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On the cover: Remote areas of the central and northern plains states have little alternative to railroads in the transport of wheat. Wheat shipments involve large scale movements of low value bulk commodities over long distances. Trucks are not competitive for these movements and many wheat origins are remote from barge loading locations. The implications of these facts is examined by Michael Babcock and Bebonchu Atems in "Intramodal and Intermodal Competition Impacts on Railroad Wheat Rates."

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A Message from the JTRF Co-General Editors

The Fall 2015 issue contains the usual wide variety of contemporary transportation topics that is the distinguishing characteristic of JTRF. Topics in this issue include the following:

- Technologies and data to measure travel time on urban streets
- Performance evaluation of public transit
- Forecasting future traffic needs
- Competition impacts on railroad wheat rates
- Northern plains farm truck marketing patterns
- Potential policy changes for Canada's grain transportation system

In "Comparative Evaluation of Technologies and Data Sources to Capture Travel Time at Section-Level on Urban Streets," Pulugurtha and co-authors capture travel times on urban streets in Charlotte, North Carolina, using three different technologies (Bluetooth, INRIX and GPS). The authors found that the ability of the technologies to measure accurate travel tim,e increases with increases in traffic volume. Also accurate measurement of travel times varies by time of day. The authors concluded that Bluetooth is less accurate and undependable compared with GPS and INRIX

Kamrul Islam and co-authors develop a model based on the Markov Chain technique to evaluate the performance of a public transport route in "A Simplified Method for Performance Evaluation of Public Transit Under Reneging Behavior of Passengers." The model addresses a special situation where a passenger left behind by a bus leaves the system without any further waiting. The authors offer insights to the problem faced by transit system designers with regard to fleet size and the size of vehicles. The authors used the following metrics to evaluate performance: number of passengers served by the system, number of passengers that were unable to use the service because of space unavailability, and number of unused spaces throughout the transit operation. Authors conclude that their analysis provides insights for optimum selection of fleet size and vehicle size.

In "Traffic Impact Analysis (TIA) and Forecasting Future Traffic Needs: Lessons From Selected North Carolina Case Studies," Pulugurtha and co-authors conduct an evaluation of TIA case studies, review current practice, and recommend procedures that could be used to better forecast and plan future traffic needs. The authors found that considering regional traffic growth rate, peak hour factor, heavy vehicle percentage, and other off-site developments would yield better forecasts.

Michael W. Babcock and Bebonchu Atems study the relationship of intrarailroad competition and rail rates for wheat in the nine largest wheat producing states in "Intrarailroad and Intermodal Competition Impacts on Railroad Wheat Rates." The overall objective is to investigate railroad pricing behavior for wheat shipments. The rate model was estimated with OLS in double-log specification utilizing the 2012 Confidential Waybill sample and other data. The authors found that the distance from origin to destination and the total shipment weight had the expected negative relationships with railroad wheat rates and were statistically significant. The distance from origin to the nearest barge loading location had the expected positive relationship to railroad wheat rates and was also significant. The weight of each covered hopper car and the Herfindahl-Hirschman Index were both non-significant. However, the authors used other data to determine that the intrarailroad competition for wheat shipments within states appears to be present in most of the nine states.

In "Northern Plains Grain Farm Truck Marketing Patterns," Kimberly Vachal conducted a survey of 6,000 farm operators in the Northern Plains region to gather information about on-farm storage and truck markets. The objective was to provide information about farm truck grain marketing patterns since there is no other source for these data. The author found that 79% of the wheat and soybeans was delivered to elevators, whereas the share of corn delivered to elevators was 54%. The author noted that farmers could use the results for their investment assessments and that local and regional planners and policy makers can use the information in calibrating travel demand and freight flow models for investment and asset management choices.

Savannah Gleim and James Nolan examine both transportation allocation and infrastructure capacity problems associated with moving grain from western Canada to export position. The analysis is conducted with GIS software using grain industry data. After developing and estimating base model results, the authors simulate the impact of larger trains with capacities of 50, 100, and 150 cars. This scenario resulted in significantly fewer total hours traveled and total distance traveled. The authors simulate the impact of greater grain volumes moving through the system (i.e., grain demand and supplies are doubled). The authors found railroad network capacity should not constrain any major expansion of grain movement in the system for the foreseeable future.

Michael W. Babcock
Co-General Editor – JTRF

James Nolan
Co-General Editor – JTRF

Comparative Evaluation of Technologies and Data Sources to Capture Travel Time at Section-Level on Urban Streets

by Srinivas S. Pulugurtha, Rahul C. Pinnamaneni, Venkata R. Duddu, R.M. Zahid Reza

This paper focuses on capturing section-level (a signalized intersection to the next) travel times on urban street segments using Bluetooth detectors as well as from INRIX data source and comparing it with manual and Global Positioning System (GPS) floating test car methods (test car with a trained technician and GPS unit to capture travel time between selected points) for each travel time run. Results obtained indicate that section-level travel time data captured using Bluetooth detectors on urban street segments are less accurate and not dependable when compared with GPS unit and INRIX. The role of various on-network characteristics on the percentage difference in travel time from GPS unit, INRIX, and Bluetooth detectors was also examined.

INTRODUCTION

Travel demand has been increasing with the development of modern civilization, growth in population and need for more travel. The subsequent effect of this increasing travel demand is overcrowding or congestion of the existing transportation network. Addressing congestion has been one of the primary goals of transportation network managers, planners, and engineers. The Federal Highway Administration (FHWA) recommends using the travel time experienced by users to quantify the effect of congestion (AASHTO 2008). Travel time is also a useful measure for motorists or network users to make route choice, mode choice, or departure time decisions.

The most conventional means of collecting travel time data is using a floating test car method. In the floating test car method, a test car is driven by a driver along the study corridor at the speed of traffic. A trained technician in the test car notes down time and position of the test car at regular intervals to calculate travel time between selected points. The sample size from this method is typically very limited. It is also a tedious, expensive, and time-consuming data collection method.

Travel times are also captured using sensors that emit radio waves or a laser beam by installing magnetic loops in pavement that detect the presence of vehicles and by automatically matching license plates through recognition systems, vehicle identification tag reader systems, and video surveillance cameras (Haghani et al. 2010; Vo 2011). A few other means of collecting travel time data include cell phone tracking, Global Positioning System (GPS) equipped floating test cars, and transit buses with GPS or automatic vehicle location units (Kim et al. 2011).

Besides the aforementioned technologies, Bluetooth detectors are an alternative and inexpensive means of accurately estimating travel time (Vo 2011). Bluetooth detectors compute the travel time based on Media Access Control (MAC) addresses (a unique identification number for each Bluetooth enabled device) of Bluetooth enabled devices in the vehicles. In recent years, private sources of data pertaining to travel time and average speed, such as INRIX, Tom Tom, and HERE, have emerged as a valuable source of travel time information. The sources of data such as INRIX provide real-time, historical, predictive traffic services, and incident data on freeways, highways, and secondary roