltered travel times is less skewed with a fewer observations in the right tail.

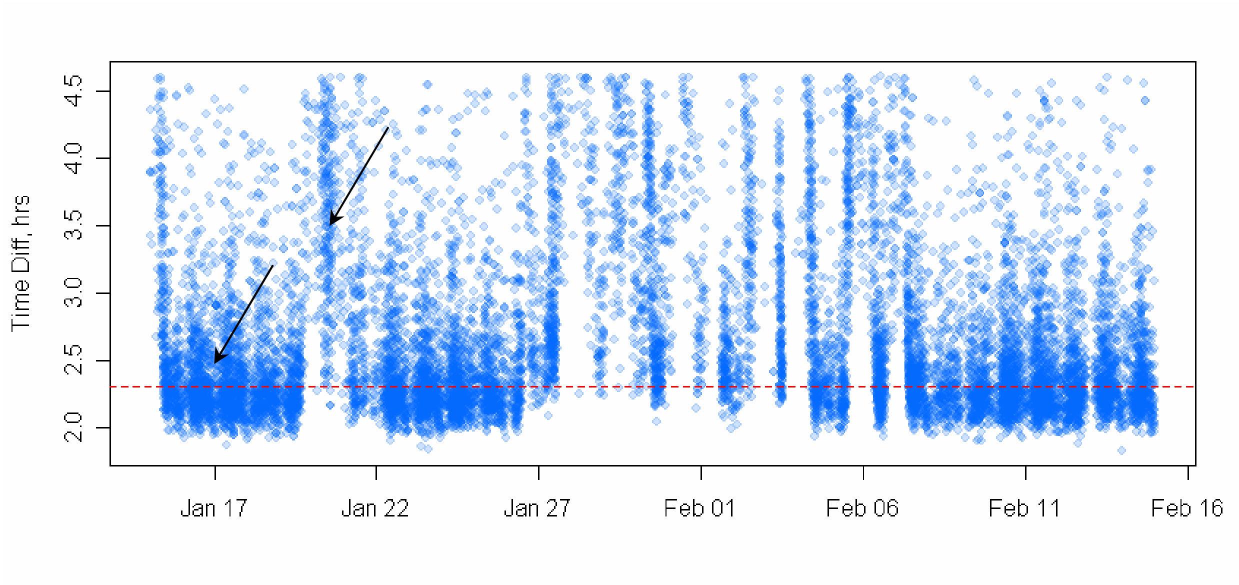


Figure 4.5: Time Series of Unfiltered Travel Times, Link 201, Farewell Bend to Emigrant Hill I-84 WB, 1/15/08-2/16/08

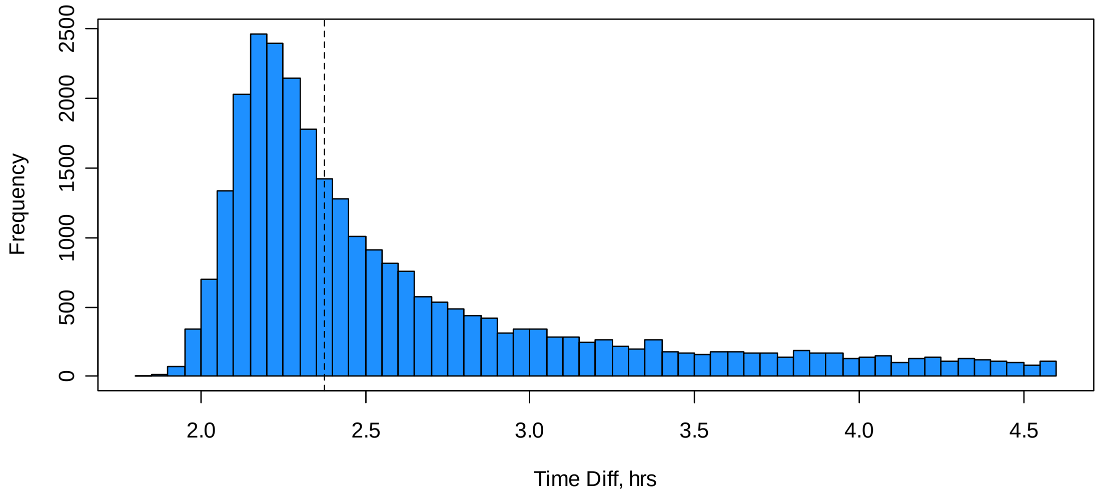


Figure 4.6: Histogram of Unfiltered Travel Times, Link 201, Farewell Bend to Emigrant Hill I-84 WB, 1/15/08-2/16/08

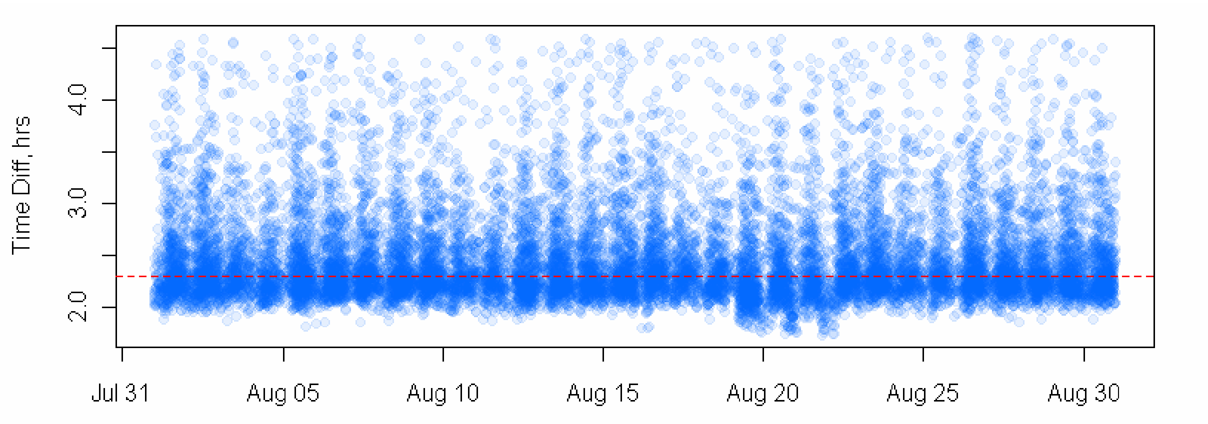


Figure 4.7: Time Series of Unfiltered Travel Times, Link 201, Farewell Bend to Emigrant Hill I-84 WB, 8/1/2007-8/31/2007

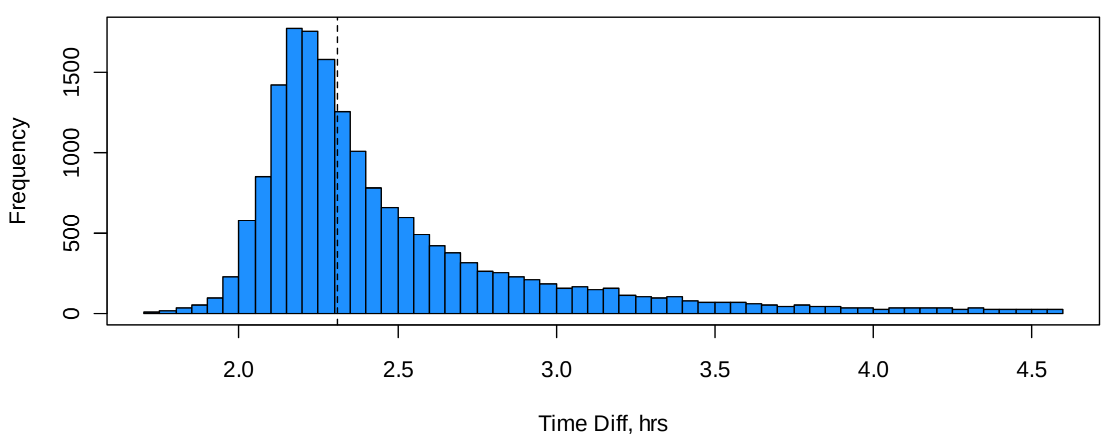


Figure 4.8: Histogram of Unfiltered Travel Times, Link 201, Farewell Bend to Emigrant Hill I-84 WB, 8/1/2007-8/31/2007

Next, the filter was applied to the January-February winter data. A series of plots showing the filter results are plotted in Figure 4.9. The top most plot is identical to Figure 4.5 which shows all matched trucks between stations. The middle plot shows the vehicles that were removed by the filter (not through). The lower plot is trucks that have been identified as through. From the figure, it is easy to see that the method has identified several of the same clusters of increased travel times in Figure 4.5 as through trucks. Presumably these through trucks that are traveling much slower than the average travel time due to some kind of disruption, due to incidents, weather, both, or something else.

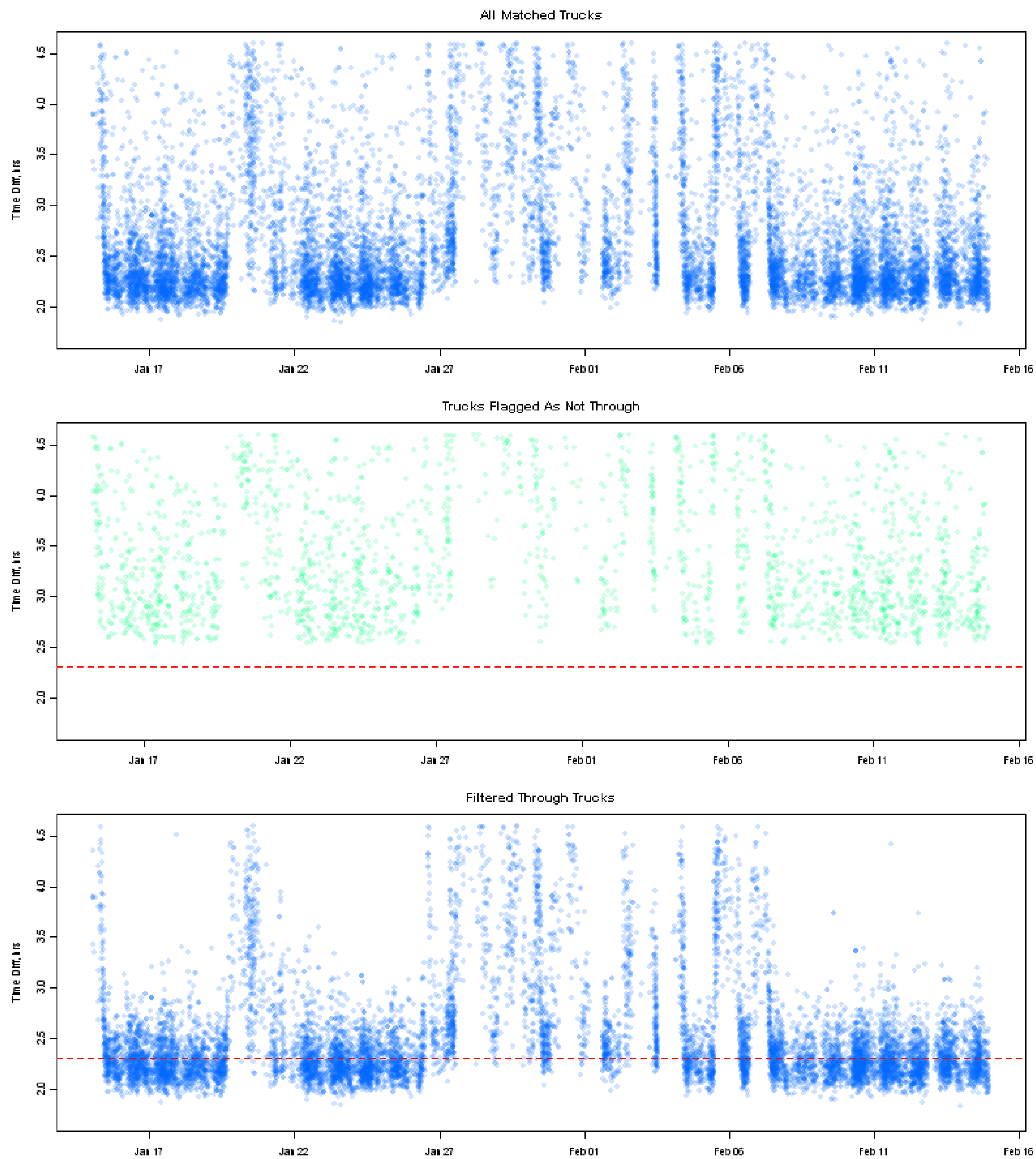


Figure 4.9: Series of Figures Illustrating Filtered Transponder Data, Link 201, Farewell Bend to Emigrant Hill I-84 WB, 1/15/08-2/16/08

The next step in the validation process was to see if weather data correlated with these delays. Figure 4.10 shows the same distribution of travel time differences with temperature data from the Ladd Summit RWIS station (on I-84, between Farewell Bend and Emigrant Hill) superimposed over it. Temperature (in degrees F) is plotted on the second *y*-axis. The data clearly shows a preponderance of freezing temperatures, culminating in a dip into the -10 to 10 degree Fahrenheit range. This extreme weather corresponds convincingly with one of the detected travel time disruptions near February 6th. The temperature's correlation with the other travel time disruptions is less clear, though it certainly is below freezing for all of them, and icy or snowy conditions are plausible. Figure 4.11 is the same plot with relative humidity superimposed rather than temperature. Relative humidity is dependent on temperature and pressure. It corresponds to cloud formation and precipitation. However, no apparent trend is visible in the figure. Indices, combining temperature, humidity and other data were explored but not presented here.

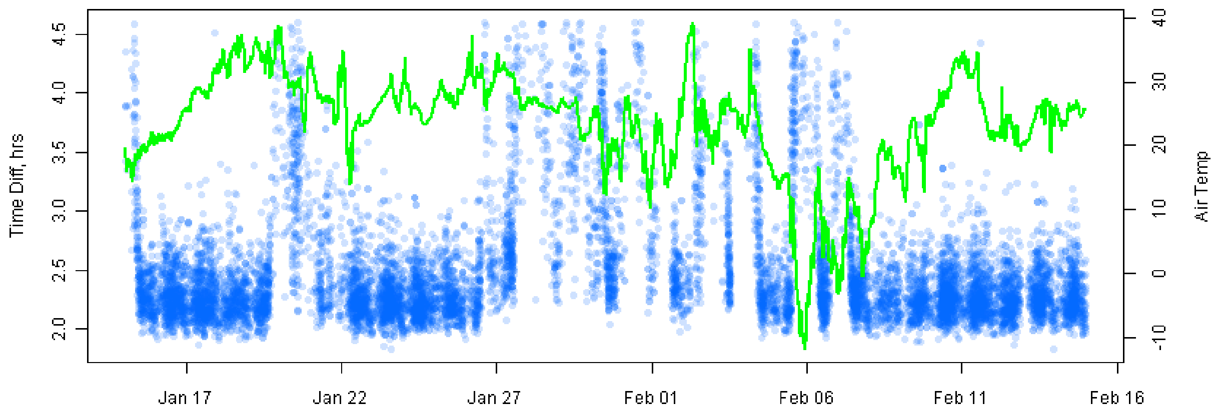


Figure 4.10: Plot of Filtered Trucks and Temperature Data, Ladd Summit RWIS

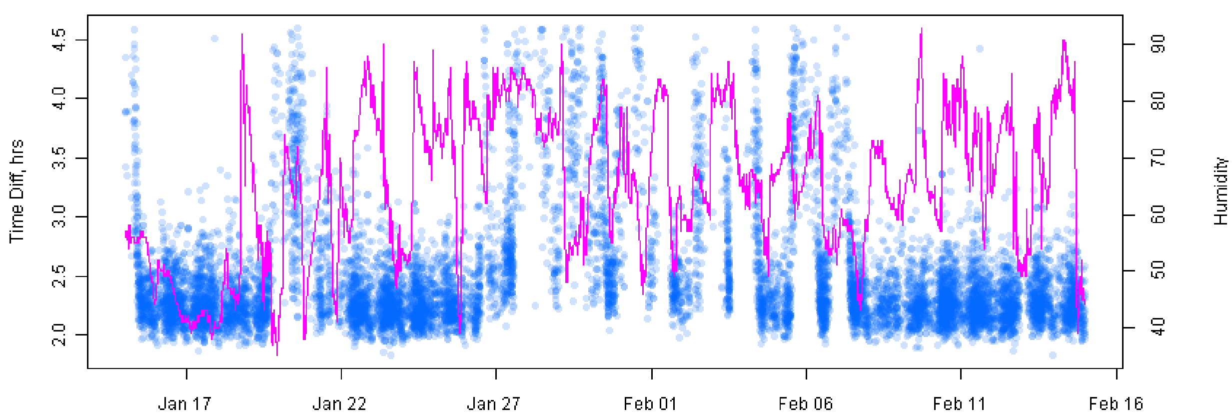


Figure 4.11: Plot of Filtered Trucks and Relative Humidity Data, Ladd Summit RWIS

The RWIS stations did not record precipitation data which might also be a clue to weather delays. The nearest NOAA weather station that records precipitation data is located in Pendleton, OR. Figure 4.12 shows three stacked plots. The lower plot is again the filtered travel times as before. The middle plot shows the type of weather and intensity that was observed. The time scale on the x-axis is the same. The top plot shows the water-equivalent precipitation. There are clearly precipitation events in the clustered around the times of the traffic disruptions, but the correlation is far from perfect. However, this highway segment from Farewell Bend to Emigrant Hill travels over some mountainous terrain (summit elevation of 3619 ft), while the weather data collected from Pendleton (elevation 1493) is more representative of lower elevations. Given this geographic separation, the depicted precipitation does appear to be plausibly consistent with the detected disruptions. Analysis was conducted for eastbound traffic on the link and similar conclusions reached.

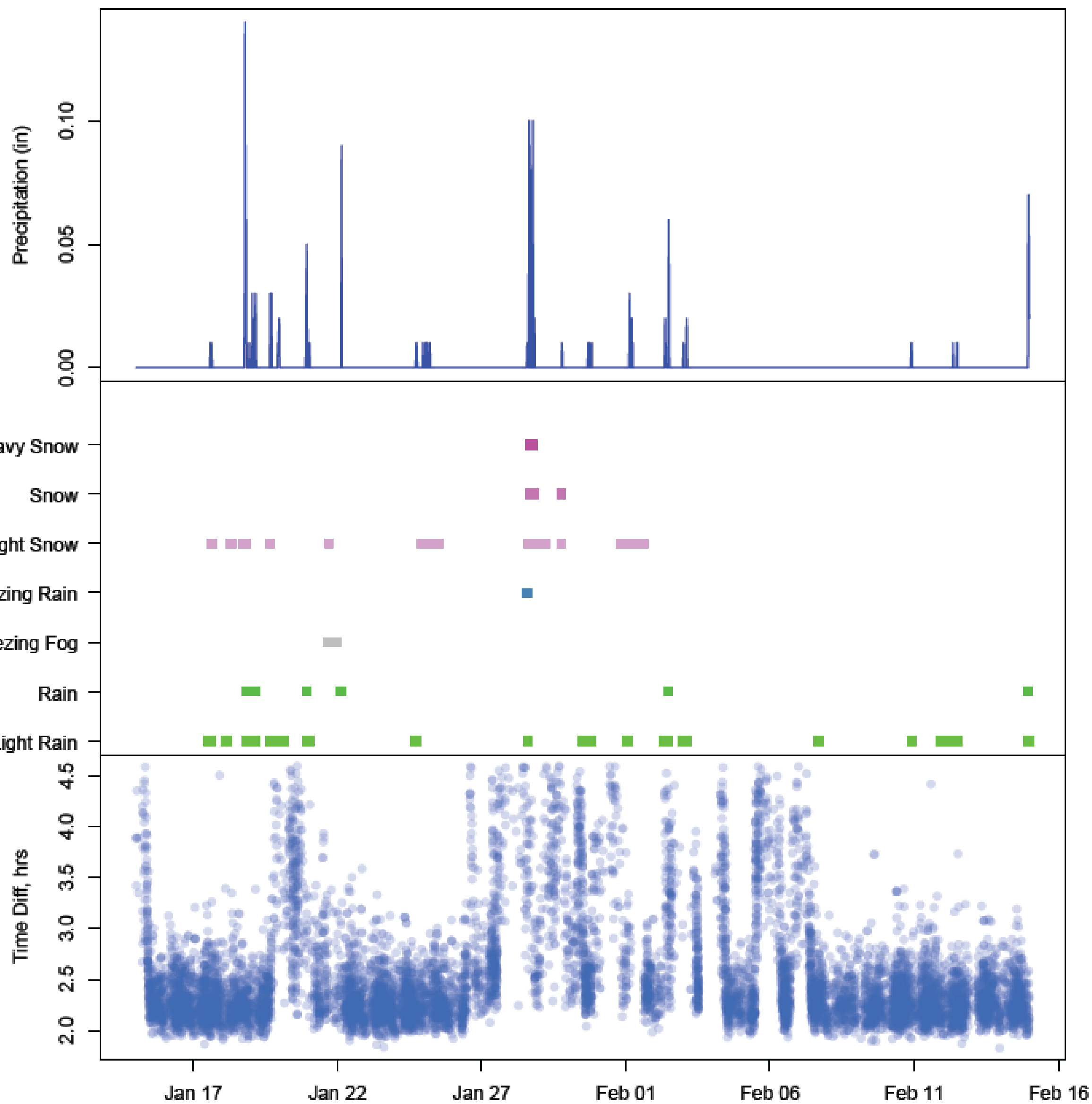


Figure 4.12: Plot of Filtered Trucks and Precipitation and Weather Intensity Data

None of these weather-based plots provides definitive validation of the through truck filter. There are clearly delays but they could not be correlated perfectly with observed weather. This is partially due to the fact that using weather data to validate the filter is less than ideal. First, there are many permutations of "poor" weather that could produce delays. For example, even with no precipitation or snow, freezing temperature and blowing snow could produce weather delays. Second, the uncertain time lag between weather events and observable delays makes correlating disturbances difficult. This is compounded by the length between stations. For example, if intense snow delays vehicles there is a delay from when this weather event occurs and when it is recorded. There will also be a lag from when this delay is evident in the through truck data. Finally, weather stations are not always representative of on-road conditions.

However, the plots strongly suggest that poor weather was present on this link. Knowing that the weather was inclement enough to intermittently close the freeway provides suggests that the filter does a reasonable job of identifying through trucks that have encountered some delay. Inspection of several other links with known weather delays revealed similar evidence.

4.2.2 Sensitivity Testing

With the assumption that the filter is reasonable, the next step was to explore the sensitivity of the parameters in the filter. The following parameters are variable in the algorithm:

1. the free-flow travel time;
2. the upper travel time;
3. the number of previous and after trucks to compare the selected travel time (*X*); and
4. the threshold (*Y*).

Parameters 1 and 2 are fixed for the link as properties. Parameter 3 and 4 are selectable. Table 4.2 shows the effects of changing these parameters on the method's measurement of average travel time of through trucks on link 201, from Farewell Bend to Emigrant Hill, in January and February of 2008:

Table 4.2: Average Travel Times with Parameter Estimates, Link 201

Number of trucks in sample (*X*)	*5*	*5*	*5*	*5*	*15*	*15*	*15*	*15*
Threshold (Y)	10 %	15 %	20 %	25 %	10 %	15 %	20 %	25 %
Average through truck TT	2.45	2.48	2.5	2.52	2.42	2.46	2.48	2.5
Number of trucks in sample (X)	10	10	10	10	20	20	20	20
Threshold (Y)	10 %	15 %	20 %	25 %	10 %	15 %	20 %	25 %
Average through truck TT	2.43	2.47	2.49	2.51	2.42	2.45	2.48	2.5

The measured travel time of through trucks goes down as more trucks are in the sample, and goes up as the threshold is increased. This makes sense, as smaller samples would be more prone to have a high median travel time due to occasional concentrations of non-through trucks, while increasing the threshold above the median travel time directly identifies trucks with longer travel times as through trucks. The method is not particularly sensitive to either effect, however, yielding a range of travel times from 2.42 to 2.52, depending on the values of the parameters – a difference of only 4 percent.

For applications of the filter that follow we used X=10 and Y=15%. To demonstrate, Figure 4.13 shows the filtered data (only through trucks) of all that was presented in Figure 4.7.

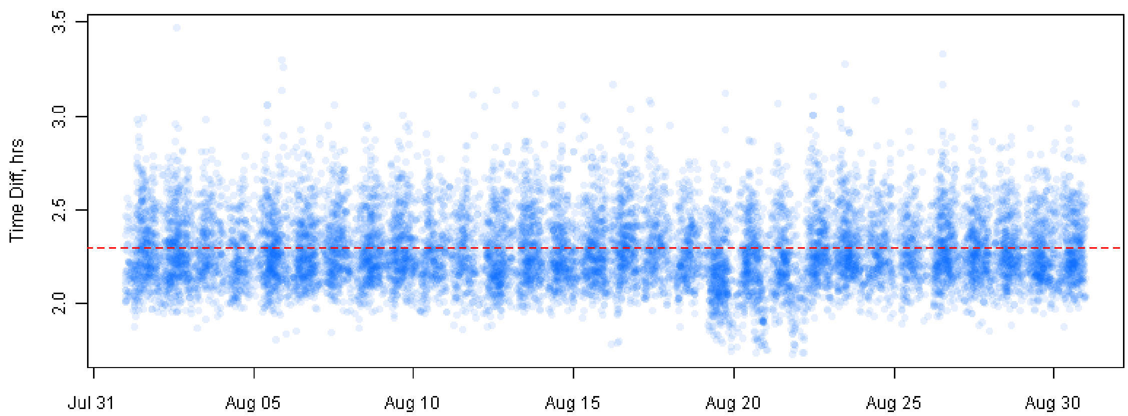


Figure 4.13: Time Series of Filtered Travel Times, Link 201, Farewell Bend to Emigrant Hill I-84 WB, 8/1/2007-8/31/2007

4.3 RESULTS

For all trucks that were identified as through by the filter, the travel time difference for each observation was calculated. In 2007, 811,492 through trucks were observed. In 2008, 524,913 through trucks were observed. Data availability and quality issues are the primary reasons for the discrepancy but the trucking industry overall saw reduced activity with the economic recession that began in early 2008.

To present the results, the travel times were converted to an average speed using the distance between stations. Data were aggregated in 24 hour and month bins. The average and standard deviation was calculated for each link for 730 days and 24 months. The results of these calculations and aggregations for one link are presented in Figure 4.14 and Figure 4.15. In the figures, time is presented on the x-axis and average speed is shown on the y-axis. The solid line represents the average speed and the dashed lines represent one standard deviation of the mean. The width of the standard deviation band can be interpreted as the reliability of the link travel time (average speed). For comparison, the free flow travel speed (assumed to be 55 mph) is presented as the dashed horizontal red line.

The figures show the smoothing effect of data aggregation. Figure 4.14 which shows average speeds by bay is more variable; Figure 4.15 with monthly aggregations smoothes the data and masks the day-to-day variation. Note that in the month plot, a trend line is presented but does not imply continuous measurements. Month averages are plotted with an open circle. Missing months are excluded but the trend line is extended from previous to subsequent months. The figures also show how the width of the standard deviation band varies. Wider bands indicate less reliable (i.e. more variable) travel times. In a very common trend, changes from "average" conditions are accompanied by an increase in the standard deviation band. For freight, the reliability of the travel time is nearly as important as the actual travel time (since it easier to plan for more consistent travel times though is less of an issue on rural routes with limited recurring congestion).

Figure 4.15 shows two other interesting events. These events highlight both the usefulness of these data and the challenges in using them. The graphs are the estimated average speeds for graph for link 201: Farewell Bend to Emigrant Hill (I-84WB) for 2007 to 2008. This is the same link that was used in the validation of the weather-induced delay. For most of 2007, the month average travel speed is essentially equivalent to the free flow travel speed (55 mph). In December 2007, January 2008, and February 2008, the average speed drops and the standard deviation band increases. This decrease in performance should be considered a valid measurement. The second event is in May 2008, where an improvement in average travel speed is noted (and remains consistent until the end of the year). Inspection of the underlying data reveals that this "improvement" is associated with data issues rather than real change in performance.

These data issues can also be seen in other links. In Figure 4.16 a time series of the estimated average speed for the Klamath Falls to Lowell (Link 234). Inspection of the figure reveals that the observations a fairly constant while there are disturbances in and around the winter months there are no sudden data jumps or gaps that would suggest data issues. Given that this route traverses the Cascade Mountain range, these disturbances are entirely reasonable. In contrast, similar data is presented for LaGrande to Olds Ferry (Link 210) in Figure 4.17. By inspection, it is clear that a systematic error occurs around February 2008. The average speed has dropped significantly as well as the variation in these data. This is an obvious data error; an average speed of 35 mph on an interstate freeway is unreasonable;. Perspective on this issue is included in the concluding discussion section of this chapter.

Ignoring data quality issues, the 1,336,405 filtered through truck observations were processed. The data are presented in two sets of figures. For clarity, the remaining results are presented aggregated at the month level though the information can easily be presented at any time aggregation. The average speed is reported for the primary and secondary link categories shown in Table 4.1. As a reminder, the primary routes are those where the path of the vehicle for through trucks is very certain. The links include the interstates and primary highways monitored by WIM stations. These results are presented in Figure 4.18. Secondary routes (those involving more than one highway and with less certainty about the actual truck path) are presented in Figure 4.19. None of the tertiary routes had enough observations (a minimum of 30) to be considered reliable estimates of the corridor performance. Coupled with the disclaimer that the paths assumed on these tertiary routes are much less certain, it is reasonable to conclude that they are not suitable for monitoring the performance of any specific facility.

For the primary corridors, when the stations are reporting data correctly, there are a sufficient number of sampled trucks. For the primary links, a minimum of 1000 trucks per month was required to be plotted. This threshold was to remove months with few data points (indicating a data issue). Because of data availability and quality, average travel speeds are not reported for link 208 (Cascade Lock to LaGrande), link 219 (Woodburn SB to Wilbur), link 230 (Wilbur to Ashland). Links 219 and 230 are essentially replaced with link 220 – Woodburn SB to Ashland. Link 208 exhibited consistent data problems for both years. Inspection of Figure 4.18 appears to reveal some significant changes in performance for many of the corridors. On investigation of the source data patterns, the apparent drops in performance on links 210, 227, and 231 are data related. When the station data are acceptable, reasonable trends and data appear. Most of the interstate links have average travel speeds near the free flow speed. As expected links with grade have lower average speeds than those without (e.g. link 211 Ashland to Booth Ranch vs. 214 Booth Ranch to Woodburn). In addition, the non-freeway links (227, 231, and 235) have average speeds below the free flow speed for all observations.

Figure 4.19 shows the same results for the secondary links. For these figures, the inclusion threshold was lowered to 500 vehicles per month. Again, because of this and data issues, performance measure for link 204, 209, 228, 226, 236, 238, and 239 are not presented. For these links, only the change in 237 appears related to a data quality issue. Some interesting trends and comparisons were found. Link 205 and 217 are opposite travel direction. Link 205 is I-84WB, I-205SB, I-5SB while 217 is reversed. The average speed for the northbound direction is about five miles an hour lower. The exact routes of vehicles between these stations is not known with certainty. As will be presented in section 6.2.1, the freight activity on these links are different (more vehicles appear to make deliveries on link 217, while more pickup activity happens on link 205). This highlights the challenges of generating corridor performance if the there is uncertainty about the route. Another link pair – 221 Woodburn South to Klamath Falls and 234 – Klamath Falls to Lowell use primarily the same route. Note that Lowell is only westbound. The average speeds are similar but the data on 234 is better (note the missing months of data in 221). The 234 data clearly exhibits the winter weather patterns discussed previously.

Time series plots of all through trucks by link for 2007-2008 can be seen in the Appendix.

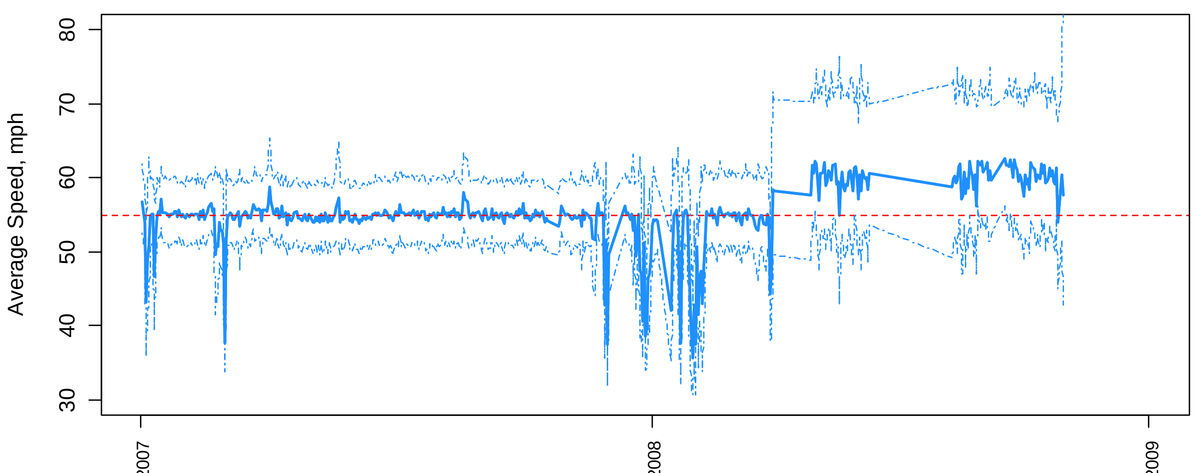


Figure 4.14: Plots of Average Travel Speed, Link 201, Aggregated by Day

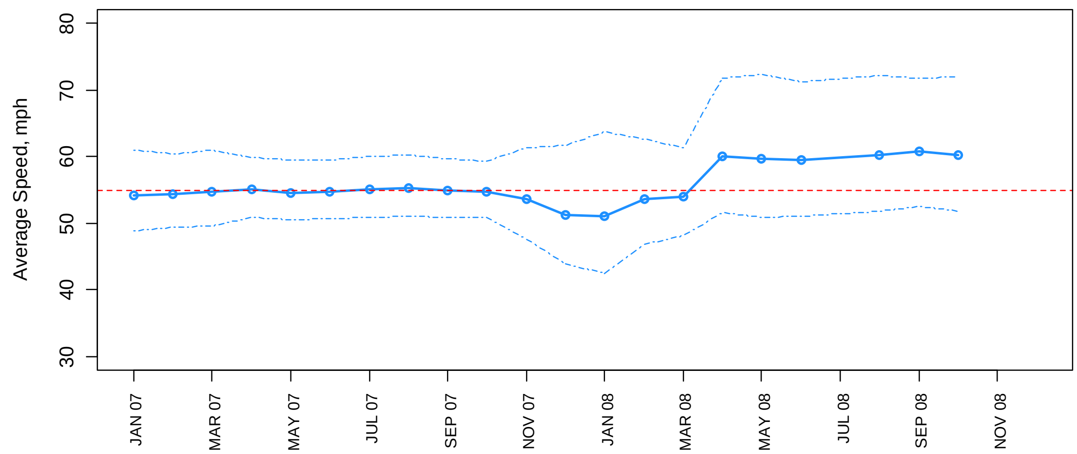


Figure 4.15: Plots of Average Travel Speed, Link 201, Aggregated by Month

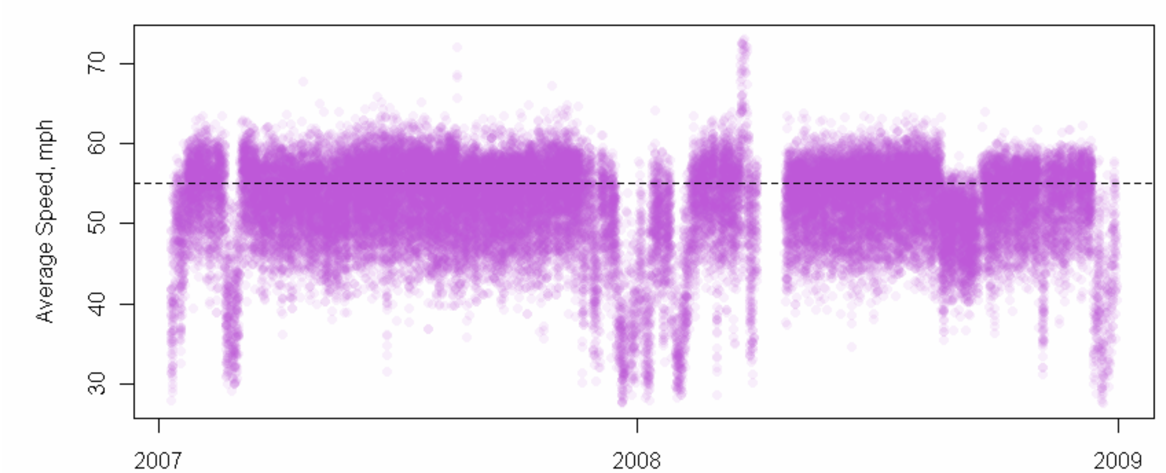


Figure 4.16: Time Series of Filtered Through Truck Average Speed, Link 234 KFP to LWL

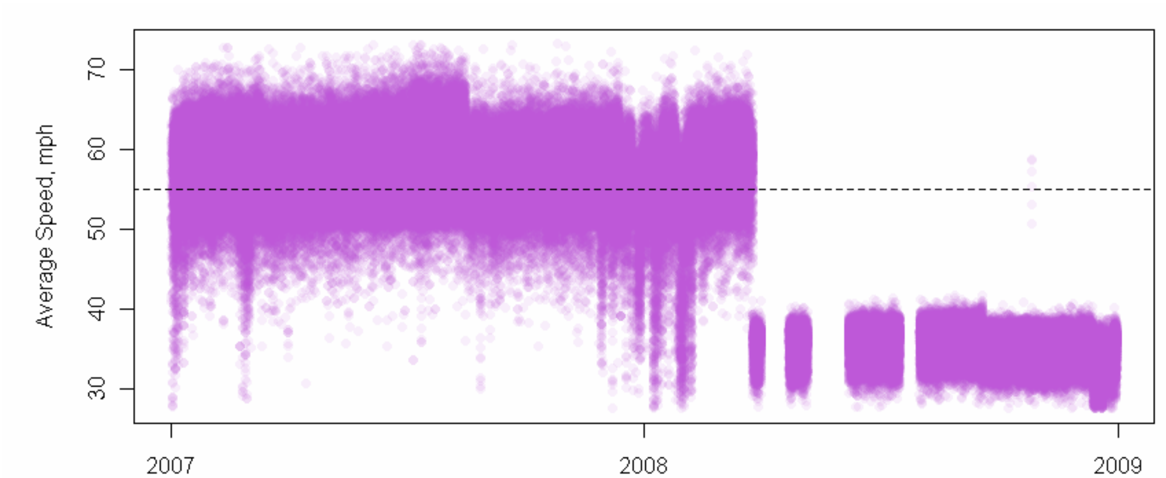


Figure 4.17: Figure 5.5 Time Series of Filtered Through Truck Average Speed, Link 201 LGR to ODF

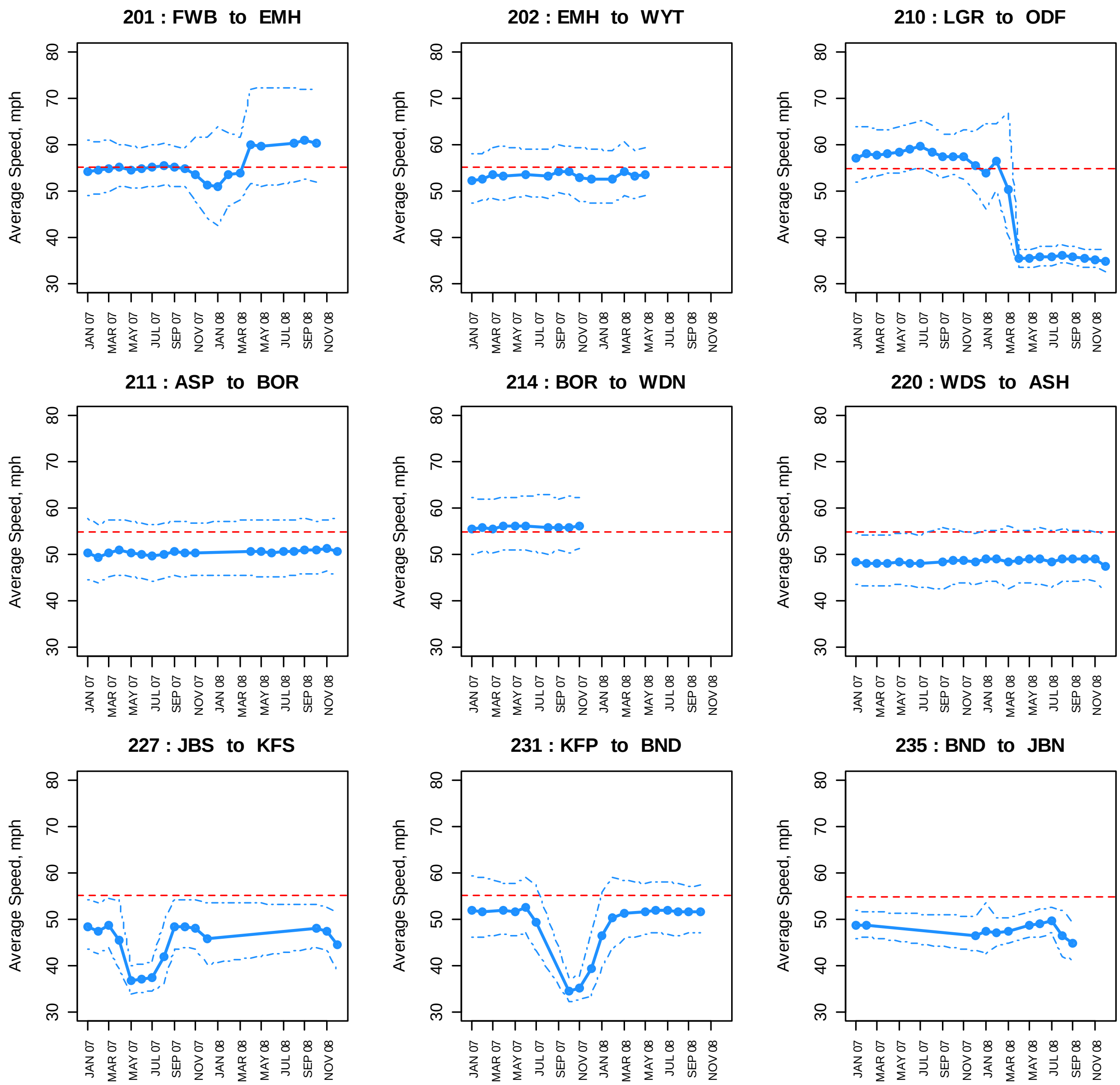


Figure 4.18: Average Travel Speed +- 1 standard deviation, by month, 2007-2008, Primary Links (min 1000 obs)

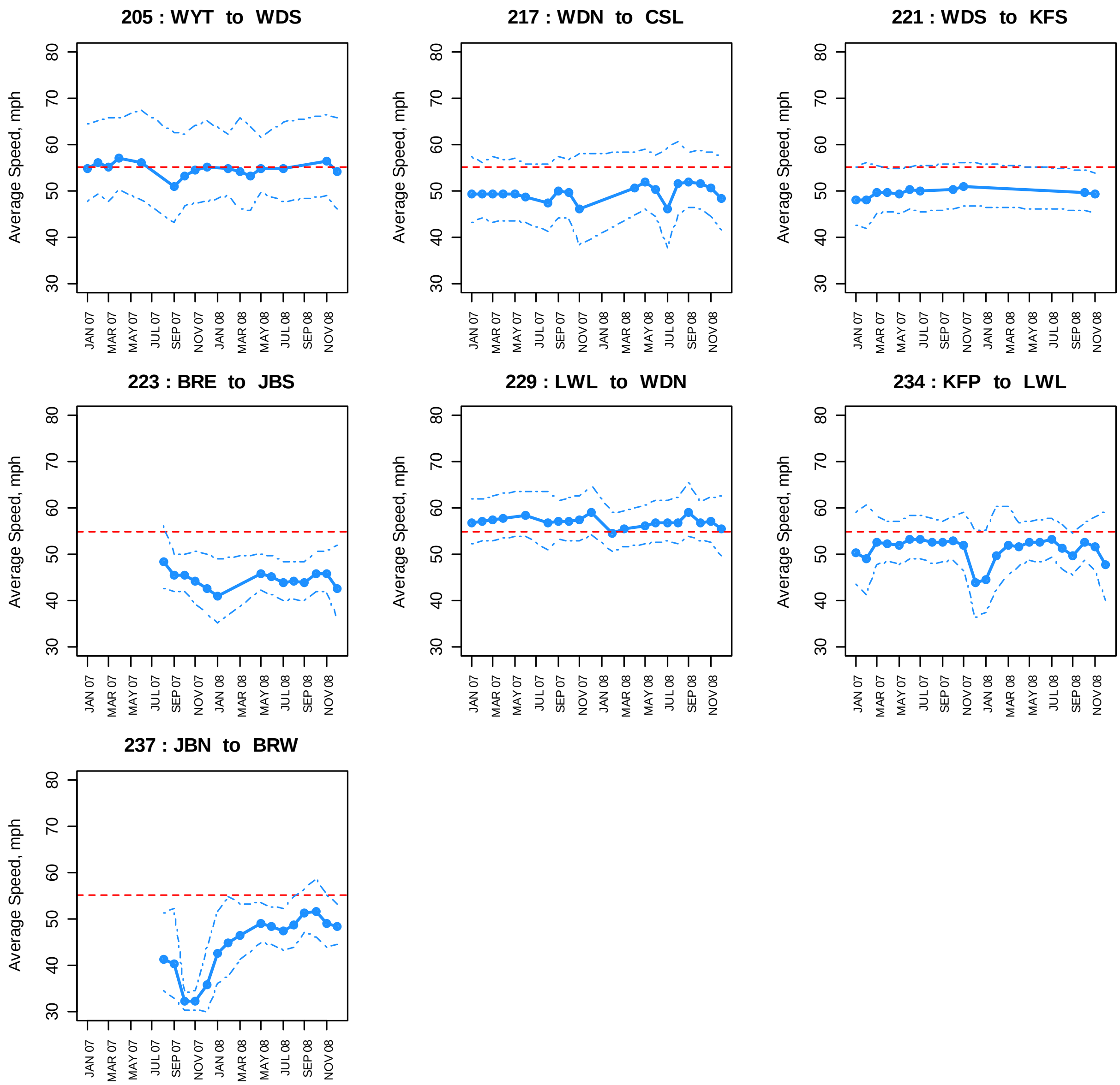


Figure 4.19: Average Travel Speed +- 1 standard deviation, by month, 2007-2008, Secondary Links (min 500 obs)

4.4 DISCUSSION

The research intend to explore the possibility of using the existing ITS infrastructure for real-time traveler information and as a means to establish historical corridor performance measures. A number of issues were discovered; they are discussed in the following paragraphs.

First, it is clear from the analysis that on the primary links, there are a sufficient number of trucks with tags (both numbers and frequency) to establish travel times between stations assuming data issues can be resolved. On some of the secondary links, there may not be enough trucks for real-time use. However, even with sufficient numbers of matching vehicles there are a number of challenges to using these data for real-time purposes.

First, the long distance between most station pairs implies that for an incident or delay causing event to be identified in the data it must be significant. For long travel distances, even delays of 20 or 30 minutes could be "erased" by increasing travel speed downstream of the incident. Thus, the distance between observations controls the minimum duration of an incident that could be detected. This concept can be illustrated in Figure 4.20 which presents the monthly standard deviation (in hours) of the filtered through trucks for each station against the distance between stations. As one can see, the variability increases with the distance. Because the filter accepts more trucks as "through" the accuracy identifying through trucks (either false positives or missing through trucks) decreases with distance.

Two improvements are possible that would improve the feasibility of using the WIM systems for real-time traveler information. First, additional sensors to read transponders could be installed to improve the accuracy and decrease the latency of time estimates. Spacing would best be determined on a corridor by corridor basis. Figure 4.20 suggests that sensor spacing of 100 miles or less is reasonable. However, shorter spacing may be required around typical areas of delay and places where routes diverge or are uncertain. The hardware and labor for additional transponder readers are estimated to cost $9,000 each (*McCormack 2008*). This would not include the cost of integrating these sensors with the current WIM system data.

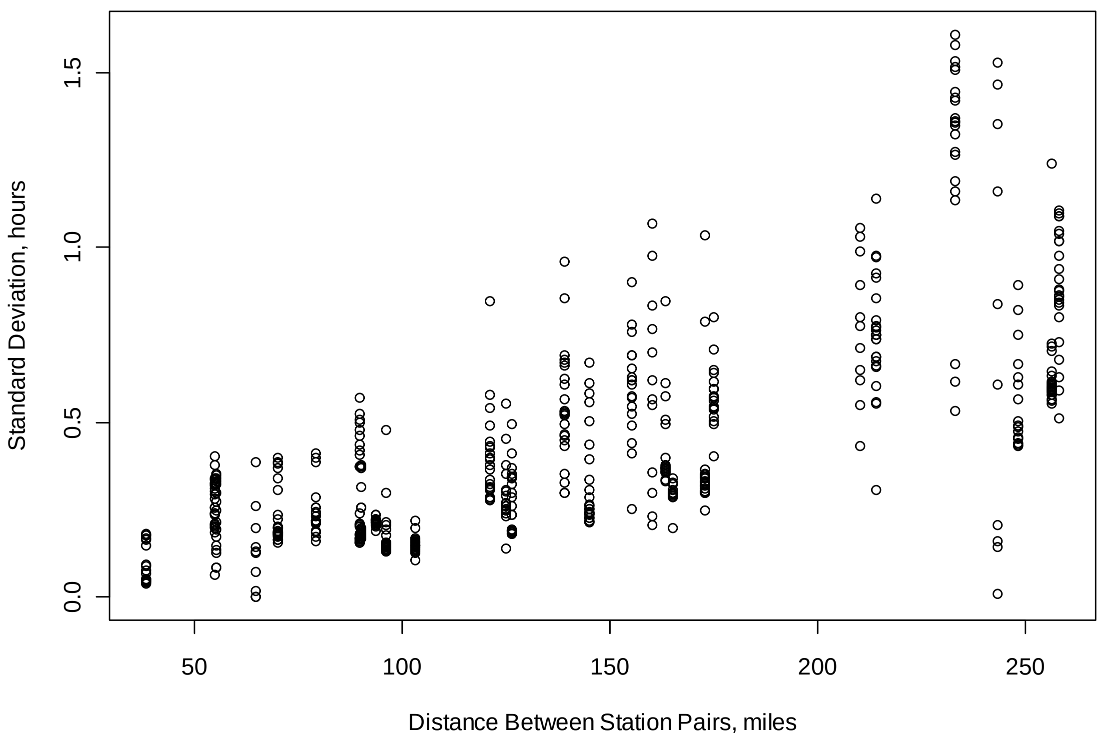


Figure 4.20: Plot of Monthly Standard Deviation in Filtered Travel Time by Distance between Station Pairs, 2007-2008

Another possible improvement would be to do additional work to improve the filter. More sophisticated algorithmic approaches (e.g. Kalman Filter) could possibly be used. The filter did not take advantage of the vehicle attribute data (weight and axle) that could be used as an additional screen for through vehicles. For example, if vehicle's weight parameters of vehicle configuration changed significantly it could reasonably be assumed to have made a stop between stations. These vehicles would most likely be detected by the current filter configuration but it would improve it, especially if weight and spacing data are confirmed to have high accuracy. Another improvement would be to add a time window to the trucks that are considered by the filter. Presently, the filter considers a number of consecutive matched vehicles for comparison, whether that is for 10 minutes or one hour. The filter could be adapted to only consider trucks in a specific time window. Because of the high frequency of matches on the main links, this modification would have marginal improvement but could help accuracy on secondary links. Lastly, the usefulness of the upper travel time parameter could be explored.

Without actual knowledge of through trucks a complete validation of the filter was not possible. Fleet or satellite-based truck data could be used as validation data set to more accurately establish through vehicles. Access to this type of data was not explored as part of this research effort (though it is available from ATRI with strict confidentiality limits for some highways in Oregon).

With respect to long term corridor performance monitoring, however, it appears that it is very feasible to use the archived data. With long-term corridor monitoring, the need for accuracy in travel time estimates is reduced, and the long distances between stations are less of an issue. As was shown, the average speeds and standard deviations were readily calculated and when data quality is good, the methodology appears capable of detecting delay (especially weather-based).

The archived WIM data has not been used to generate travel times before and it is not unexpected to find data errors in large datasets where the primary purpose of the data is not what is being explored. After missing data due to planned station maintenance or other activities, the primary data quality issue appears to be incorrect timestamps in one or both stations. This is rather common. Inspection of time series plots for many of the links exhibit sudden changes in observed time differences that return to normal. None of the changes align with daylight savings time changes. However, most of the differences appear to be approximately one hour off. While the exact nature of the error has been pinpointed, in order for these data to be used for systematic reporting this issue would need to be resolved. An automated method that identifies data quality would need to be examined.

5.0 GROUND TRUTH COMPARISON

In order to validate the concept of using matched truck transponder data for traveler information, actual (ground truth) travel times were collected and compared to the truck estimated travel times. The collection and analysis of probe travel times was done to answer two primary questions: 1) does the tag matching produce reasonable travel times; and 2) could truck-based observations be used to inform the general motoring public of travel conditions and delays? Passenger vehicles do not have the same travel times as trucks because of difference in performance, operations, and driving characteristics. This chapter presents the results the estimates from the ground truth probe vehicles and analysis to establish a relationship between truck and passenger travel times.

5.1 PROBE DATA

To establish ground truth, one typical research method is to dispatch controlled probe vehicles to collect data in the study corridor(s). Ideally, the ground truth data in this study would be from both passenger cars and trucks. However, the interest in question 2) suggested that the probe data should be collected from passenger cars rather than trucks if only one could be obtained. While many trucking companies use automatic vehicle location (AVL) technology for fleet management and know the locations of their vehicles in real-time they do not like to share data for competitive reasons. Occasionally, third party providers will make the data available (such as the ATRI data described in the performance measurement section) but these data are often limited in time or space resolution to avoid competitive concerns. As such, collection of passenger-car based probe data was pursued.

The long distances and project budget led the research team to consider using state employees on official business as the probe vehicle drivers. Researchers prepared a proposal for the use of human subjects for review by Portland State University's Human Subjects Research Review Committee (HSRRC). The committee approved the application. A copy of the HSRRC approval letter is in the Appendix. The researchers followed the protocol specified in the application in terms of data collection, informed consent and data management.

After some discussion, the director of the State Motor Pool agreed to allow state employees (either from the Oregon Department of Transportation or other agencies) who are using vehicles from the state motor pool or the Oregon DOT fleet to specific destinations as probe vehicles. Subjects were recruited based on a declared destination made at the time of their reservation. Drivers on trips that involve the following city pairs were asked to participate in the study:

- Portland to LaGrande, via I-84
- Portland to Bend, via US-26
- Portland to Klamath Falls, via US-26/US-97
- Portland to Ashland, via I-5

- Salem to LaGrande, via I-5/I-84
- Salem to Bend, via US-26
- Salem to Klamath Falls, via –OR-58/US-97
- Salem to Ashland, via I-5

These routes are shown in Figure 5.1. Each driver was given a small data logging device that records the latitude and longitude of a vehicle at a specified time interval using GPS. Subjects were given a brochure on the purpose of the study, given instructions on the use of the GPS device, and an informed consent letter. Drivers were instructed to drive as they normally would. When the devices were returned from the field, the raw position data were downloaded, cleaned of data, recharged, then returned to the field. A sample data stream and photograph of the GPS data logging device is shown in Figure 5.2

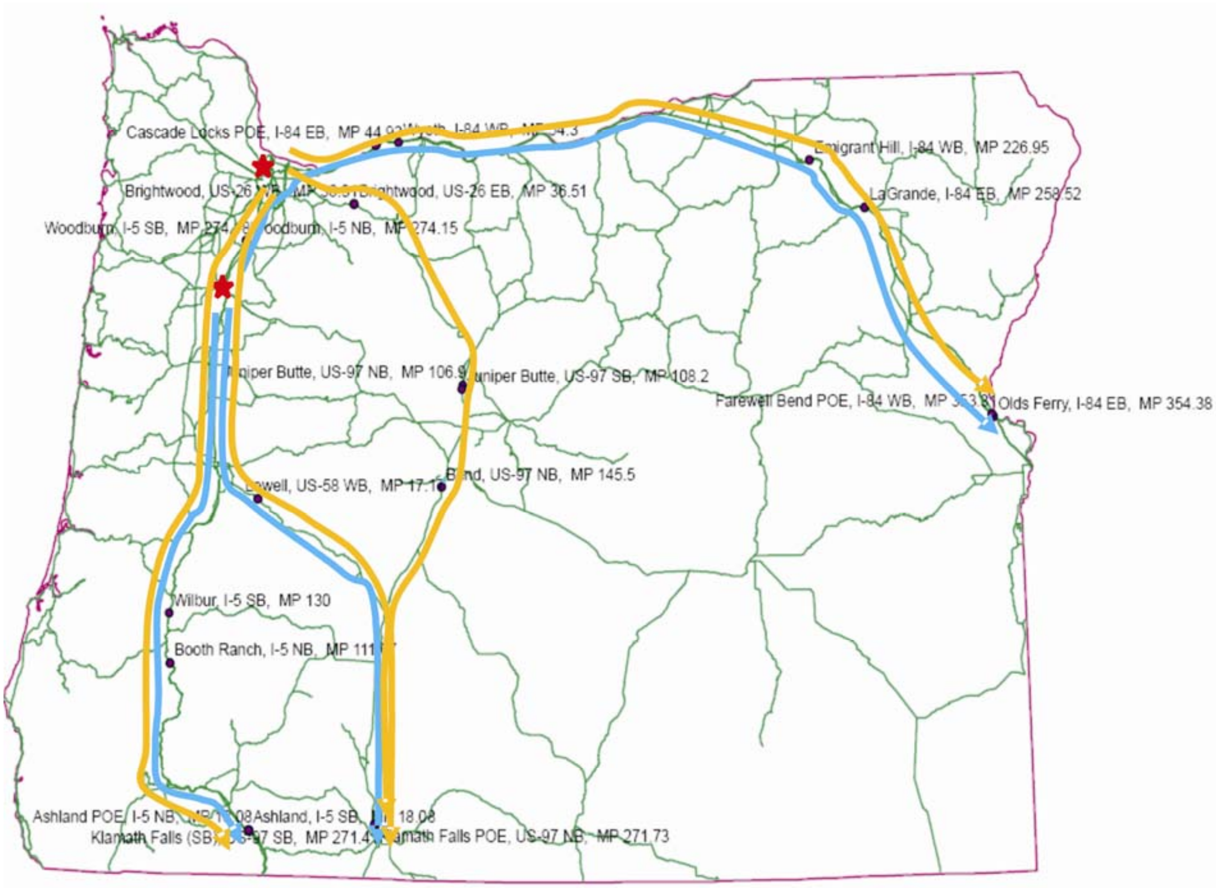


Figure 5.1: Routes for Motor Pool Fleet Probe Data Collection

```
Tag,$GPGGA,UTC(hhmmss.sss),Latitude,N/S,Longitude,E/W,Fix quality,Number Of
Satellites,Horizontal dilution of position,Altitude,Height of geoid,,Checksum
Tag,$GPRMC,UTC(hhmmss.sss),A,Latitude,N/S,Longitude,E/W,Speed(knots),Course(degre
es),Date(ddmmyy),,Checksum
---,$GPGGA,162807.000,3205.5748,S,11548.6228,E,1,46,226.6,7990.0,M,00.0,M,,*73
---,$GPRMC,162807.000,A,3205.5748,S,11548.6228,E,0.00,46.00,080800,,*2B
---,$GPGGA,162807.000,3205.5749,S,11548.6228,E,1,46,226.6,8502.0,M,00.0,M,,*7A
```

Figure 5.2: GPS Data Logging Device and Sample Data

5.1.1 Data Processing

A total of 4,283.13 mi and 371:54:57 hrs of probe data were collected. A manual procedure was developed to clip trip segments where the probe vehicle was traveling between to 2 consecutive stations. All probe runs were processed through an R script to produce keyhole-markup-language (KML) file of each vehicle's travel path. This R script is available in the Appendix. These KML files could be viewed in Google Earth or Maps. In the KML file, the speed recorded by the GPS devices was used to color–code each individual vehicle point observation to help identify locations where the probe vehicle left the highway or stopped en-route. An example of this output is shown in Figure 5.3. The points – or "breadcrumbs" – shown in figure are plotted from the latitude, longitude and speed reported by the data logging devices. These points were numbered sequentially based on time of occurrence. All points shown in the figure are 3 seconds apart in time. Black-colored points represent stopped vehicles; red from 0-5 mph; orange from 5 to 25 mph; yellow from 35 to 45 mph; green is greater than 45 mph. Note that the colors of points are not visible in a black and white print.

To illustrate the clipping procedure, a sample vehicle path is shown in Figure 5.3. First, the points where the probe passed the two weigh stations are established. The timestamps of these points serve as the start and end time for comparison to the truck estimates. Next, any deviations from a through trip were identified. In the figure, the probe vehicle traveling southbound (points 8038, 8039, 8046) exits the freeway, travels east across the interchange and (not shown) does some activity for some time, then returns to the freeway. This can be seen clearly by examining the order of the breadcrumbs and the color, representing speed. In the analysis, the time between the departure from the freeway (point 8041) and return to the freeway (point 9358) would be removed and subtracted from the probe's overall travel time. As long as this delay is not long, removing the non-through portion of the probe's journey should not significantly affect comparisons (especially if there are no delays in the remaining portion of the trip).

To increase the comparison sample, if the probe did not completely traverse a route between two stations but was reasonably close to the downstream weigh station, the probe's path was extrapolated based on the average speed that was most recently observed. These exceptions are noted in the data.

Table 5.1 presents a summary of the probe data after assembly, processing, and clipping to links identified in the previous chapter. Probe data could be associated with 15 separate links for comparison to truck travel time estimates. The probe runs listed below the "*Data Issues with WIM records*" are explained in the following section.

Figure 5.3: Extracting Probe Runs

Table 5.1: Probe Vehicle Data Summary

Link	Date	Upstream Station	Downstream Station	Distance (mi)	Start Time	End Time	Duration	Avg. Speed (mph)
211	10/02/08	7 ASP	8 BOR	80.99	18:33:42	19:45:09	01:11:27	67.96
217	10/22/08	9 WDN	4 CSL	73.35	14:26:20	15:49:16	01:22:56	53.02
217	10/27/08	9 WDN	4 CSL	72.05	16:00:09	17:20:18	01:20:09	54.04
220	09/30/08	10 WDS	16 ASH	225.09	12:20:22	15:56:45	03:36:23	62.41
220	10/02/08	10 WDS	16 ASH	226.10	16:30:03	20:17:00	03:46:57	59.76
220	10/27/08	10 WDS	16 ASH	204.40	14:55:13	18:40:47	03:45:34	54.39
223	10/22/08	11 BRE	13 JBS	91.94	21:18:02	22:52:21	01:34:19	58.50
Data Issues with WIM records								
202	08/05/08	2 EMH	3 WYT	155.43	23:35:44	02:14:35	02:38:51	58.65
205	09/23/08	3 WYT	10 WDS	86.30	19:14:54	21:51:54	02:37:00	32.98
218	10/22/08	9 WDN	11 BRE	81.93	15:56:37	18:43:01	02:46:24	29.54
205	10/22/08	3 WYT	10 WDS	81.25	20:20:27	21:44:23	01:23:56	58.04
208	10/27/08	4 CSL	5 LGR	221.44	17:31:18	21:36:51	04:05:33	54.12
214	10/27/08	8 BOR	9 WDN	162.57	00:27:50	02:47:18	02:19:28	69.92
219	10/22/08	10 WDS	15 WLB	144.68	15:01:27	17:12:15	02:10:48	66.27

5.2 RESULTS

Despite the best efforts of the research team, the probe-based data collection suffered from data issues in both the data logging devices and outages at key WIM stations. The data logging devices performed adequately for the first batch of data collection but suffered battery problems and data corruption in the later stages data collection efforts. Every effort was made to salvage any useable probe runs as described in the methodology section. In addition, because the WIM data was not obtained in real-time there was a lag in knowing if all WIM stations were collecting data for comparison. The data transfer, upload, and processing effort also required time so for most probe runs, it was 3-4 months or longer before the probe data could be compared to the WIM data. To summarize, comparisons were not possible between probe and truck if 1) probe data were poor; or 2) WIM data was missing or poor. Unfortunately, one of these two events conspired to reduce the number of available links for comparison from fourteen (14) to seven (7).

However, a decision was made to attempt to salvage some of the probe records with WIM data errors. To do this, it was first confirmed that the probe vehicle did not encounter any unusual events or congestion. If the run was free of delay, an attempt was made to identify a similar day of the week, time of day, and weather conditions that were comparable to the probe run and matched through trucks from the WIM data were available. Five additional probe runs were identified and processed that matched to “similar” WIM data. These runs are clearly identified in Table 5.2.

For each of the links with useable data, the probe's trajectory was plotted in the time-space plane. Samples of two of these plots are shown in Figure 5.4 and Figure 5.6 (the remaining trajectories are presented in the Appendix). As customary, the *x*-axis is time and *y*-axis is distance in miles. The probe position in time and space is plotted as the solid blue line. The difference between the start and end time is the travel time, dividing the link distance by this value gives the average speed. Likewise, the slope (*dx/dt*) at any point on the probe's trajectory represents its speed at that point in time. The plots also show any through trucks that passed the upstream station (starting station) within 30 minutes of the probe vehicle as dashed lines. Because only the truck' starting and ending time are known, all truck trajectories are estimated as straight lines.

In Figure 5.4, the probe vehicle traveled from the Woodburn NB station on I-5, along I-205 NB to I-84EB to the Cascade Locks station. This is the same path that the trucks were assumed to travel. As can be seen in the figure, the slope of the probe vehicle trajectory is nearly parallel to the estimated truck trajectories. Indeed, for this link the probe and average truck estimates differ by only 2 minutes and 13 seconds. This surprising equality between the truck estimates is likely due to the fact that both vehicles were in congested afternoon traffic conditions and the route is very flat. Under these conditions, it is plausible that trucks and passenger vehicles could have similar travel experiences. Traffic conditions for a portion of the assumed travel path on that day can be verified from archived freeway data as shown in Figure 5.5. This plot shows the distance on the *y*-axis and time on the *x*-axis. Average travel speed is plotted in color (with the index shown on the right of the figure). The Woodburn NB station is approximately 14.1 miles from the start of I-205, so the congestion in the Figure at milepost 15 around 15:00 corresponds to the slow speed of the probe vehicle at mile 30 of its trip.

This is only one probe run– other passenger vehicle drivers might exhibit different driving patterns. In fact, another probe run on this same link on October 27, 2008 yielded a 16 minute and 51 second difference. Figure 5.6, however, demonstrates the expected relationship between probe and truck travel. This probe traveled the 90 mile link from Ashland to Booth Ranch on I-5NB. This section of the freeway has significant and numerous changes in grade and alignment. The probe is clearly faster and its travel speed differs from by 38 minutes and 15 seconds from the average truck travel time.

Table 5.2 presents a summary of the comparison of travel times for the remaining links. The probe vehicles are always faster than the average truck estimates. For typical probe-based travel times studies it is customary to compare probe times to the estimated method using the paired *t*-test. However, this assumes an expectation that the travel times will be equal; in these data there is no expectation of equal times. To normalize the comparison (since the lengths of each link is not constant) the percent error was calculated and shown in the table. With the exception of the one observation described already for link 217, the probe travel times are between 18 and 54 percent faster than the average truck times. Even with this limited sample, it is confirmed that truck travel times are substantially different than passenger car travel times.

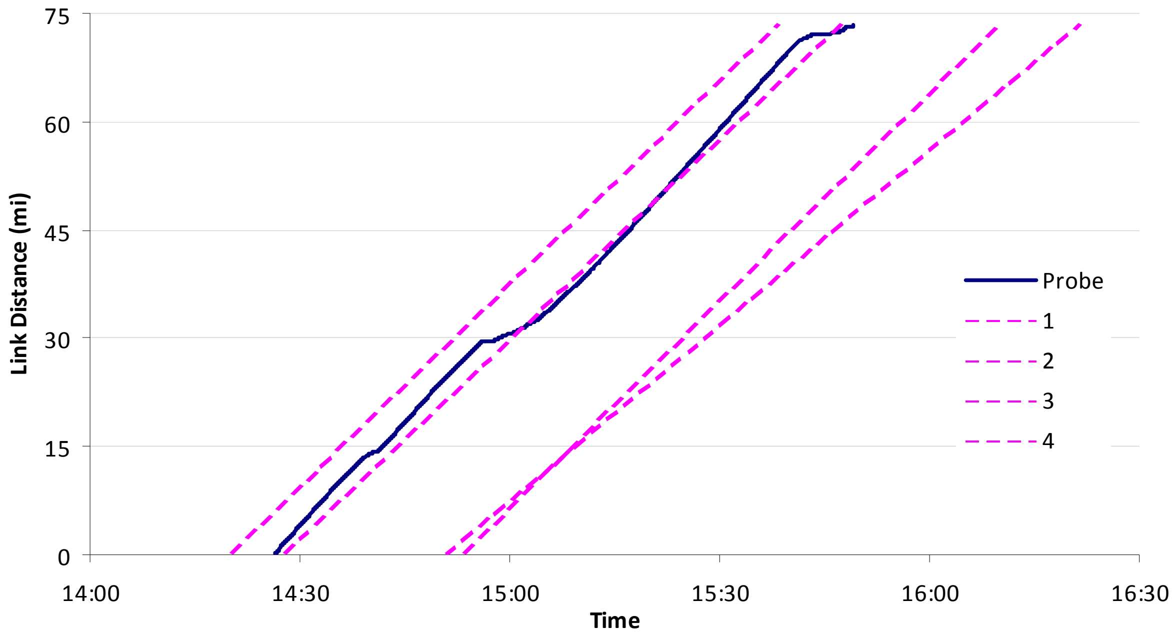


Figure 5.4: Trajectory of Probe Vehicle and Estimated Truck Trajectories, Link 217 WDN to CSL, Oct 22, 2008

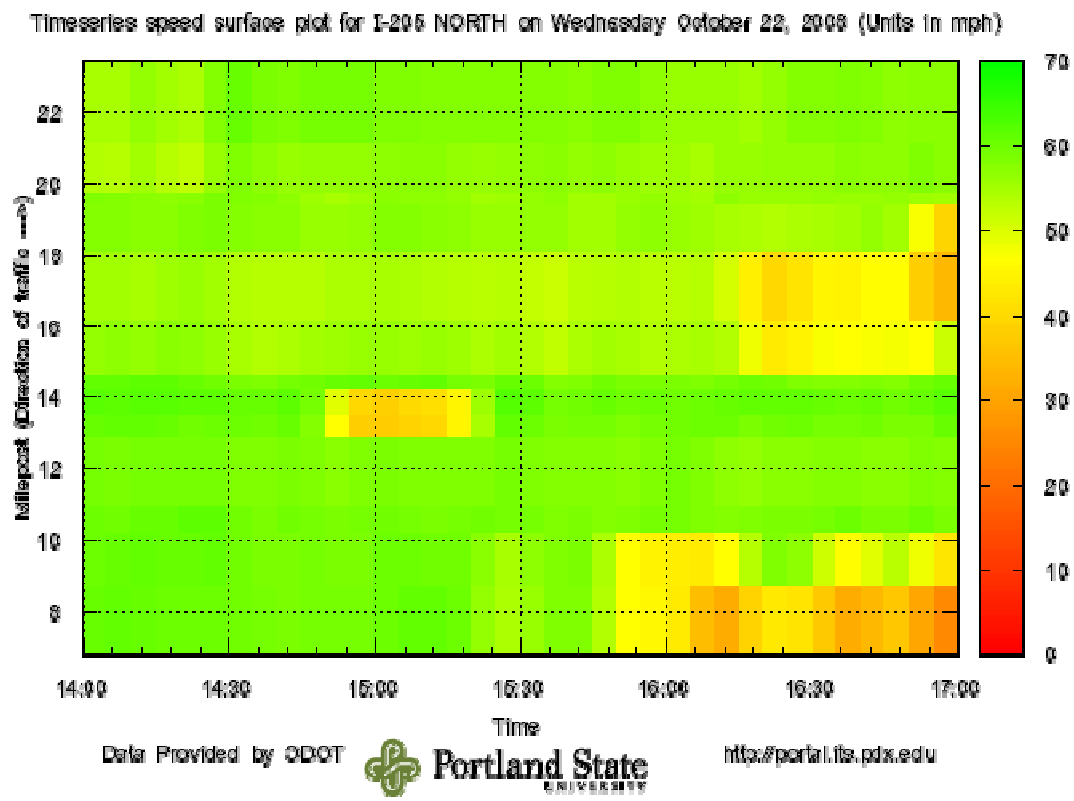


Figure 5.5: Time Series Speed Contour Plot of Speed Conditions on I-205 NB, Oct 22, 2008

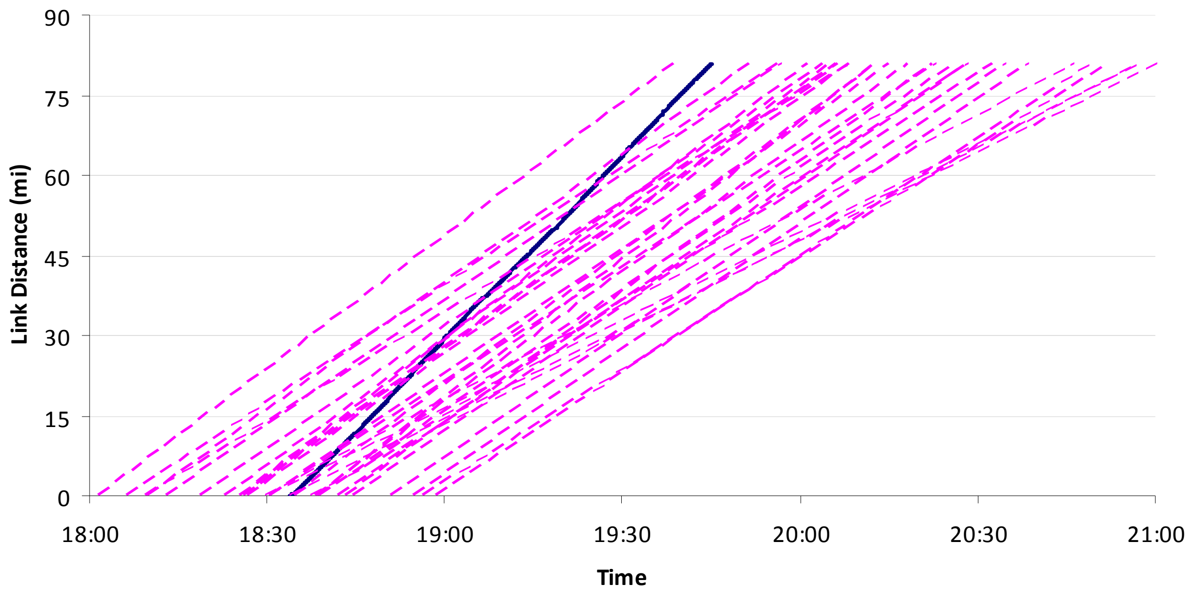


Figure 5.6: Trajectory of Probe Vehicle and Estimated Truck Trajectories, Link 211 ASP to BOR, Oct 2, 2008

Table 5.2: Summary of Probe Data Comparison

Link	Date	Probe Travel Time (hh:mm:ss)	Truck Average Travel Time (hh:mm:ss)	Difference	Percent Error (%)
*Link_202	08/05/08	02:38:51	03:33:17	00:54:26	34.27
*Link_205	09/23/08	02:37:00	01:15:23	01:21:37	51.99
*Link_205	10/22/08	01:23:56	01:21:18	00:02:38	3.14
*Link_214	10/22/08	02:19:28	02:47:26	00:27:58	20.05
+Link_211	10/02/08	01:11:27	01:49:42	00:38:15	53.53
+Link_217	10/22/08	01:22:56	01:20:44	00:02:13	2.67
+Link_217	10/27/08	01:20:09	01:37:00	00:16:51	21.02
+Link_223	10/22/08	01:34:19	01:52:00	00:17:41	18.75
*Link_218	10/22/08	02:46:24	01:26:00	01:20:24	48.32
+Link_220	09/30/08	03:36:23	05:14:04	01:37:41	45.14
+Link_220	10/02/08	03:46:57	05:24:18	01:37:21	42.89
+Link_220	10/27/08	03:45:34	05:11:36	01:26:02	38.14

+ Links with probe data and WIM data for comparison.
* Links with probe data but WIM data from another similar day (due to station outages)

5.2.1 Regression Analysis

It is clear from the previous summary (and common knowledge) that truck travel and car travel experiences are dissimilar. Two conditions contribute to this difference. First, in Oregon the maximum speed limit for trucks on all highways is 55 mph. On rural freeways, passenger vehicles have a posted maximum speed limit of 65 mph. Actual travel speeds can significantly exceed these limits (*Monsere et al. 2004*). Second, trucks are significantly more affected than passenger cars by grades, primarily uphill.

To establish a relationship between passenger cars (probe) and trucks a linear regression methodology was attempted. A decision was made to only use the seven probe runs with matching WIM data for this analysis. The regression model is based on seven observations for four links. The seven observations are one for link 211, two for link 217, three for link 220, and the last is for link 223. For all links, ODOT Integrated Transportation Information System (ITIS) was used to establish grade profiles for all of the four links. These profiles are shown in the Appendix. From these grade profiles, four variables were created to be considered in the regression analysis. These variables are defined as:

- Average weighted uphill grade of the link (i.e.: [Σ Uphill length*Grade%] / Σ Uphill Length)
- Percentage of the total uphill grade length with respect to the total length of the link (i.e.: [Σ Uphill length / Total link length]*100)
- Uphill length in miles of grade more than 2 % on the probe travel time
- Total link length

Models were fitted for probe travel time (dependent) and a combination of independent variables (truck travel time, length of segment and the four variables above).

For brevity only final selected model is presented. The results from the other models are presented in the Appendix. In all models, the truck travel time variable was significant. However, additions of any other variable either was insignificant or reduced the overall model fit. As such, the final model only contains the truck travel time variable. The model summary is presented in Table 5.3. As a measure of fit, the R-squared value was very good (0.98) and both the coefficient and intercept were significant. A plot of the data points (red circle points) and the fitted model (black line) is shown in Figure 5.7. For additional reference, the five (5) additional probe runs with salvaged WIM data are shown with (+). The limited amount of data limits usefulness of this simple model, however, the fit is very good.

Using this simple model, the relationship between the observed truck travel time and a passenger vehicle travel time can be expressed as:

Passenger Car Travel Time, hrs = 0.30519 + 0.64441(Truck Travel Time, hrs)

Table 5.3: Summary of Selected Regression Model Output

Estimate	Coefficient	Std. Error	t value	Pr(>|t|)
(Intercept)	0.30519	0.13446	2.27	0.0725
Truck_TT	0.64441	0.03653	17.64	1.07e-05

Residual standard error: 0.1736 on 5 degrees of freedom
Multiple R-squared: 0.9842, Adjusted R-squared: 0.981
F-statistic: 311.2 on 1 and 5 DF, p-value: 1.074e-05

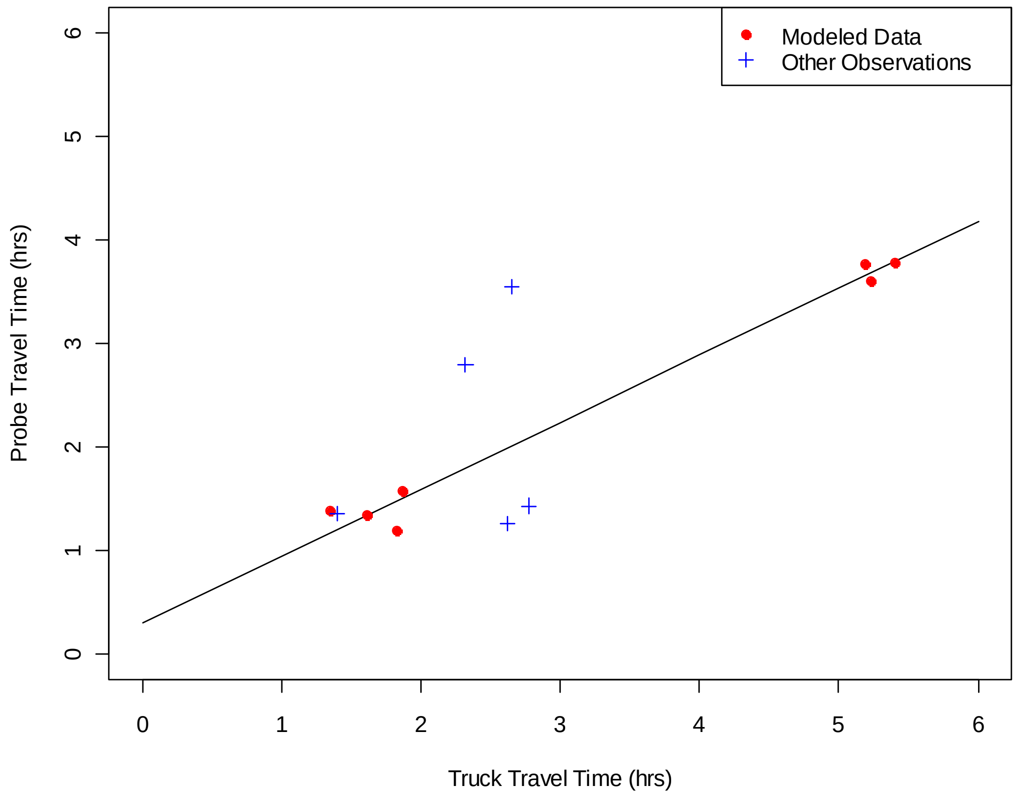


Figure 5.7: Plot of Probe Travel Time vs Truck Travel Time and Fitted Model

5.3 DISCUSSION

The analysis of the probe data reveals that in order to use truck data for generic traveler information some correction for the different operating capabilities of the vehicles will be needed. The regression analysis determined this relationship; however, additional analysis would need to be conducted before this could be considered reliable. Given that probe data is difficult and expensive to obtain, one alternative would be to develop a simple simulation model that could realistically replicate truck and car performances for links to generate additional validation data. Calibration of these performance relationships would likely need to be calibrated on a link-by-link basis. It is not clear if the relationship would hold for truck travel in winter weather since the probes did not encounter any winter weather.

6.0 OTHER FREIGHT PERFORMANCE MEASURES

The WIM data archive developed for this research presents a number of interesting opportunities for truck-based corridor performance measures. Potential performance metrics fall into one of three categories:

1. Station level – Metrics produced from this category do not leverage the transponder information. These are traditional metrics that can be extracted from a WIM data source.
2. Matched trucks - These are truck-pairs on each link observed within a window (here 2 times the free flow travel time). These are not necessarily through trucks.
3. Filtered matched truck data - These are trucks that have been filtered by the travel time algorithm. Travel time was the key measure for these data and was presented in the previous chapter.

All of these performance metrics have been presented in this chapter as box, bar, and line plot formats. They could easily be presented spatially (in a GIS). None of these data have yet been filtered for quality of the WIM observations (i.e. calibration of the load cell). Detecting WIM errors and estimating quality is the focus of another research project sponsored by OTREC[1]. Further, the metrics shown may be affected by missing observations. A procedure (perhaps borrowed from traffic monitoring approaches) would need to be applied prior long term application of these metrics.

6.1 STATION LEVEL

The station-only data does not leverage the transponder information to estimate probable routes of vehicle. These would be considered traditional metrics that can be extracted from a WIM data source. For each combination presented summary statistics could be produced such as:

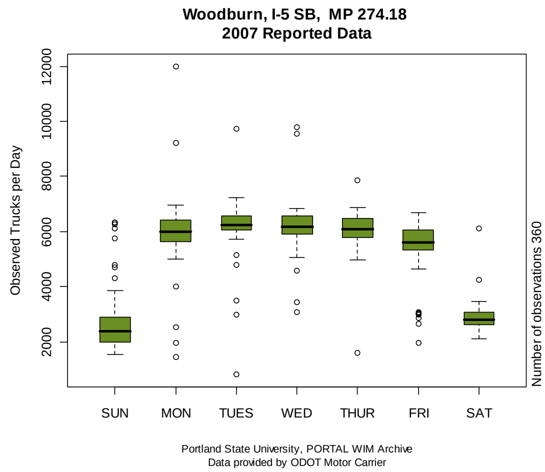
- Average
- Median
- Min
- Max
- Standard deviation

ANOVA tests could also be conducted to test for significant variations by factor groups. For simplicity, only one sample of the performance metric is shown. However, all of the following metrics could be presented by the any permutation of the following variables: by station; by truck classification; as well as the following temporal classification: by day of week; by hour of day; by month; by year; by season.

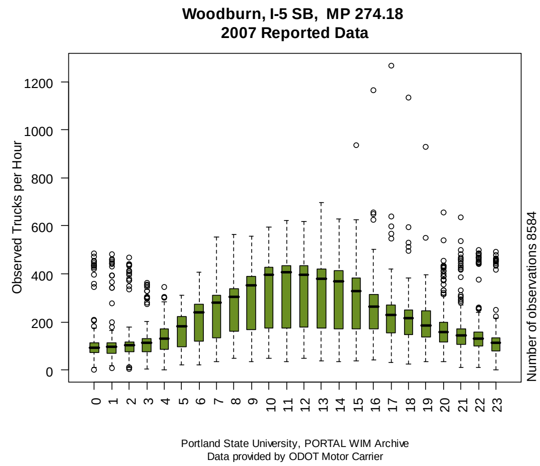
[1] In a concurrent project, basic data quality metrics developed by Pelphrey et al (*2008*) to the entire data set. The filters have been applied to the data set but not to these graphs.

6.1.1 Counts of Trucks

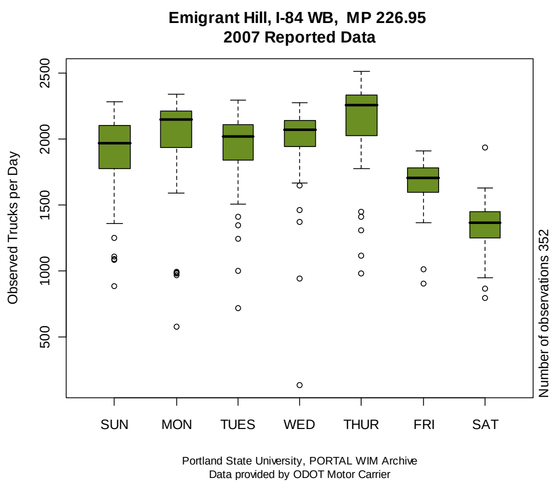
Simple counts of trucks at the WIM stations are a useful and easy metric to derive at the station level. Many temporal (month, week, seasonal, hour of day) variations could be produced. Additionally, these metrics could be further classified by the type of truck. Figure 6.1 shows boxplots of the number of trucks observed at each station by day of week and hour of day for all trucks in 2007. The boxplots show the median, IQR (1st and 3rd quartiles), and outliers for each factor group. No data quality or adjustments for missing data were applied prior to making these plots. A note to the lower right of each plot indicates the number of data points used to produce the boxplot. For the day of the week plots, 365 observations should be expected (at least one truck observed on a day). For the hour of day plots, 8760 observations should be expected (at least one truck per hour per day). The plots highlight the differences between truck patterns at each station. The Woodburn station has pronounced differences between weekend and weekday traffic while the Emigrant Hill station does not exhibit these characteristics. These data include all trucks so the Woodburn station is likely capturing smaller “delivery” trucks while the Emigrant Station is primarily long-haul freight. The hourly plots also show a different distribution between the two stations.



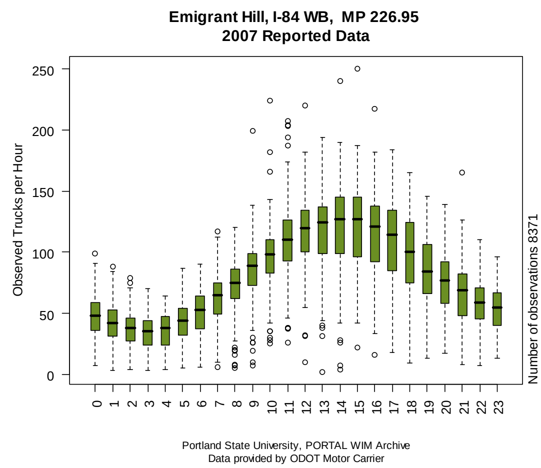
a) All trucks by day of week, 2007



b) All trucks by hour of day, 2007



c) All trucks by day of week, 2007

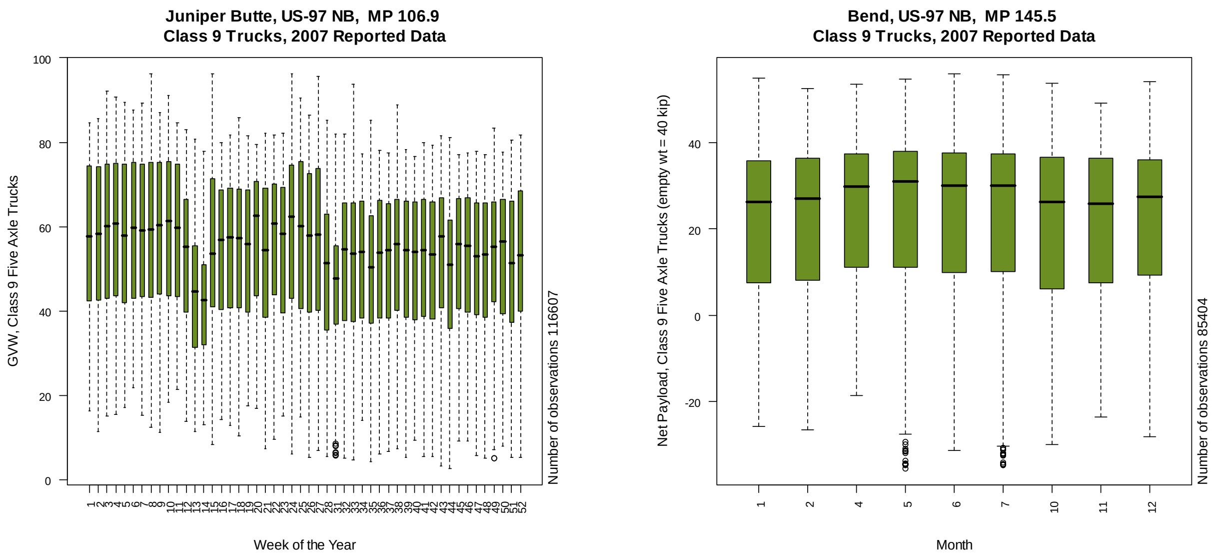


d) All trucks by hour of day, 2007

Figure 6.1: Boxplots of Truck Counts at Stations

6.1.2 Gross Vehicle Weight and Payload Estimates

Since the weight of the observed trucks is also known, additional information can be produced from the station level data. All of the weight related data is subject to WIM errors since these data have not been filtered for quality. The boxplot below in Figure 6.2a) shows the gross vehicle for Class 9 (ODOT Class 11, or 5-axle truck semi-trailer) at the Juniper Butte station by week of the year. No apparent seasonal trend is apparent though there is a drop in weeks 10-15. The plot in b) essentially shows the same data but an assumption about the empty weight of a Class 9 vehicle has been made. Using published data in the Federal truck study (*USDOT 2000*), the average empty weight of a class 9 truck was assumed to be 40 kips. So, in Figure 6.2b) the weight of the vehicle has been removed and the payload is plotted for month at the Bend station. Trucks appear to be carrying more cargo in the May, June, July months (note that August and September observations are missing). Another variation of these same data (not plotted here) would be classify Class 9 trucks +-40 kips as “empty” and display counts of these trucks. In many freight modeling efforts, properly accounting for empty trucks is a challenge and would be a useful.



a) GVW, Class 9 trucks by week of the year, 2007

b) Net Cargo, Class 9 trucks by month, 2007

Figure 6.2: Boxplots of Gross Vehicle Weight of Class 9 Trucks at Juniper Butte, by week, 2007

6.1.3 Percentage of Trucks with Transponders

This metric is related to the Green Light program. The percentage of vehicles with transponders at each station is plotted for all of 2007 in Figure 6.3. The *y*-axis and *x*-axis are scaled the same on each plot.

6.1.4 Overweight Vehicles

Because stations record every vehicle (even when the weigh station is not open) another metric that could be generated relates to overweight vehicles. Unfortunately, there is no clear "overweight" threshold since vehicles in Oregon may legally operate at weights up to 105.5 kips with ubiquitous trip permits. In the plots in Figure 6.4, the number of trucks that exceed 80,000 lbs (80 kips) per month are plotted in the green. In Figure 6.5 the number that exceed 105,000 lbs are plotted in purple. It is clear that I-84 stations are more consistently more likely to have heavy trucks (Farewell Bend, Emigrant Hill, Wyeth, Cascade Locks, LaGrande, Olds Ferry). The station that exhibited the greatest number of heavy vehicles was the Woodburn stations on I-5. Interestingly, the stations near the border with California on I-5 and US-97 (Ashland and Klamath Falls) have comparably lower counts of heavy vehicles. It should be noted that California has more restrictive weight limits, which do not allow trucks over 80 kips.

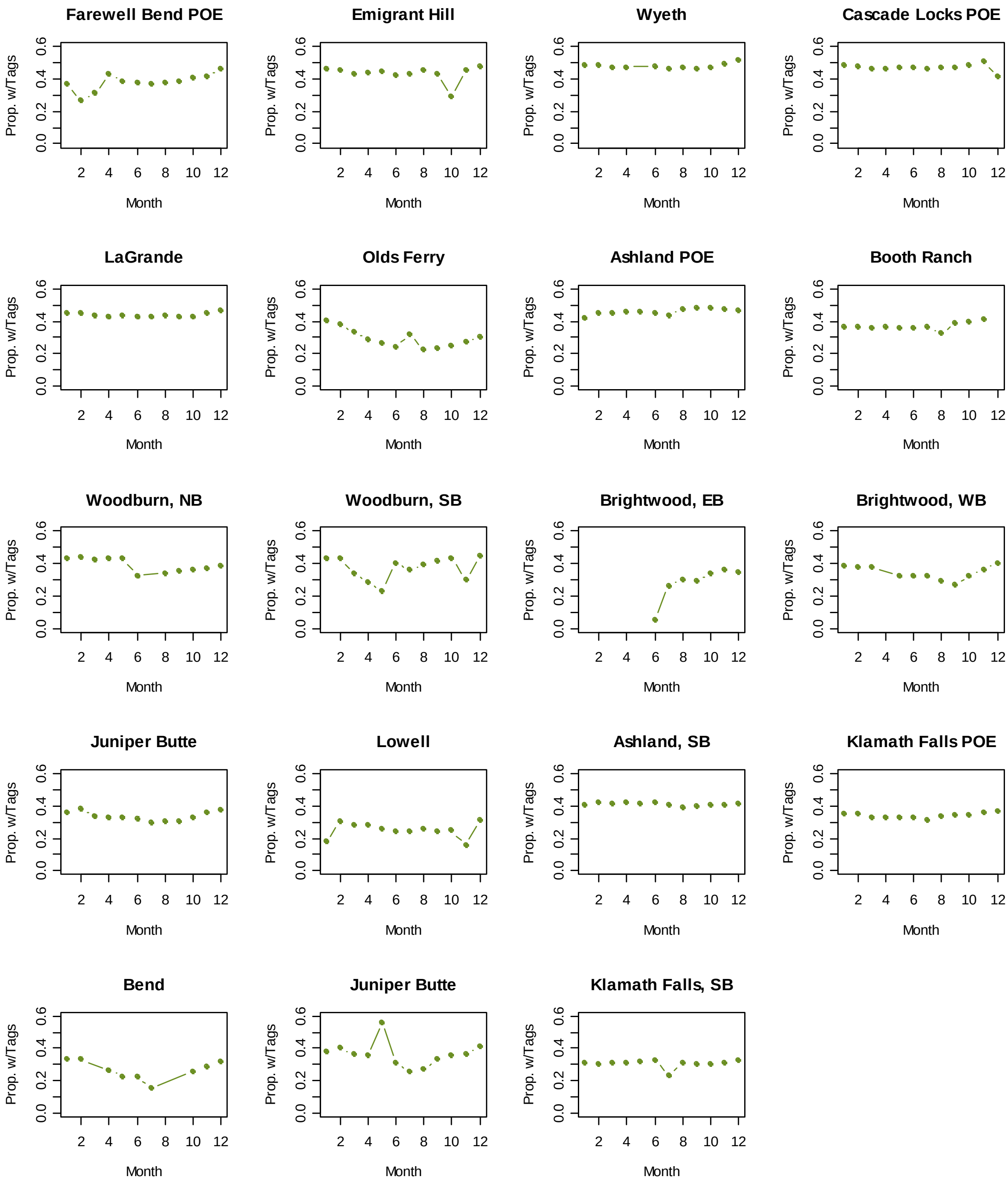


Figure 6.3: Percent of Trucks Observed with Transponders, 2007

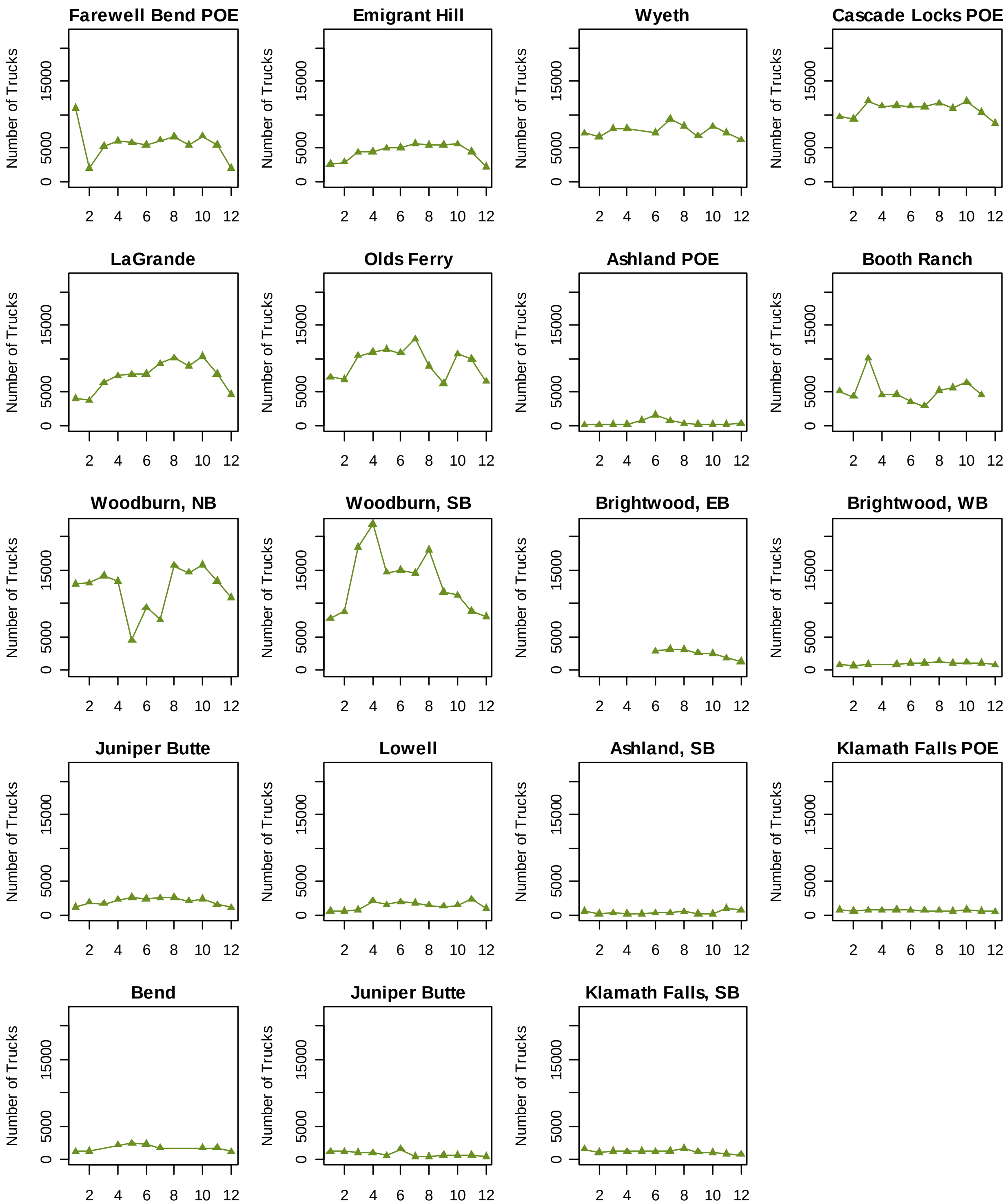


Figure 6.4: Number of Trucks Exceeding 80 kips by station, 2007

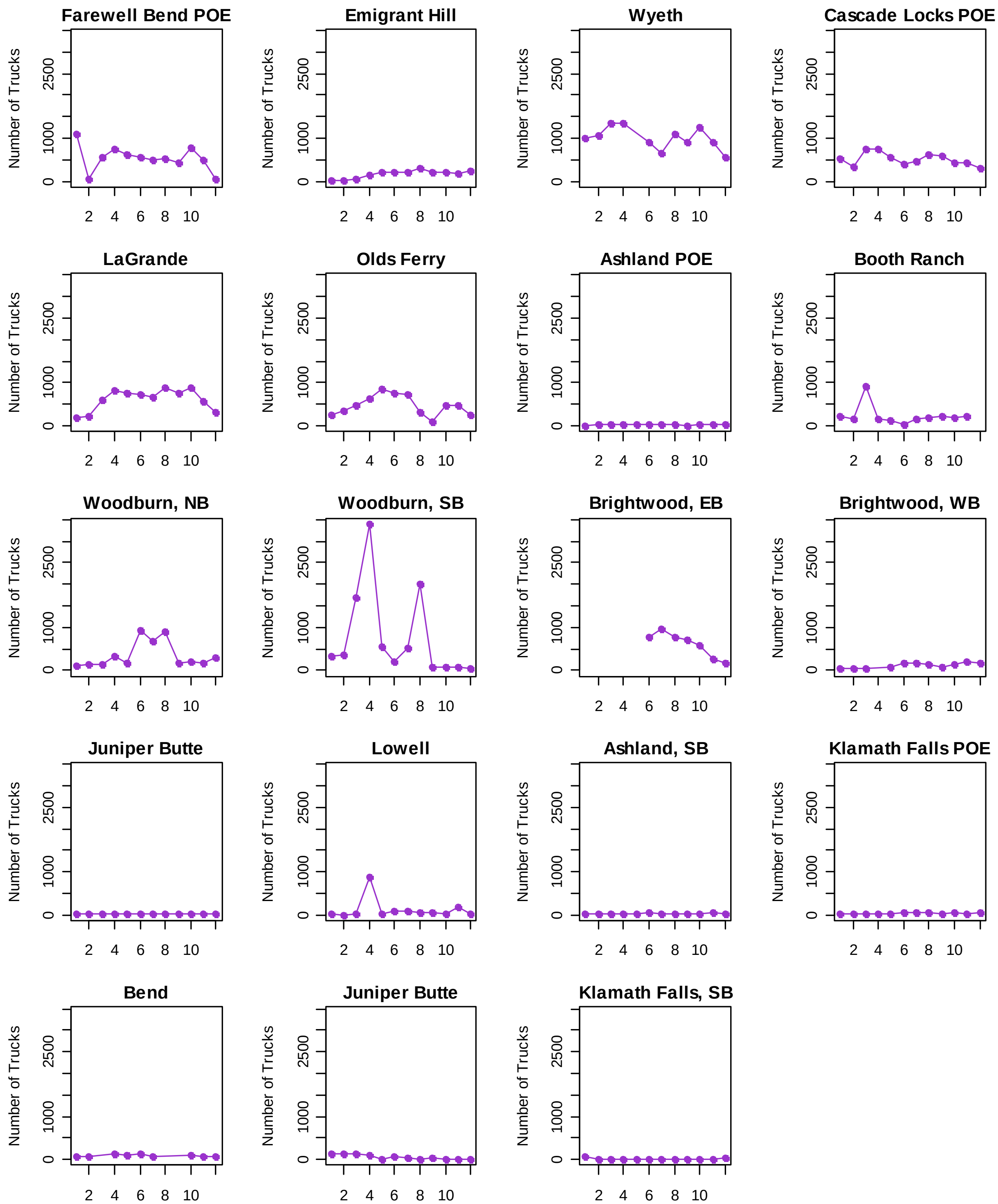


Figure 6.5: Number of Trucks Exceeding 105.5 kips by station, 2007

6.1.5 Observed Truck Speed

The WIM stations also monitor and record the point speed. These data are not necessarily useful as a performance measure for a corridor because it is an observation at only one point. However, these data could be summarized by station, by truck classification, or by hour of day. In Figure 6.6, the speed data are shown for the Lowell station by hour of day. As one might expect, speeds (median) appear to slightly greater in the late evening and early morning hours. These data support the assertion that truck travel time speeds are sensitive to the cost of fuel. Figure 6.7 shows a time series of diesel fuel prices (reported by ODOT and the average speed of all trucks observed at the Emigrant Hill station by month). Data quality limit the speed time series but the decrease in average speed has the expected relationship with increasing fuel cost.

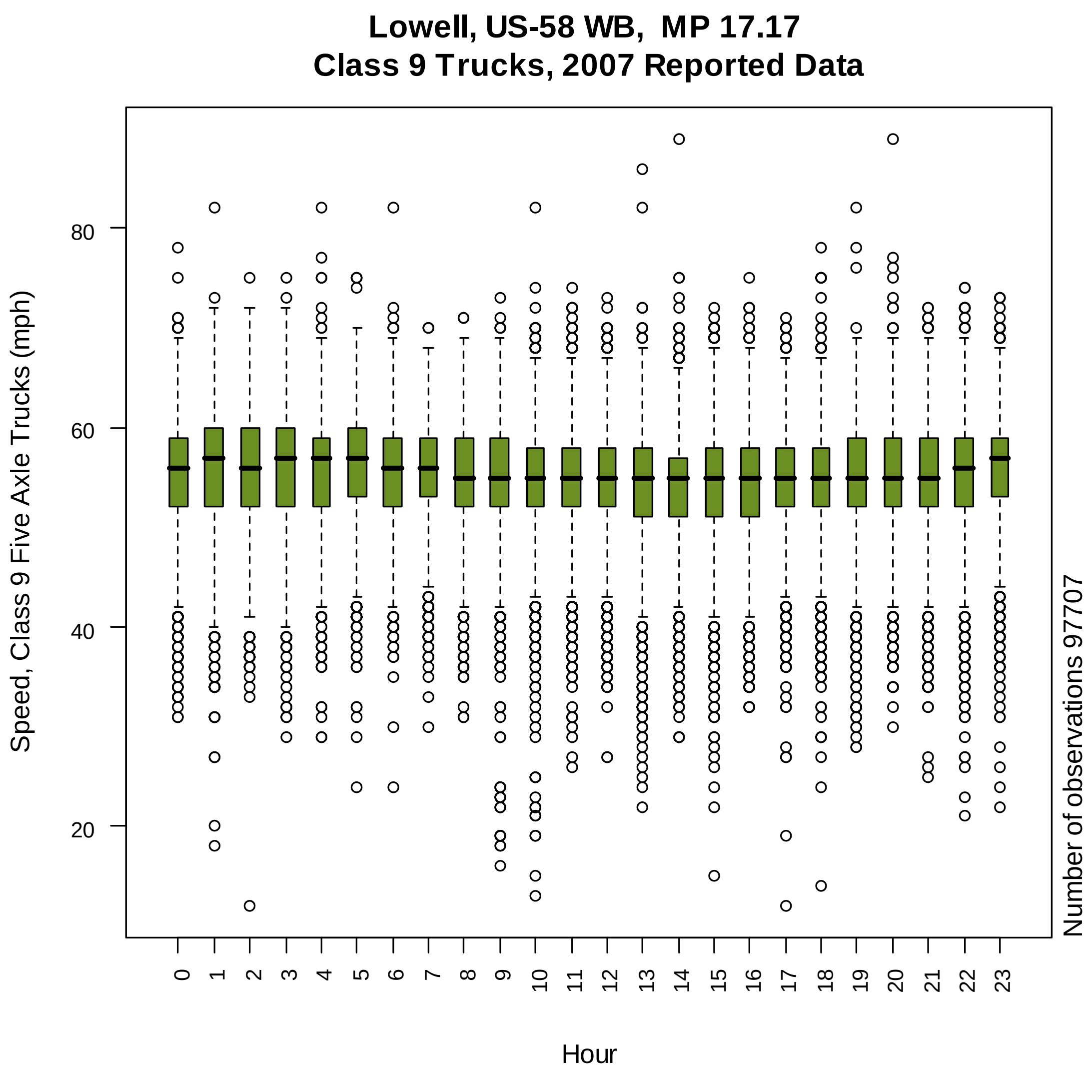


Figure 6.6: Speed Observations at Lowell by hour of day, 2007

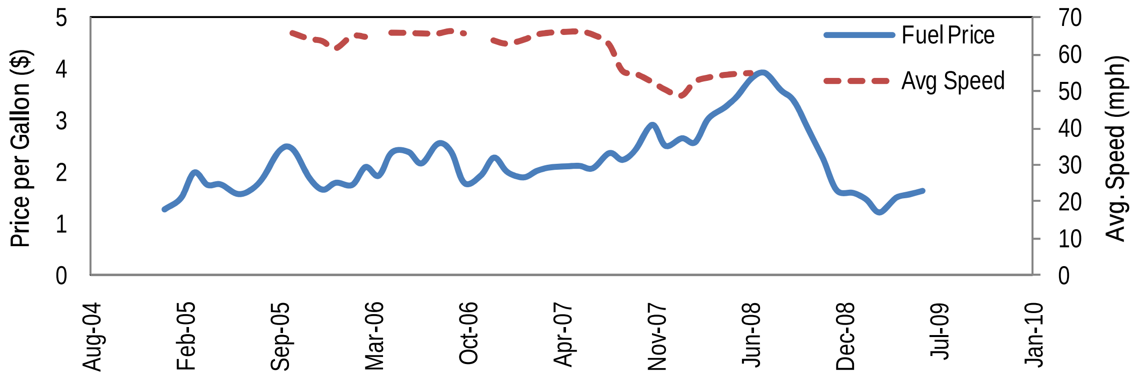


Figure 6.7: Diesel Fuel Prices, Oregon, $US/gallon and Average Speed at Emigrant Hill

6.2 MATCHED TRUCK DATA

The data generated by tag matching algorithm contains trucks that are observed at the upstream station and the downstream station within 2 times the free flow travel time. Free flow speed was assumed to be 55 miles per hour. These data have not yet had the through truck filter applied so it includes trucks making freight deliveries or pick-ups between stations. However, because of the constrained time search window, not all "activity" would be captured (i.e. a truck that takes longer than the free-flow time to leave the facility deliver or pick up cargo and return to the route would not be captured). Because of the long run time of the search algorithm and data storage limitations, a full-scale sensitivity of longer search windows was not done as part of this research.

6.2.1 Estimated Freight Activity on Corridor

The weight observations of trucks at both the upstream and downstream are known. Assuming that the WIM observations are reasonably accurate, the gross vehicle weight from the upstream observation can be subtracted from the downstream observations. Vehicles with greater weight downstream can be assumed to have picked-up cargo, while vehicles losing weight can be assumed to have dropped off cargo. The strength of these assumptions depends on the accuracy of the WIM weight observations. A truck that both dropped off and picked up cargo within the time window will fall in to one of these categories but its true activity will be undetected. These results only include trucks with transponders; additional research would need to be conducted to determine how or if trucks with transponders are different than the total truck population.

The following four plots in Figure 6.8 demonstrate the type of information that could be produced with these data. In the plots, all matched trucks between stations are subset into "increasing weight" or "decreasing weight". For each month, the difference between the downstream and upstream gross vehicle weight is summed (accumulated) and plotted. The increasing weights are red circles and decreasing weight in blue squares. The addition of these cumulative lines is shown in orange. The grey horizontal line represents zero and the *y*-axis of all plots is at the same scale. Plots with the orange line below zero have a net freight "loss" while those with orange line above zero have "gained" freight. This could be interpreted as production (those links with a net increase in truck weight) and consumption (those links with a net decrease) activity on a particular link.

In the upper left, the link represented Juniper Butte to Klamath Falls on US-97 which passes through Bend. From the plot, it can be seen that more trucks lose weight than gain. A possible conclusion is that freight is being distributed in Bend, OR (the only major consumption point between the stations). The same trend appears in the second plot (Ashland POE to Booth Ranch, I-5 NB) with Medford being the consuming center. The third plot, Woodburn NB to Cascade Locks would presumably capture trucks traveling through the Portland area on the I-205NB. Here there is a net gain (trucks have picked up freight between the stations). However, this link (217) does not have a particular large number of matches within the time window compared to the others. The fourth plot shows link 205 from I-84WB to I-5 SB at Woodburn. Trucks between these stations would presumably travel through the Portland metropolitan area. Here again, there appears to be a net loss in freight. Finally two links in opposite direction on I-84 presented. The westbound link has a cumulative loss while the eastbound link has approximately a zero net. This trend is an unexpected and needs further investigation.

6.2.2 Freight Patterns

For stations with multiple downstream destinations, it is possible to represent the percentage of matched truck traffic to each. Given the geography and lack of alternate routes for truck traffic in Oregon, this calculation is only interesting for a handful of stations. Also, the downstream destination of the untagged trucks is unknown – this around roughly 60 percent of traffic at each station. It is not known if these vehicles are different than tagged trucks.

6.2.3 Ton Miles

Using the average of the upstream and downstream weight observations a ton-mile metric can be created. A ton-mile is a measure of one ton moving one mile and is common metric for freight performance and modeling efforts. A sample of this metric, presented by month for four links is shown in Figure 6.9. The number of trucks is shown as gray bars plotted on the second *y*-axis. Ideally, this metric would be created for only the net payload (freight). To do that would require making an assumption about the empty weight of the vehicle as in 6.1.2. That was not done in these sample plots. Because the weights of the vehicles do not vary much on average, and both distance and empty weight are constant scalars, the value does not provide any additional trend information than just a count of matched trucks between links.

6.2.4 Emissions

There is a growing interest in measuring carbon-based fuel use and emissions. With a set of assumptions, it may be possible to estimate fuel use and emissions from these WIM data, particularly with the knowledge of truck type and gross vehicle weight. Heavy duty trucks also use more fuel at higher speeds. The drop in efficiency is largely due to a rapid increase in aerodynamic drag. Mechanically, heavier trucks will also consume for fuel for the equivalent distance. These detailed data are not normally used in emissions calculations but this data archive would allow these calculations. However, in a review of issues related to interstate speed changes, Monsere et al. (*2004*) found that there is little publicly available data on heavy truck fuel economy and it is not known if weight-based data as it relates to fuel economy readily exists. No calculations have been made; but future data and modeling is a possibility.

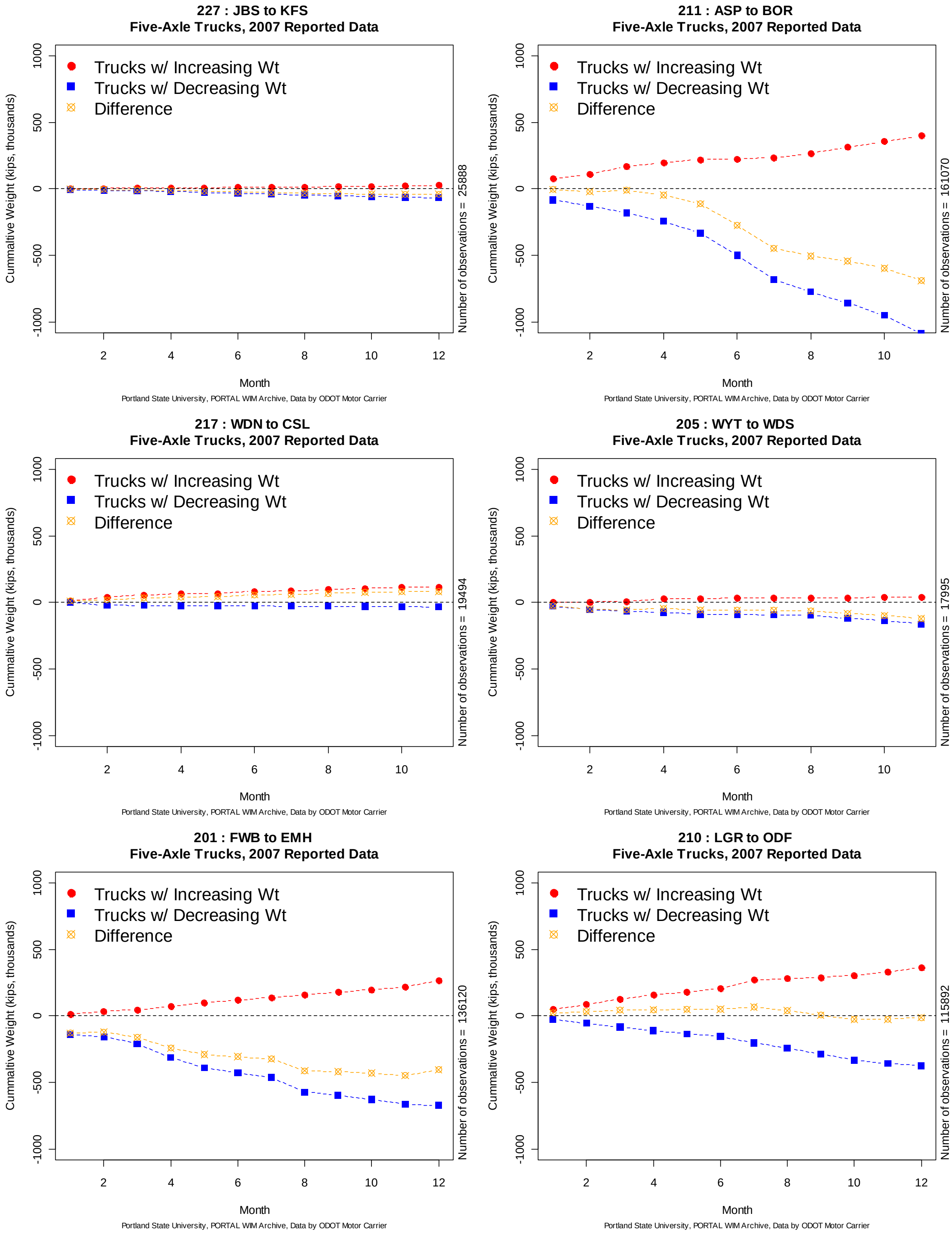


Figure 6.8: Accumulated Weight in Kips Between Station Pairs by Month, 2007

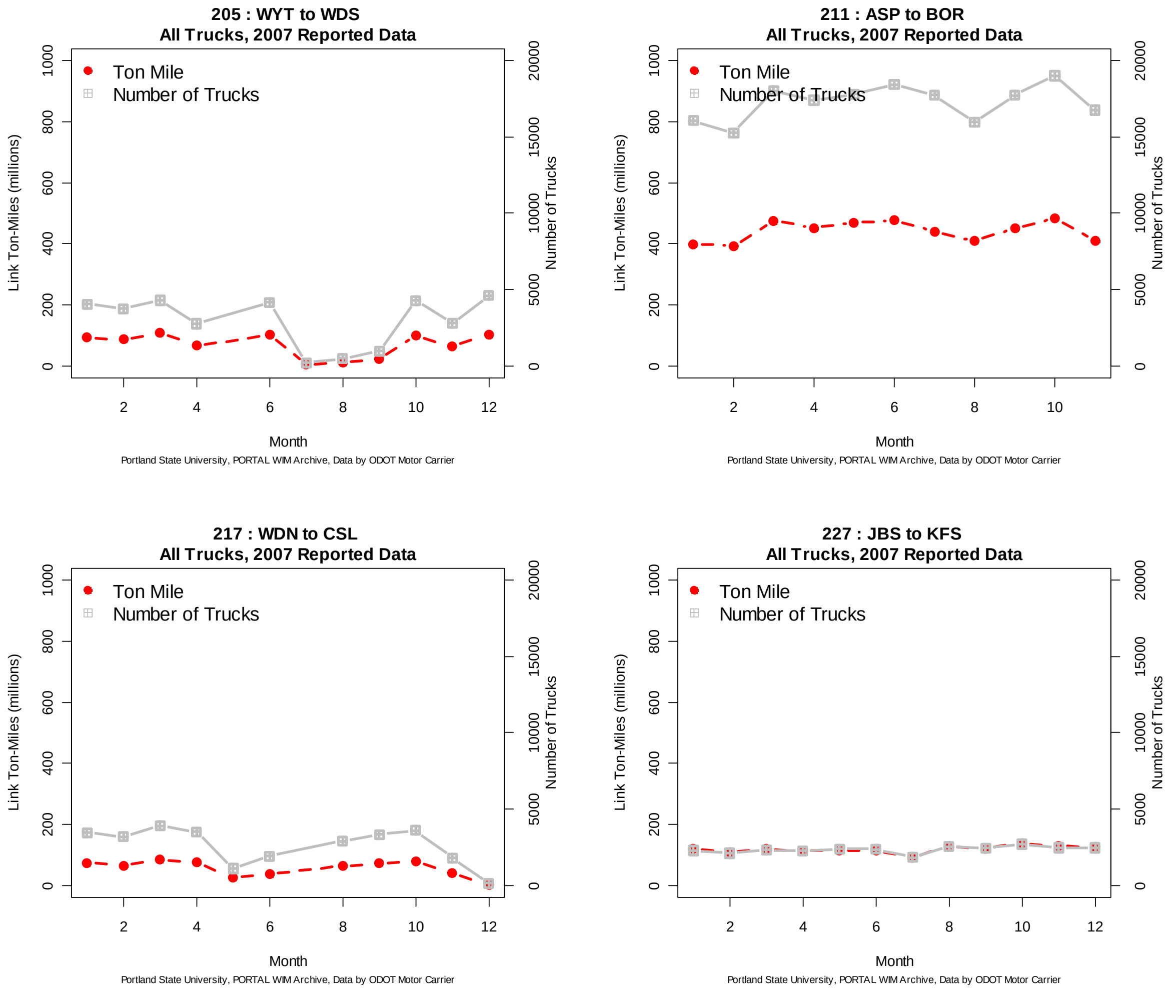


Figure 6.9: Ton Miles and Number of Trucks Between Station Pairs by Month, 2007

7.0 CONCLUSIONS

The objectives of this research were to retrospectively study truck transponder data in key corridors to determine the feasibility of producing freight corridor performance measures; and to study the feasibility of the same data to predict corridor travel times with existing infrastructure for real-time traveler information.

These objectives were accomplished by first assembling the necessary weigh-in-motion data. Monthly data from twenty-two weigh stations were obtained from July 2005 to February 2009. These data were processed and uploaded in the WIM data archive housed under the Portland Transportation Archive Listing (PORTAL) umbrella at Portland State University's Intelligent Transportation Systems Lab. PORTAL provides a centralized, electronic database that facilitates the collection, archiving, and sharing of information/data for public agencies. Nearly 42,000,000 truck records were successful uploaded to the archive. This process works smoothly and has been mostly automated.

Two separate algorithms necessary for this research were scripted, tested, and validated. The first algorithm matched trucks with the same transponder between of all vehicles in a time window between the upstream and downstream stations. The second algorithm filtered these matches for through trucks. The resulting data was used to successfully generate corridor-level travel times for trucks for 2007 and 2008. A simple relationship was established between passenger car and truck performance using probe data that were collected and compared to the observed truck travel times. Finally, potential performance metrics for station level, matched trucks, and filtered matched truck data were shown

This exploratory research successfully answered the two objectives of the research. From the perspective of long-term corridor performance it does appear feasible to use the WIM data and the methods developed in this research to develop long-term corridor performance monitoring of truck travel. The research established, based on two years of data and analysis, that generating average corridor speeds and standard deviations was possible (assuming data quality issues could be resolved). It was clear from the analysis that on the primary links, there are a sufficient number of trucks with tags (both numbers and frequency) to establish travel times between stations. On some of the secondary links at some times of the day there may not be enough trucks to accurately develop travel times. In addition, the matching of truck transponders between stations allowed some interesting additional freight performance measures to be developed. In particular, use of the weight data to track corridor production and consumption has promise for future research.

From the perspective of a real-time traveler information system, however, there are too many shortcomings in the data to implement without improvements. The large spacing of the stations can be considered the primary constraint to real-time implementation. As was shown, longer station spacings increase the likelihood that the filter estimates travel times that are more variable (and thus makes detection of short incidents more difficult). The spacing also contributes to the latency of information available. At a minimum, the travel time information can only as current as the time it takes a vehicle to travel between the observation points. Analysis of the probe data revealed that in order to use truck travel time measures to be used for generic traveler information some correction for the different operating capabilities of the vehicles will be needed. This can be considered a secondary constraint. While the regression analysis determined a simple relationship, the sample size was too small for this to be considered reliable for all corridors and in all weather conditions.

There are three solutions to this challenge that could be pursued. First, additional sensors to read transponders could be installed to improve the accuracy and decrease the latency of time estimates. The research suggests that sensor spacing of 100 miles or less is probably reasonable but spacing would best be determined on a corridor by corridor basis. Shorter spacing may be required around typical areas of delay and places where routes diverge or are uncertain. If denser network coverage is desired there is literature that suggests optimization approaches balancing sensor cost with travel information (though focused on urban areas) (*Asudegi 2009*). The transponder readers cost about $9,000 each not including the cost of integrating these sensors with the current WIM system data. Second, minor methodological improvements could be made to the through truck filter that could improve its accuracy to identify through vehicles. These include considering vehicle attributes, using a defined time window, and other filtering approaches. Third, additional work could be done to improve the method to relate truck travel times to cars. Given that probe data is difficult and expensive to obtain, one alternative would be to develop a simple simulation model that could realistically replicate truck and car performances for links to generate additional validation data. Calibration of these performance relationships would likely need to be calibrated on a link-by-link basis.

Realistically, though, recent advances in other traffic monitoring technologies such as cell phone, navigation devices, vehicle-to-vehicle, vehicle –to-infrastructure, and in particular Media Access Control (MAC) address matching may prove to be more suitable for providing real-time traveler information. With the MAC address reading devices in particular the sensors are generally less expensive to deploy and it has the advantage of detecting mostly passenger cars. Many of the results of this research could be transferred to approach. The rural nature of most links means that congestion is not normally an issue – incidents and weather are the key causes of non-normal travel conditions.

Lastly, this research highlighted some of the limitations of the WIM data for both long-term monitoring and real-time measurement. The archived WIM data has not been used to generate travel times before and it is not unexpected to find data errors in large datasets where the primary purpose of the data is not what is being explored.   The archive should be improved to include an automated method to flag data quality and thresholds. Additional resources would need to be devoted to maintenance of the WIM data collection system.

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APPENDIX

R CODE

TAG MATCHING

```
##########################################################
#
#     Truck Tag Matching Algorithm
#     C. Monsere
#     rev 1 4.1.09
#       modified loop to be more efficient (only call upstation trucks once)
##########################################################

#Set up the database connection to PORTAL
#=================================
library(RODBC)
portal <- odbcConnect("portal db", uid="portal ro")
sqlQuery(portal,"SET search path = wim, pg catalog;") #this sets the schema to wim
to eliminate wim. in front of tables

#Define Functions Used in Analysis
#=================================

#Function for Adding Time to Time Stamp
#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
#input - stamp (as timestamp), add (as decimal hours)

timeadd <- function (stamp, add) {
  window <- 3600*add
  timeadd <- strptime(stamp + window, format="%Y-%m-%d %H:%M:%S")
  timeadd
  }

#Function for Finding Timestamp of Matching Tag Downstream
#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
#input - dwnstrmstation (as integer), tag (as integer), srchmin (as timestamp),
searchmax (as timestamp)
tagsearch <- function (dwnstrmstation, tag, srchmin, searchmax) {
  qry <- paste("SELECT stationnum, tag, timestamp
  FROM wimtag08
  WHERE
  stationnum = ", dwnstrmstation, "
  AND tag = '000", tag, "'
  AND timestamp >= '", srchmin ,"'
  AND timestamp < '", srchmax ,"' ORDER BY timestamp;", sep="")
  tagsearch <-sqlQuery(portal, qry)
  tagsearch
  }



#Variable Parameters
#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
start date <- '2008-01-01'
end date <-   '2008-12-31'


# Tag Matching Loop
#=================================
#Get list of stations  (excluding the Kelso station links)
qry <- "SELECT up station FROM stationmap WHERE linkid < 240 GROUP BY up station
ORDER BY up station ASC;"
```

```
upstrmstationlist <- sqlQuery(portal, qry)
n upstrm <- nrow(upstrmstationlist)
#k <- 8
for (k in 5:n upstrm) {                #start the upstream search list (loop1)
  upstrmstation <- upstrmstationlist[k,]
  qry <- paste("SELECT stationnum, tag, timestamp FROM wimtag08  WHERE  stationnum
=", upstrmstation, " AND timestamp >='",  start date, "' AND timestamp <'", end
date, "';", sep="")
  tagstomatch <-sqlQuery(portal, qry)
  if ( nrow(tagstomatch)==0 ){        #condition 1
  } else {
  #Get list of of all links to get travel times (dwn station < 23 excludes
washington data)
  qry <- paste("SELECT * FROM stationmap WHERE dwn station < 23 AND up station =",
upstrmstation, ";")
  stations <- sqlQuery(portal, qry)
  nlinks <- nrow(stations)
  ntrucks <- nrow(tagstomatch)
  #i <-1
  for (i in 1:nlinks) {              #(loop 2)
      station <- stations[i,]  #note that only one station is 'station'
      minwin <- station$freeflow*0.75
      maxwin <- station$freeflow*2
      upstrmstation <- station$up station
      dwnstrmstation <- station$dwn station
      link <- station$linkid
      #j<-80
      for (j in 1:ntrucks) {         #(loop 3)
        #for (j in 1:10) {
        tag <- tagstomatch[j,2] #row, col get tag number for jth truck
        stamp <- tagstomatch[j,3] #row, col get timestamp for jth truck
        srchmin <- timeadd (stamp, minwin)
        srchmax <- timeadd (stamp, maxwin)
        tagmatch <- tagsearch (dwnstrmstation, tag, srchmin, searchmax)
        if (is.character(tagmatch)) {
            } else {                 #condition 2
        if ( nrow(tagmatch)==0){  #if no truck at next station, end search
          } else {                   #condition 3
            up tag <- paste("000", tag, sep="")
            dwn tag <- paste("000", tag, sep="")
            up timestamp <- stamp
            dwn timestamp <- tagmatch[1,3] #take the first truck (if duplicates)
            print ("match") #for debug
            qry <- paste("INSERT INTO link traveltime082 VALUES ('", link, "','",
upstrmstation, "', '", up tag, "', '",  as.POSIXct(up timestamp), "', '",
dwnstrmstation, "', '", dwn tag, "', '",  as.POSIXct(dwn timestamp),"');", sep="")
            sqlQuery(portal, qry)
            } # close else condition 2
            } # close else condition 3
      } #close ntruck loop 3
    } #close nlinks loop 2
  } #close else nrow  (condition 1)
} #close n upstream (loop 1)
#Reset parameters
#=================================
close (portal)
```

PROBE CSV TO KML

```
##########################################################
#     Coder: Monsere, C
#     Last update: 12.17.08
#     Description:
#         This file reads CSVs of GPS Data Logs
#         and creates KML placemark files
##########################################################
#
# Place a ***COPY*** of the csv files to be converted in ProbeData/toKML
directory (set as the wd in this script)
# Check to make sure the convert directory is empty
# Run this script
# Move converted KML files to directory

# Set working directory
#=================================
setwd ("//stash.cecs.pdx.edu/marston/Active Projects/07-03 ITS CVO Truck AVI/
Data/ProbeData/toKML")
filestoconvert <- list.files()    # get list of files to be converted
nfiles <- length(filestoconvert)-1  # number of files to convert for loop -1
for directory convert
#Start of File Conversion loop
#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
for (f in 1:nfiles) {
  probe <- read.csv(filestoconvert[f], header=TRUE, sep=",", na.strings="NA",
dec=".", strip.white=TRUE) #Read in CSV file
  probe$speed.mph <- probe$Speed.kilometer.*0.621371192  #convert kmh to mph
  j <- nrow(probe) #length of probe file
  probe$rowid <- c(1:j) #assign a rowid of the original probe file
  probe <- subset(probe, speed.mph > 0) #subset to remove zero speed records
(for speed and ease of use)
  lof <- nrow(probe) # get new length of probe file
  speedbins <- c(0, 5, 25, 35, 45, 100) #breaks for speed bins
  speedlabels <- c("black", "red", "yellow", "orange", "green") #color labels
  probe$speed.color <- cut (probe$speed.mph, breaks=speedbins,
labels=speedlabels, include.lowest=TRUE) #create column
  #Start Output of KML file
  #~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
  # Includes predefined color styles for speed labels
  # KML color is hex in the format of aabbggrr
  # where aa is opacity (use ff for solid) and bb is blue rgb, gg is green
rgb, rr is red rgb
  # all in hexdecimal - 00-FF, i.e. 0-256
  #~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
  base fname <- strtrim(filestoconvert[f], nchar(filestoconvert[f])-4)  #get
string w/o .csv
  converted fname <- paste("convert/" , base fname, ".kml", sep="")
#create string w/ .kml
  output <- file(description = converted fname, open = "w")
  writeLines("<?xml version=\"1.0\" encoding=\"UTF-8\"?>", con = output, sep =
"\n")
  writeLines("<kml xmlns=\"http://www.opengis.net/kml/2.2\">", con = output,
sep = "\n")
  writeLines("<Document>", con = output, sep = "\n")
  writeLines("<Style
id=\"blackSpeed\"><IconStyle><color>ff000000</color><scale>0.5</scale><Icon><h
ref>http://maps.google.com/mapfiles/kml/shapes/shaded
```

```
dot.png</href></Icon></IconStyle><LabelStyle><scale>0.75</scale></LabelStyle><
/Style>", con = output, sep = "\n")
  writeLines("<Style
id=\"redSpeed\"><IconStyle><color>ff0000ff</color><scale>0.5</scale><Icon><hre
f>http://maps.google.com/mapfiles/kml/shapes/shaded
dot.png</href></Icon></IconStyle><LabelStyle><scale>0.75</scale></LabelStyle><
/Style>", con = output, sep = "\n")
  writeLines("<Style
id=\"yellowSpeed\"><IconStyle><color>ff00ffff</color><scale>0.5</scale><Icon><
href>http://maps.google.com/mapfiles/kml/shapes/shaded
dot.png</href></Icon></IconStyle><LabelStyle><scale>0.75</scale></LabelStyle><
/Style>", con = output, sep = "\n")
  writeLines("<Style
id=\"orangeSpeed\"><IconStyle><color>ff00a5ff</color><scale>0.5</scale><Icon><
href>http://maps.google.com/mapfiles/kml/shapes/shaded
dot.png</href></Icon></IconStyle><LabelStyle><scale>0.75</scale></LabelStyle><
/Style>", con = output, sep = "\n")
  writeLines("<Style
id=\"greenSpeed\"><IconStyle><color>ff00ff00</color><scale>0.5</scale><Icon><h
ref>http://maps.google.com/mapfiles/kml/shapes/shaded
dot.png</href></Icon></IconStyle><LabelStyle><scale>0.75</scale></LabelStyle><
/Style>", con = output, sep = "\n")
    #Start loop for placemark creation
    for (i in 1:lof) {
      text <- paste("<Placemark><name>", probe[i,12] , "</name><description>",
probe[i,8], "-", probe[i,9] ,"</description><styleUrl>#", probe[i,13],
"Speed</styleUrl> <Point><coordinates>", probe[i,1],", ", probe[i,2]
,"</coordinates></Point></Placemark>", sep="")
      writeLines(text, con = output, sep = "\n")
    } #End of loop for placemark creation
  writeLines("</Document>", con = output, sep = "\n")
  writeLines("</kml>", con = output, sep = "\n")
  close(output)
}  #End of File Conversion loop
```

HSSRC APPLICATION AND APPROVAL LETTER

Portland State University HSRRC Memorandum

To: Christopher Monsere

From: Nancy Koroloff, Chair, HSRRC 2008

Date: April 22, 2008

Re: HSRRC review of your application titled, "Using Existing ITS Commercial Vehicle Operation (ITS/CVO) Data to Develop Statewide (and Bi-State) Truck Travel Time Estimates and Other Freight Measures" (HSRRC Proposal # 08506)

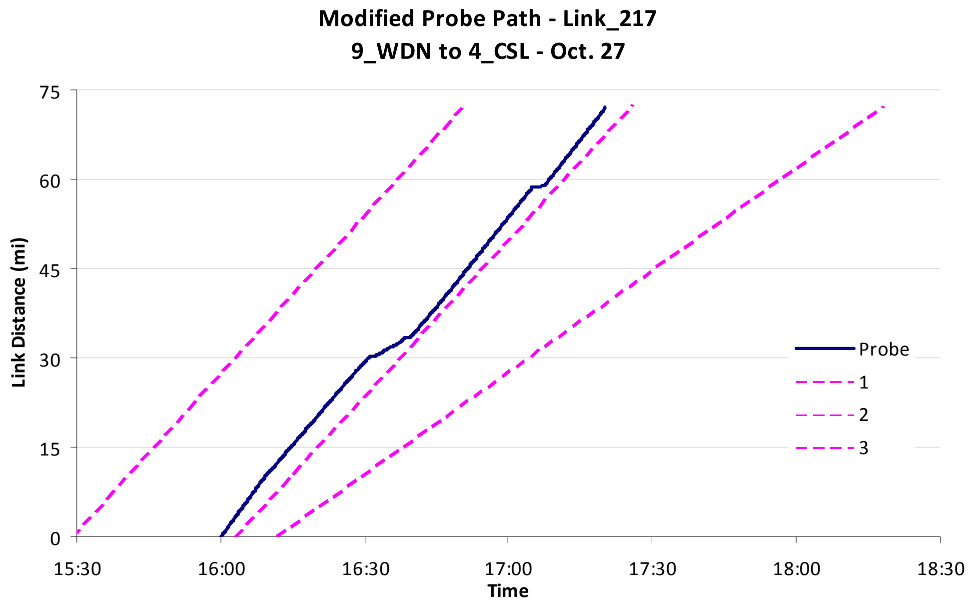
Your proposal was recently reviewed by the Human Subjects Research Review Committee. The Committee is satisfied that all provisions for protecting the welfare of those involved in the research are adequate. Therefore you may proceed with the study.

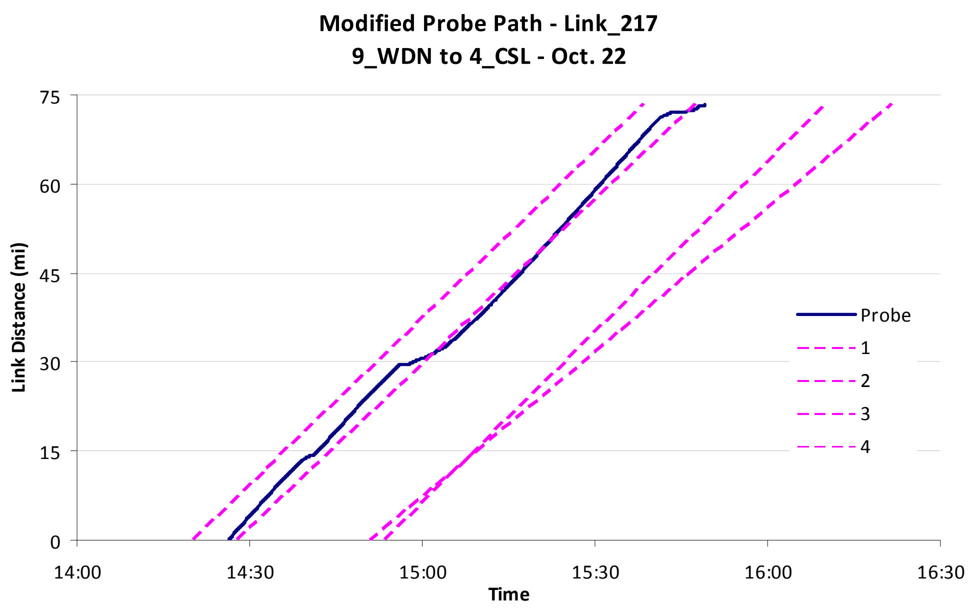
If you have questions or concerns, please contact Cathleen Gal of the HSRRC in the Office of Research and Sponsored Projects (ORSP), (503) 725-4288, Unitus Building, 6th Floor.

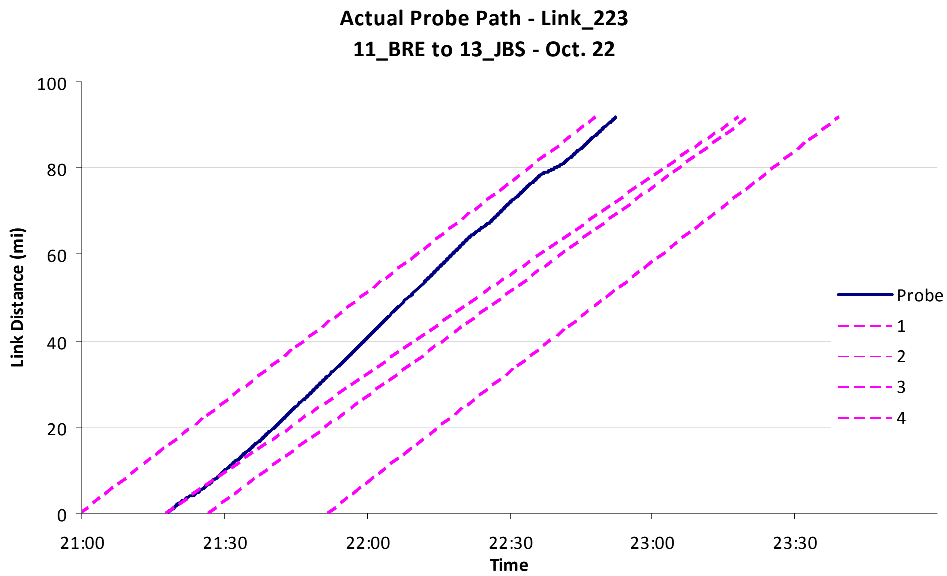
c: William Fish

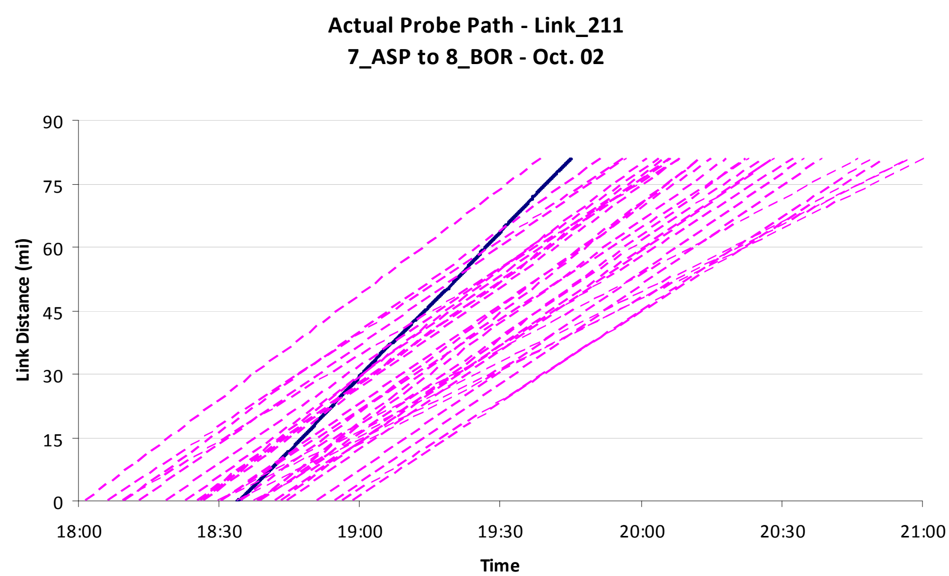
1

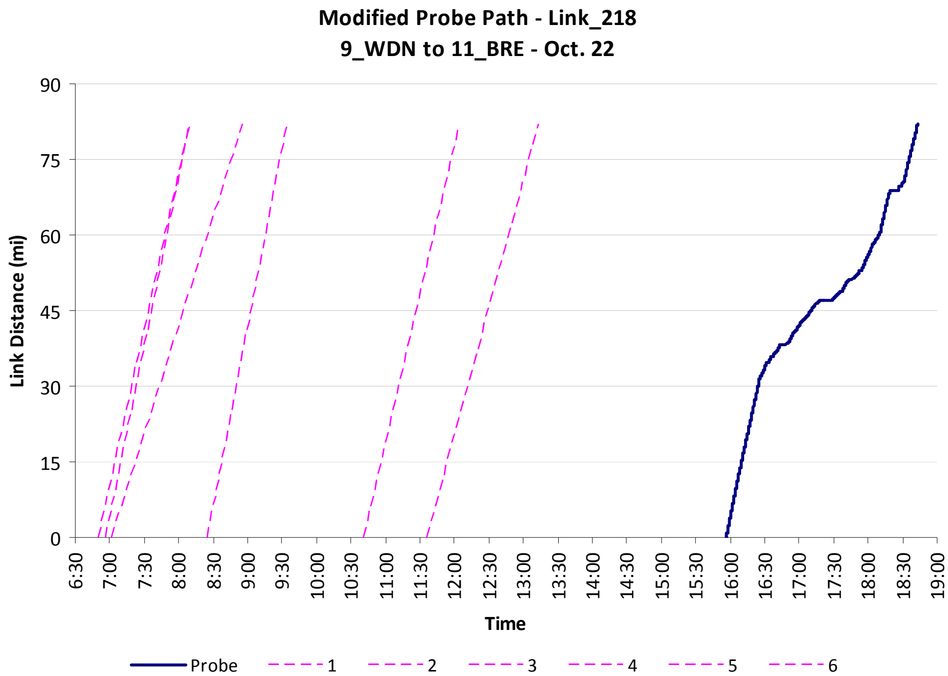
PROBE TRAJECTORY PLOTS

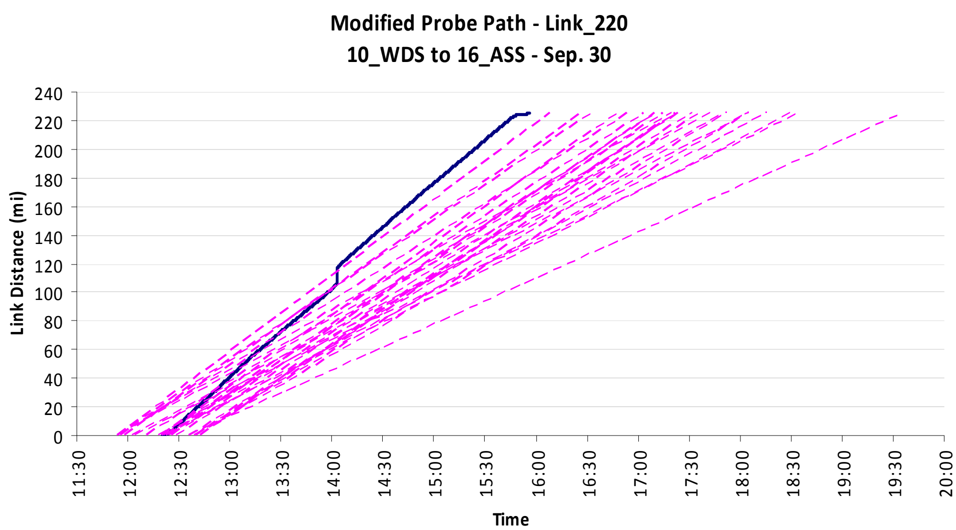


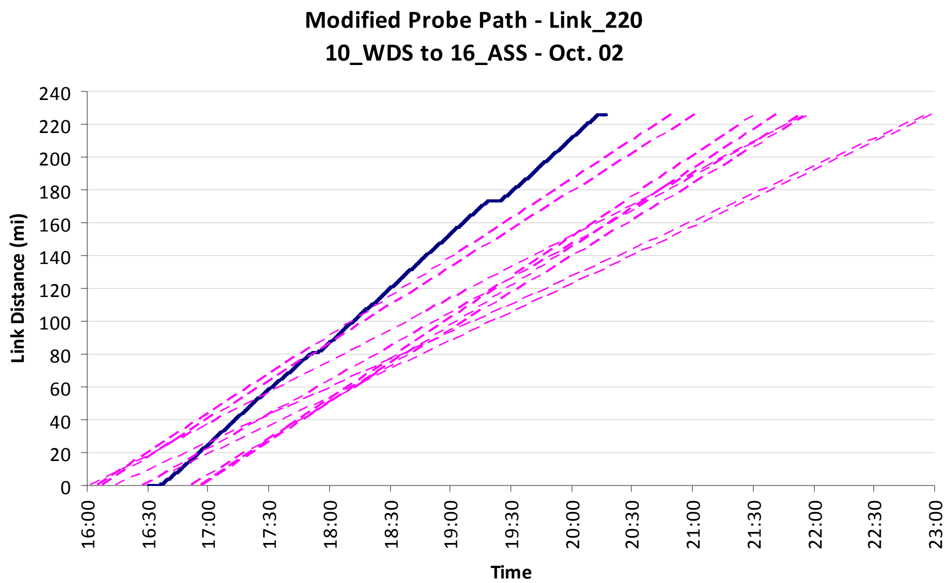



Actual Probe Path - Link_223
11_BRE to 13_JBS - Oct. 22
Link Distance (mi)
100
80
60
40
20
0
21:00
21:30
22:00
22:30
23:00
23:30
Time
Probe
1
2
3
4

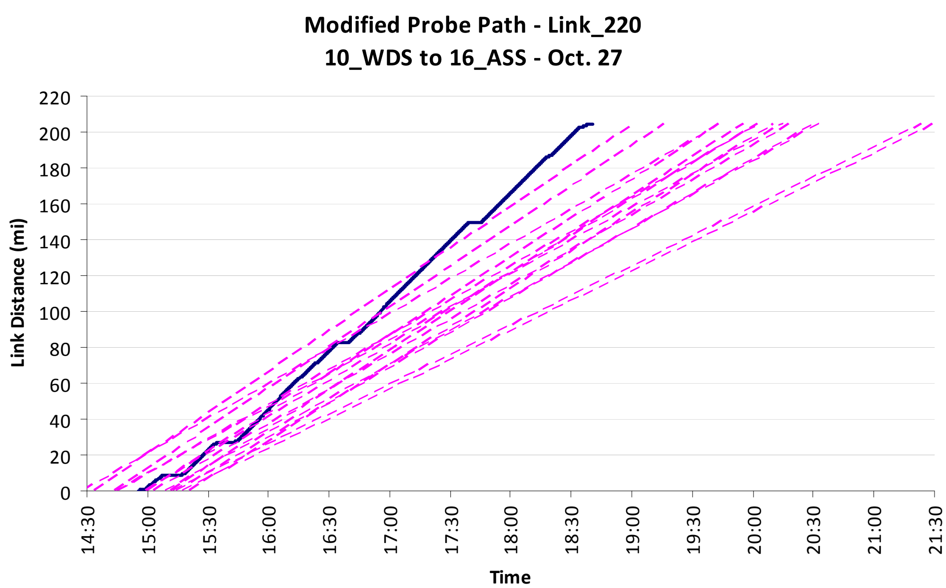

Actual Probe Path - Link_211
7_ASP to 8_BOR - Oct. 02
Link Distance (mi)
90
75
60
45
30
15
0
18:00
18:30
19:00
19:30
20:00
20:30
21:00
Time


Modified Probe Path - Link_218
9_WDN to 11_BRE - Oct. 22
Link Distance (mi)
90
75
60
45
30
15
0
6:30
7:00
7:30
8:00
8:30
9:00
9:30
10:00
10:30
11:00
11:30
12:00
12:30
13:00
13:30
14:00
14:30
15:00
15:30
16:00
16:30
17:00
17:30
18:00
18:30
19:00
Time
Probe
1
2
3
4
5
6


Modified Probe Path - Link_220
10_WDS to 16_ASS - Sep. 30
Link Distance (mi)
240
220
200
180
160
140
120
100
80
60
40
20
0
11:30
12:00
12:30
13:00
13:30
14:00
14:30
15:00
15:30
16:00
16:30
17:00
17:30
18:00
18:30
19:00
19:30
20:00
Time

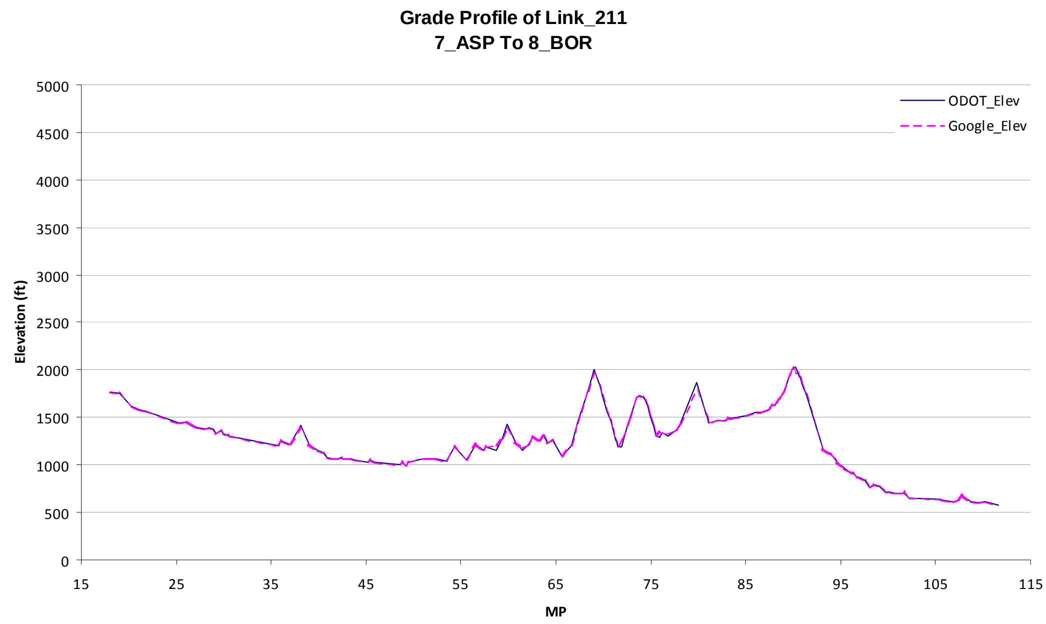


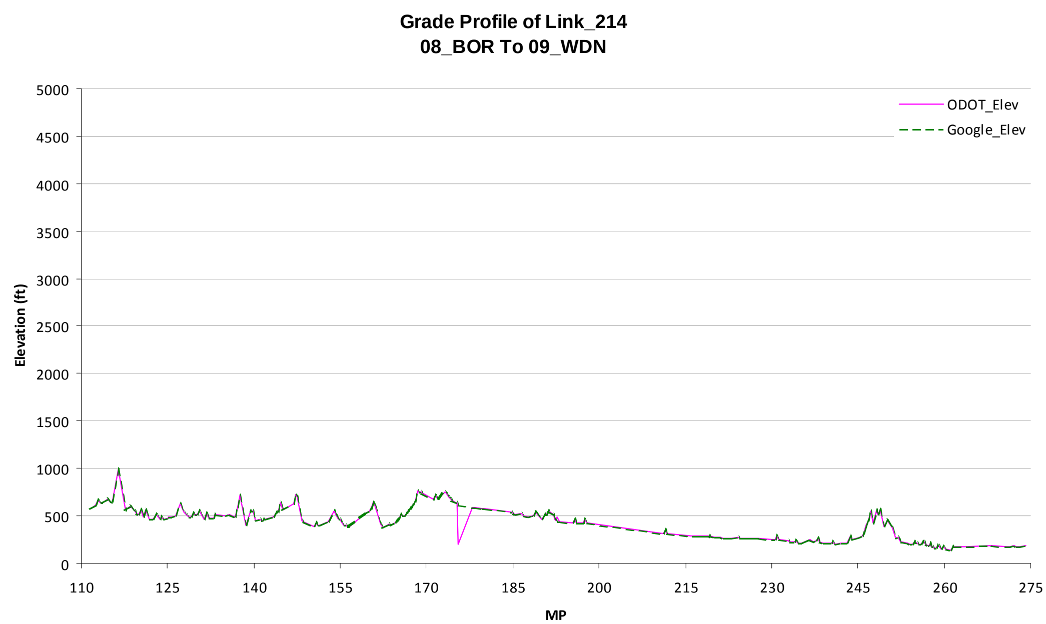
Modified Probe Path - Link_220
10_WDS to 16_ASS - Oct. 02
Link Distance (mi)
240
220
200
180
160
140
120
100
80
60
40
20
0
16:00
16:30
17:00
17:30
18:00
18:30
19:00
19:30
20:00
20:30
21:00
21:30
22:00
22:30
23:00
Time

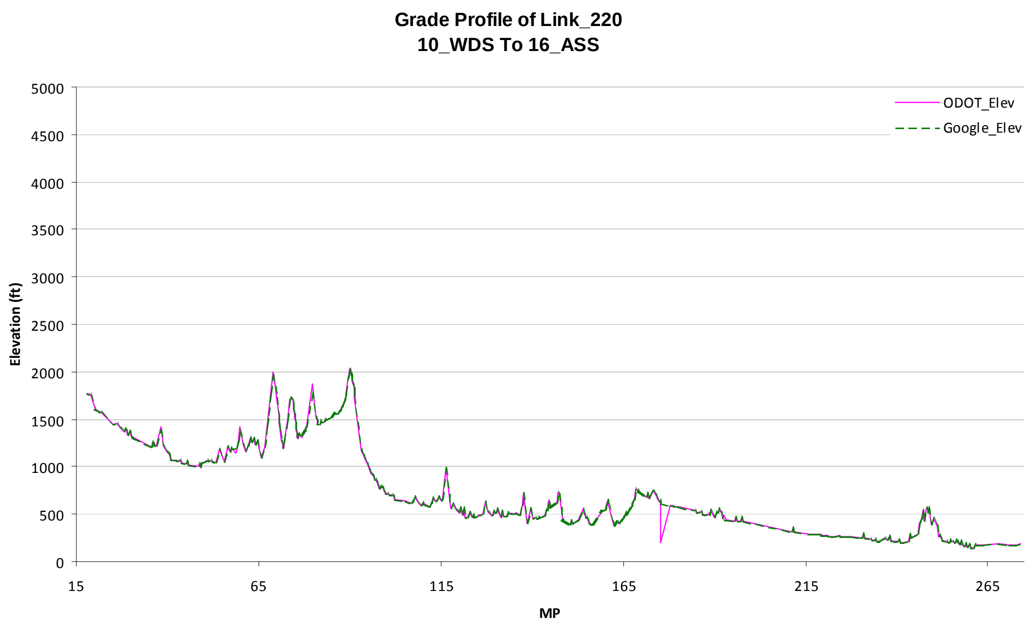


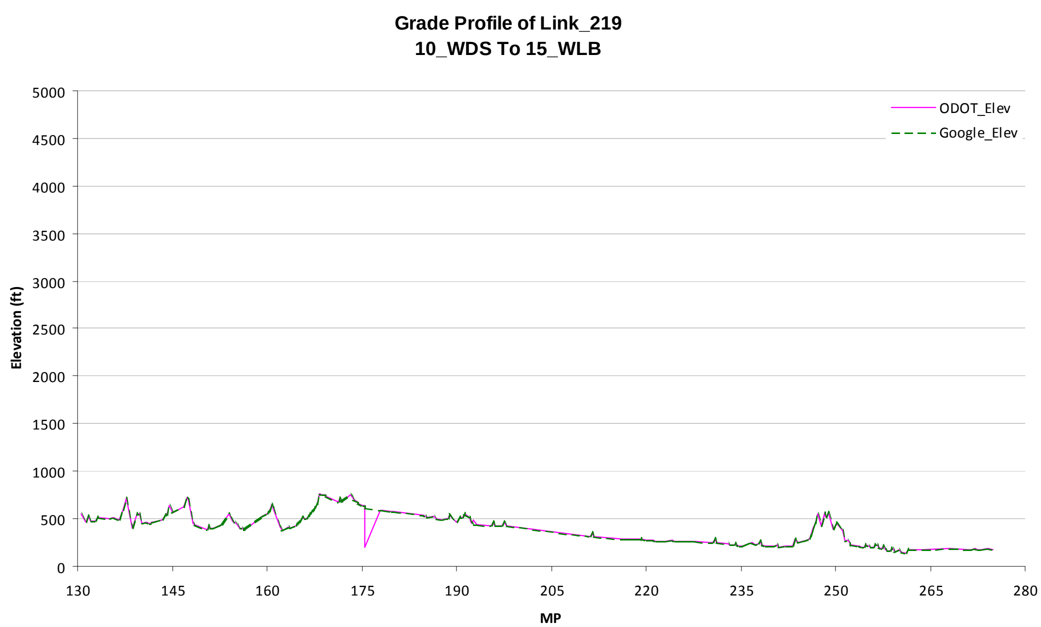
Modified Probe Path - Link_220
10_WDS to 16_ASS - Oct. 27
Link Distance (mi)
220
200
180
160
140
120
100
80
60
40
20
0
14:30
15:00
15:30
16:00
16:30
17:00
17:30
18:00
18:30
19:00
19:30
20:00
20:30
21:00
21:30
Time

GRADE PROFILES FOR PROBE LINKS

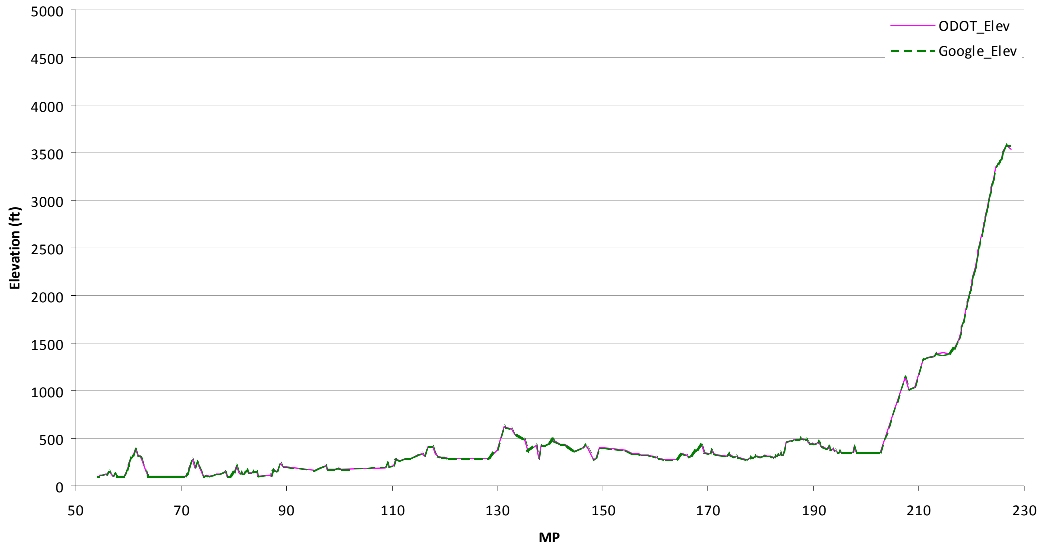




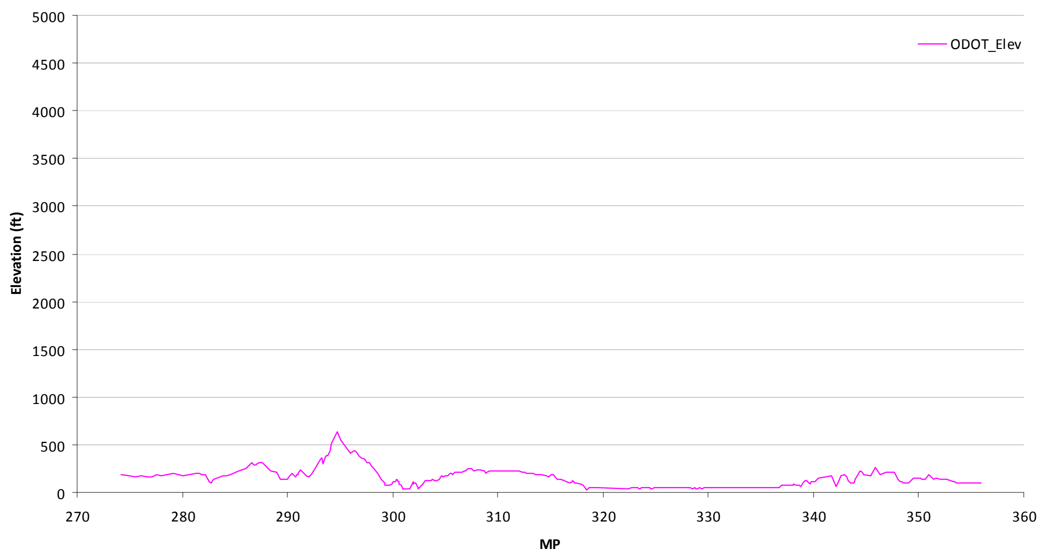

Grade Profile of Link_220
10_WDS To 16_ASS
ODOT_Elev
Google_Elev
Elevation (ft)
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
15
65
115
165
215
265
MP


Grade Profile of Link_219
10_WDS To 15_WLB
ODOT_Elev
Google_Elev
Elevation (ft)
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
130
145
160
175
190
205
220
235
250
265
280
MP

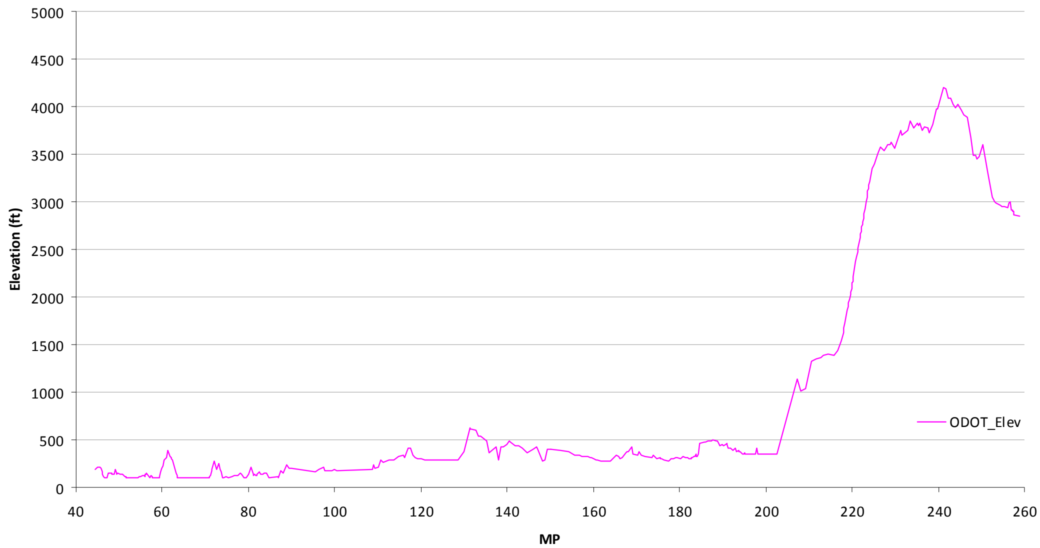
Grade Profile of Link_202
2_EMH To 3_WYT



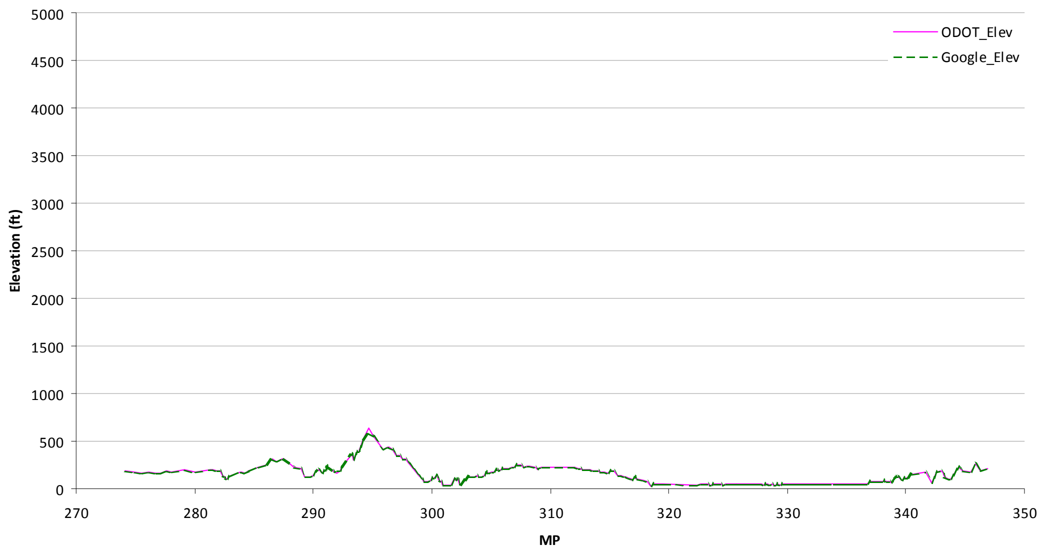
Grade Profile of Link_205
Portland To 10_WDS

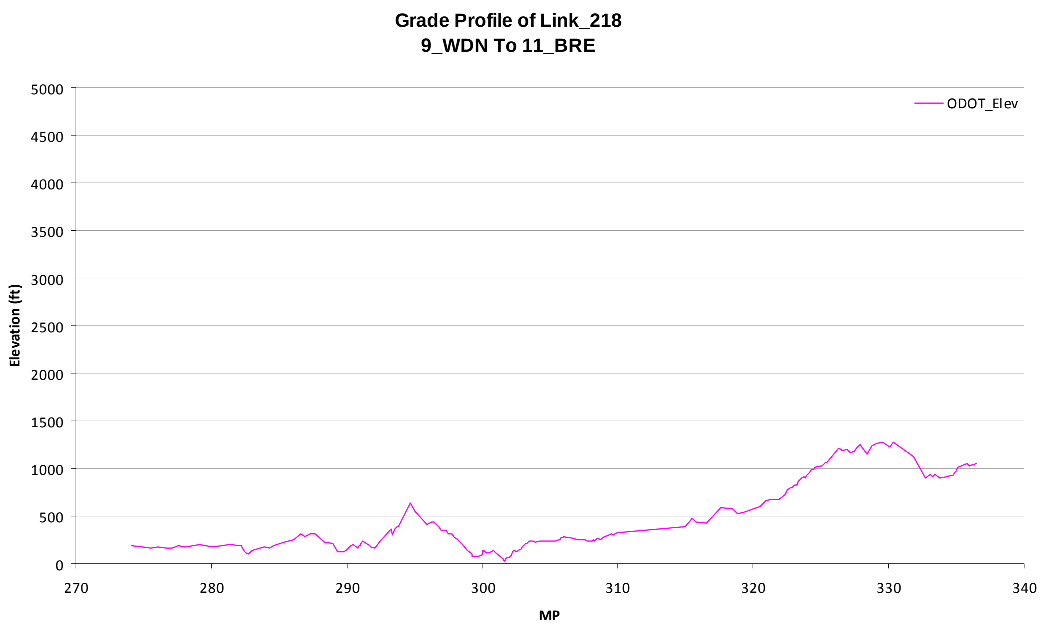


Grade Profile of Link_208
4_CSL To 5_LGR

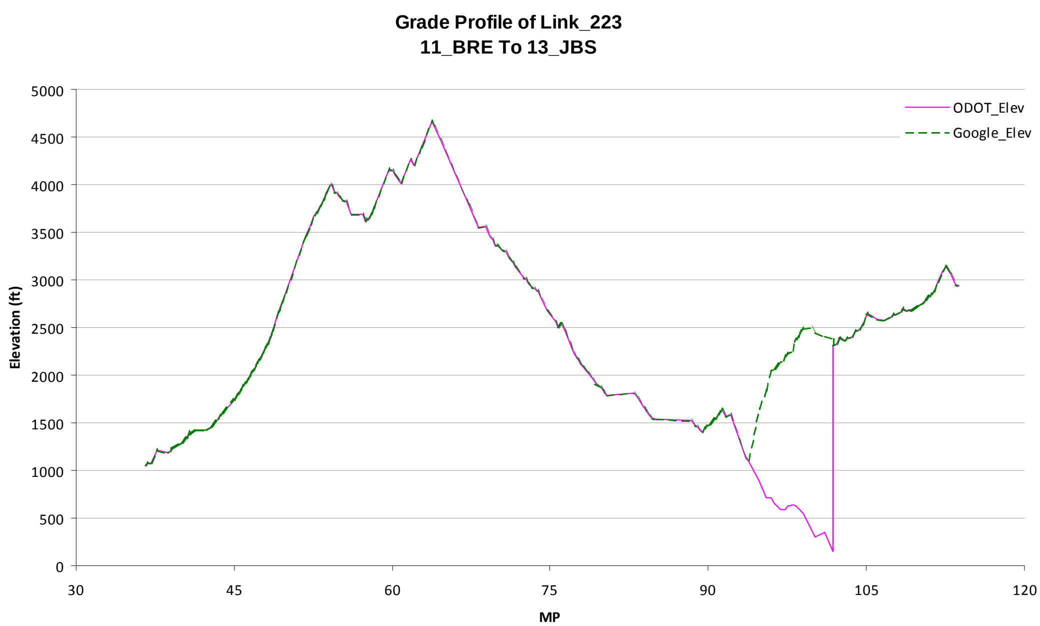


Grade Profile of Link_217
9_WDN To 4_CSL





Grade Profile of Link_218
9_WDN To 11_BRE
ODOT_Elev
Elevation (ft)
MP



Grade Profile of Link_223
11_BRE To 13_JBS
ODOT_Elev
Google_Elev
Elevation (ft)
MP

REGRESSION OUTPUT

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.997465012
R Square	0.994936451
Adjusted R Square	0.989872902
Standard Error	0.005283558
Observations	7

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.016455632	0.005485211	196.4899479	0.00061076
Residual	3	8.3748E-05	2.7916E-05		
Total	6	0.01653938			

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.011416385	0.008785191	1.299503255	0.28461696
X Variable 1	0.734089063	0.045740741	16.04891057	0.000526135
X Variable 2	-0.01150738	0.004663026	-2.467792478	0.090240959
X Variable 3	0.00039813	0.000220974	1.801704834	0.169390543

EQUATION

Car_tt = 0.01141 + 0.7341*Truck_tt - 0.01151*Grade % + 0.0004*Grade Length %

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.992299072
R Square	0.984657447
Adjusted R Square	0.976986171
Standard Error	0.007964865
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	0.016285624	0.008142812	128.3564053	0.000235394
Residual	4	0.000253756	6.34391E-05		
Total	6	0.01653938			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	0.008651546	0.013135376	0.65864474	0.546106867	-0.027818104
X Variable 1	0.653941519	0.048554761	13.46812363	0.000175844	0.519131891
X Variable 2	9.74072E-05	0.000277884	0.350532268	0.74362048	-0.000674122

Equation_2

Car_tt = 0.00865 + 0.65394*Truck_tt + 0.000097*Uphill_Length %

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.994874875
R Square	0.989776017
Adjusted R Square	0.979552035
Standard Error	0.180185681
Observations	7

ANOVA

	df	SS	MS	F	Significance F
Regression	3	9.429282143	3.143094048	96.80924338	0.001749615
Residual	3	0.097400639	0.03246688		
Total	6	9.526682782			

	Coefficients	Standard Error	t Stat	P-value
Intercept	1.157811687	0.830310702	1.394431848	0.25750945
X Variable 1	1.053201014	0.328983622	3.201378256	0.049279861
X Variable 2	-0.018328629	0.014955643	-1.225532689	0.307810729
X Variable 3	-0.002358464	0.007362305	-0.320343137	0.769724095

Equation_4

Car_tt = 1.15781 + 1.0532*Truck_tt - 0.01833*Link_Length - 0.002358*Uphill_Length %

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.992061566
R Square	0.984186152
Adjusted R Square	0.981023382
Standard Error	0.173581979
Observations	7

ANOVA

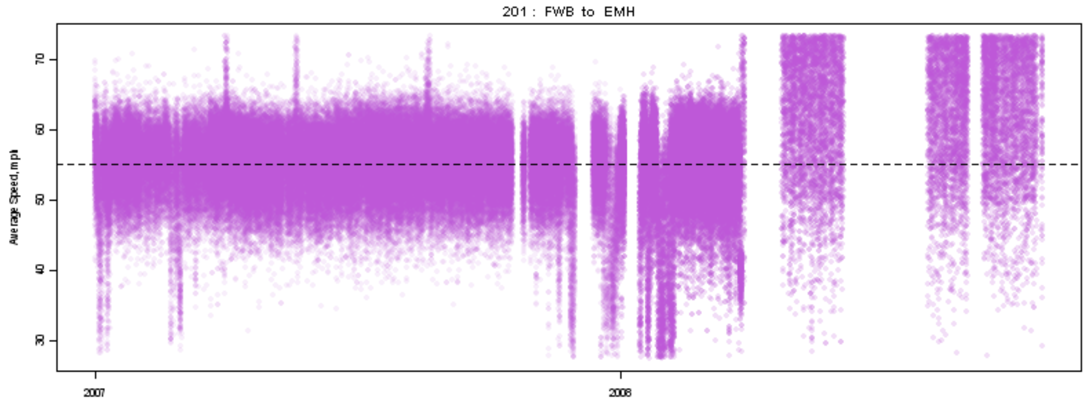
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	9.376029265	9.37602926	311.1785711	1.07384E-05
Residual	5	0.150653518	0.0301307		
Total	6	9.526682782			

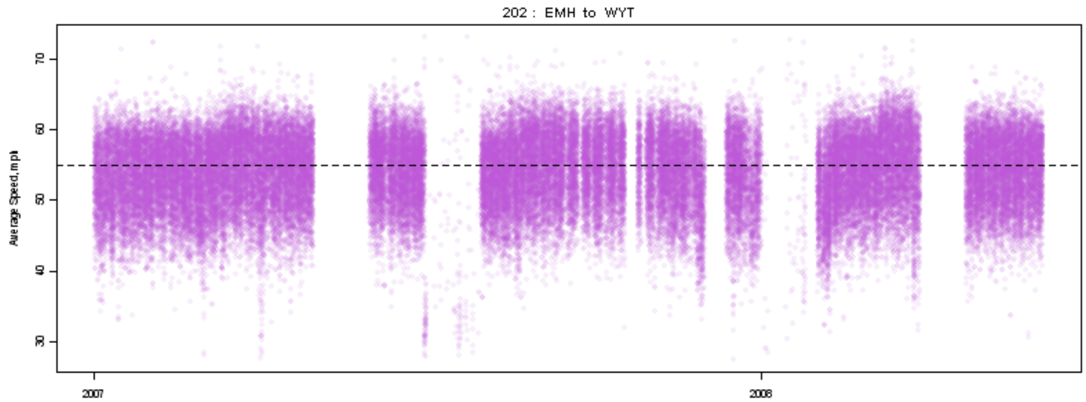
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	0.305193417	0.134460551	2.26976176	0.072460417	-0.040448433
X Variable 1	0.644411416	0.036530733	17.6402543	1.07384E-05	0.550506178

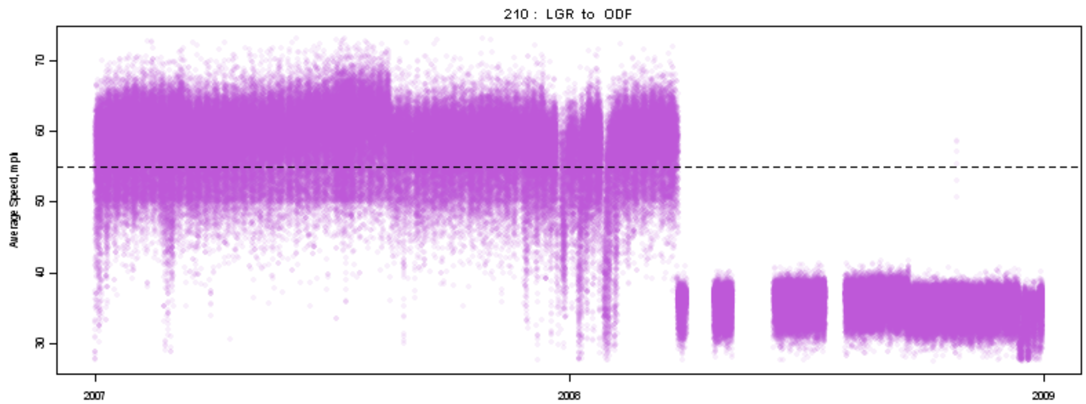
Equation_2

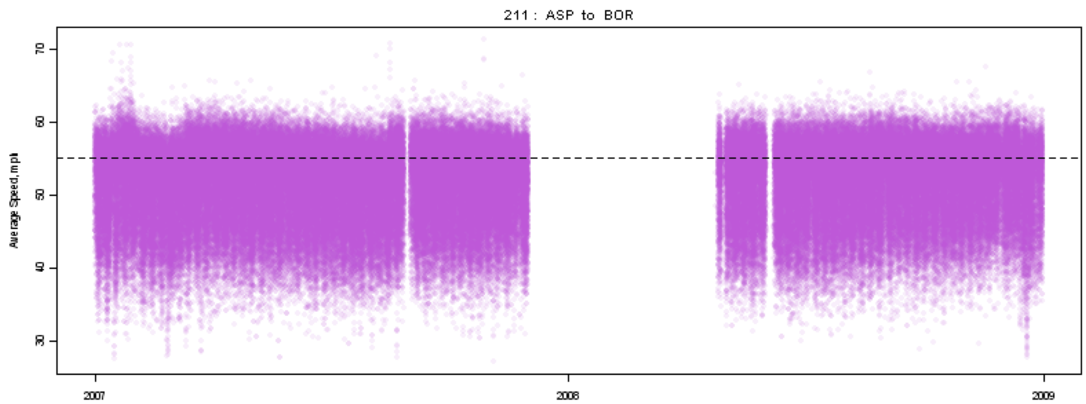
Car_tt = 0.30519 + 0.6444*Truck_tt

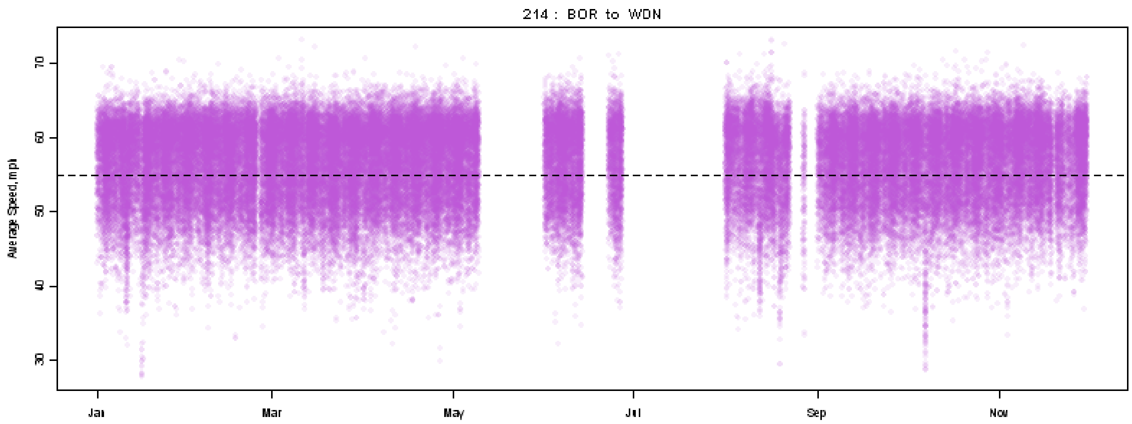
TIME SERIES PLOTS OF THROUGH TRUCKS

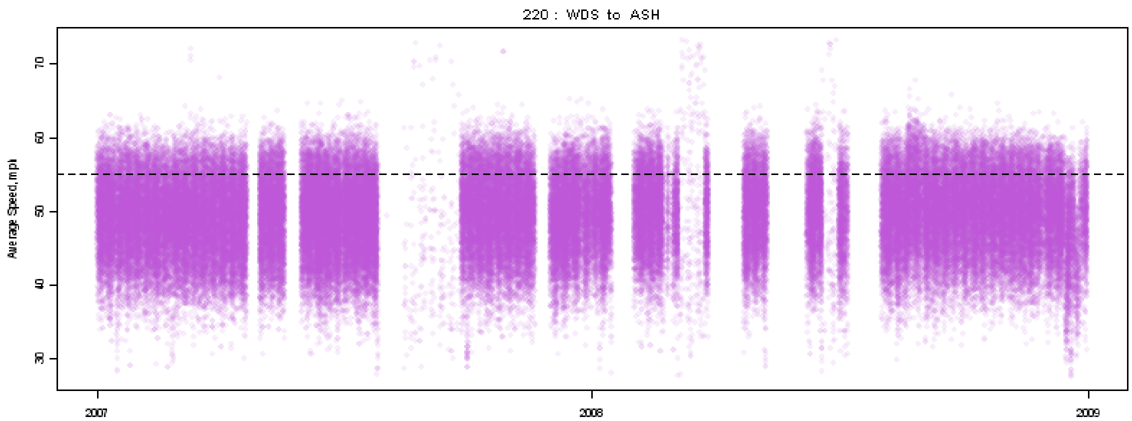


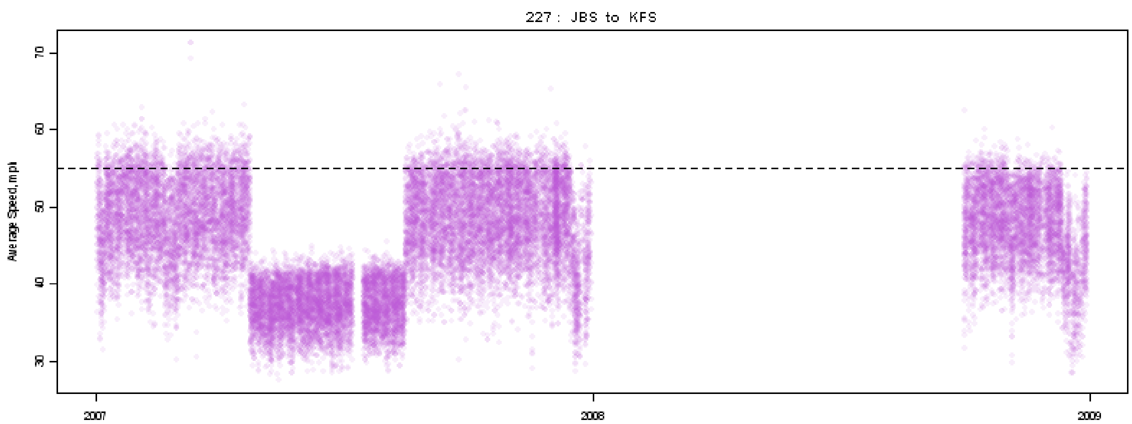


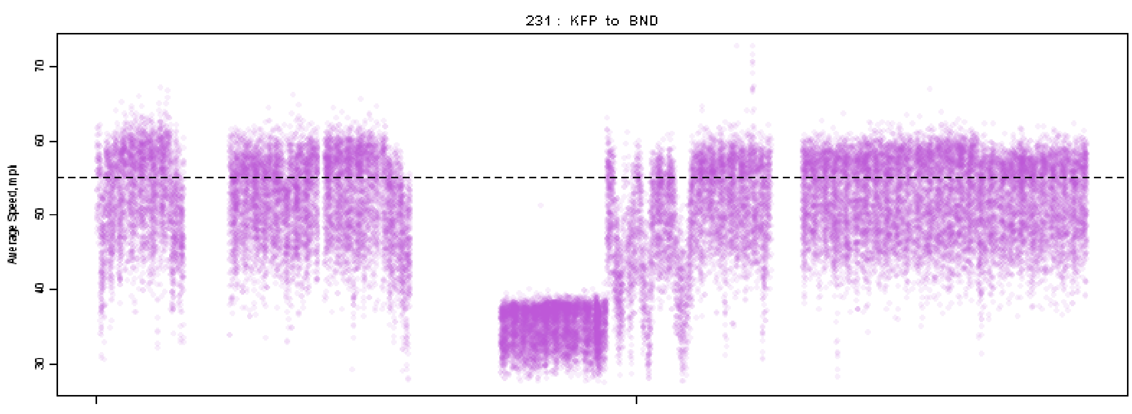


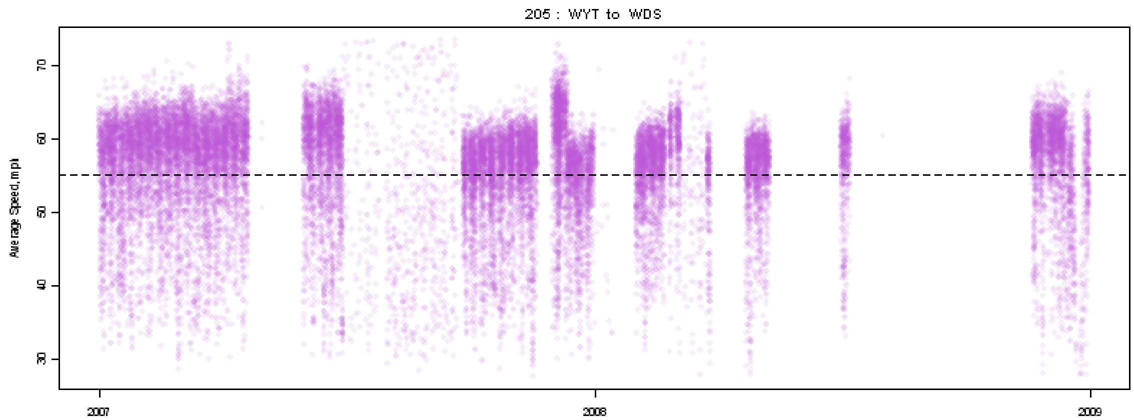


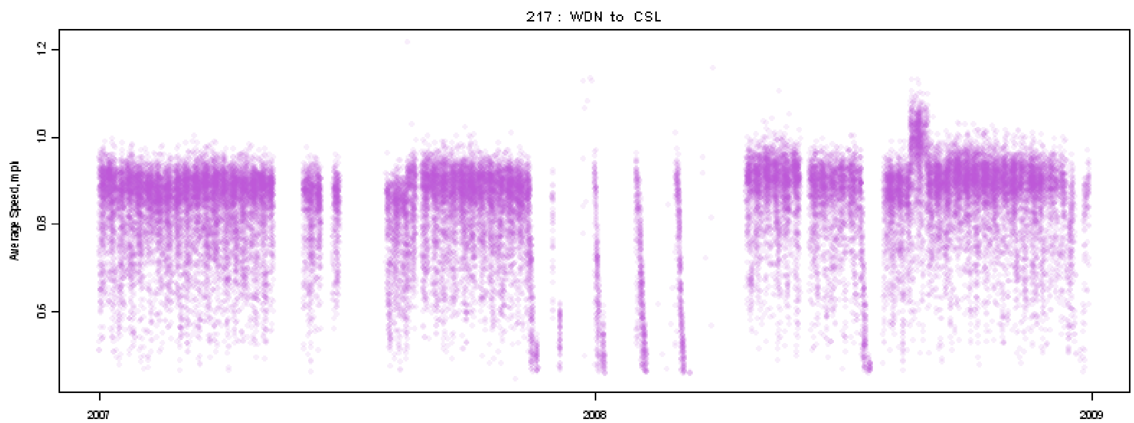

214 : BOR to WDN
Average Speed, mph
70
60
50
40
30
Jan
Mar
May
Jul
Sep
Nov

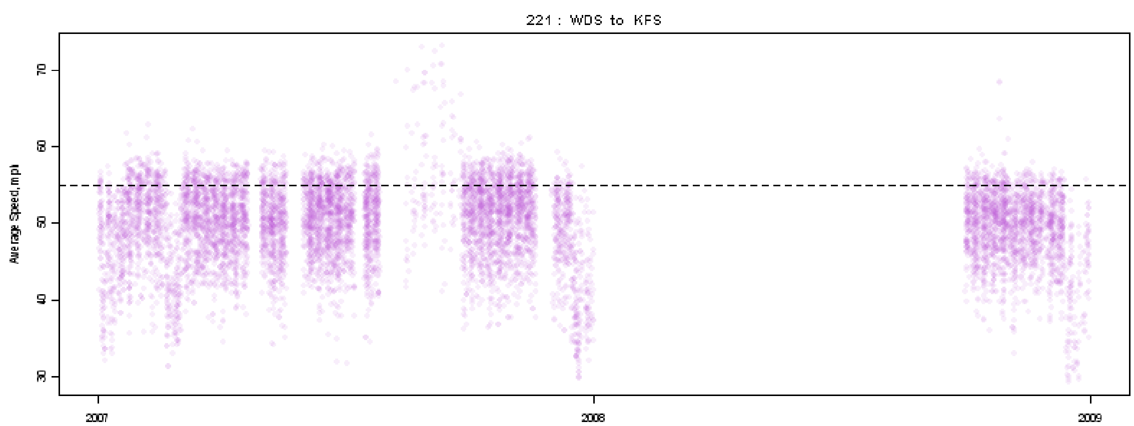

220 : WDS to ASH
Average Speed, mph
70
60
50
40
30
2007
2008
2009

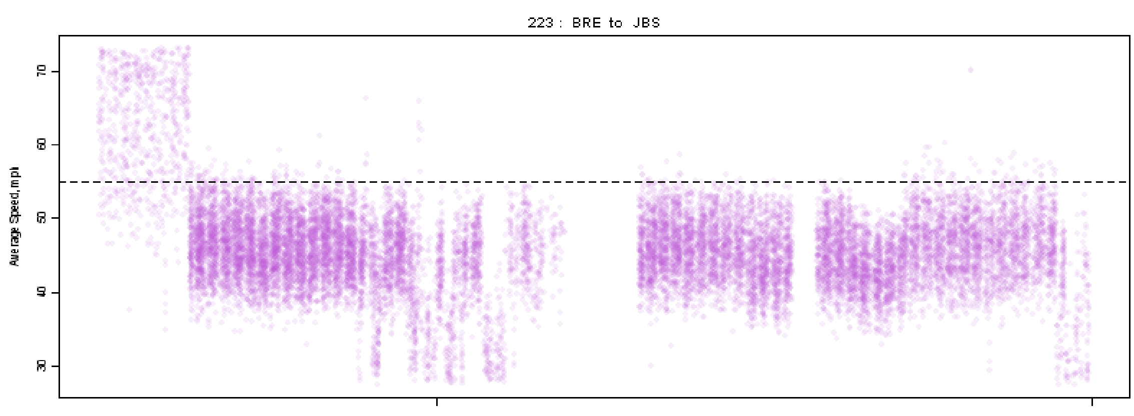

227 : JBS to KFS
Average Speed, mph
70
60
50
40
30
2007
2008
2009

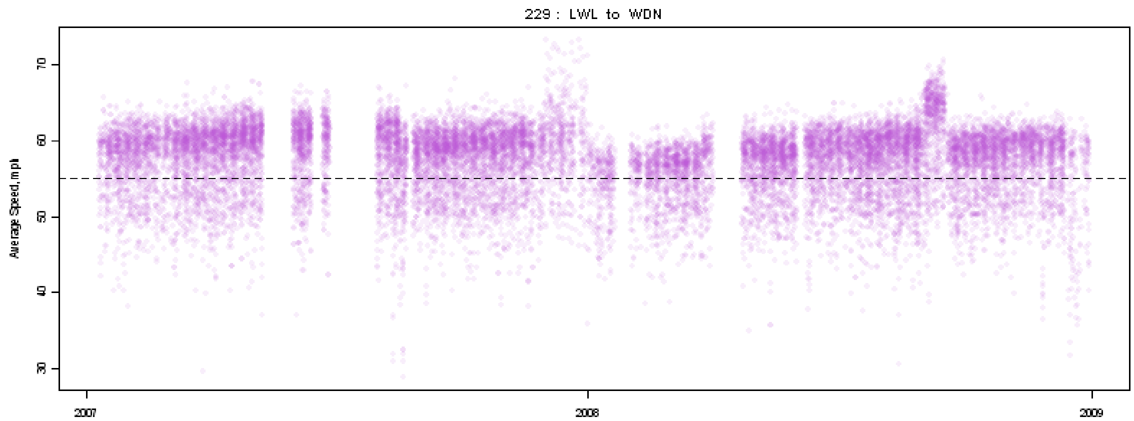

231 : KFP to BND
Average Speed, mph
70
60
50
40
30
2007
2008

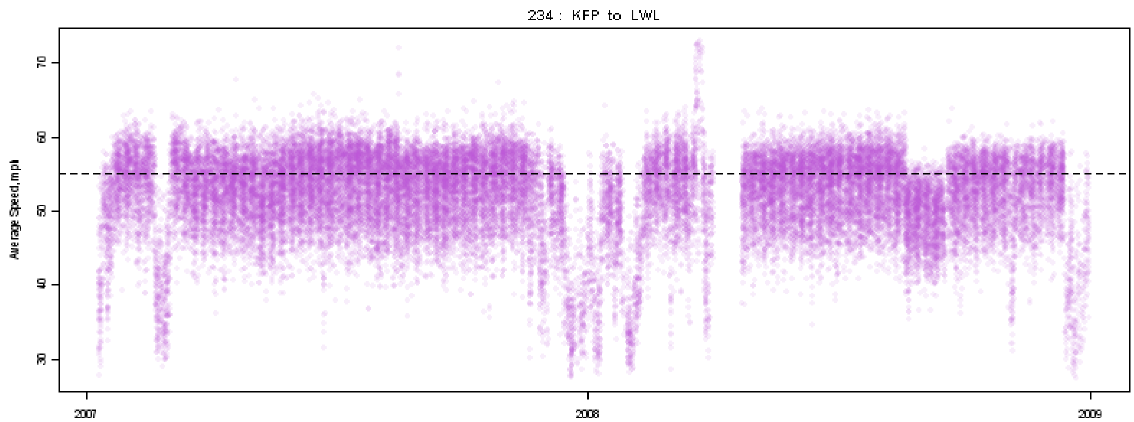

205 : WYT to WDS
Average Speed, mph
30
40
50
60
70
2007
2008
2009

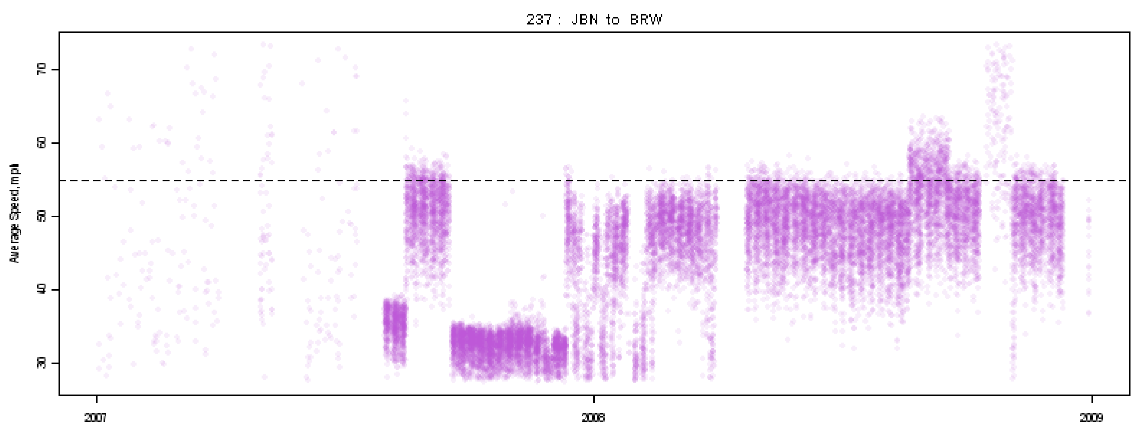

217 : WDN to CSL
Average Speed, mph
0.6
0.8
1.0
1.2
2007
2008
2009


221 : WDS to KFS
Average Speed, mph
30
40
50
60
70
2007
2008
2009


223 : BRE to JBS
Average Speed, mph
30
40
50
60
70
2008
2009


229 : LWL to WDN
70
60
50
40
30
Average Speed, mph
2007
2008
2009


234 : KFP to LWL
70
60
50
40
30
Average Speed, mph
2007
2008
2009


237 : JBN to BRW
70
60
50
40
30
Average Speed, mph
2007
2008
2009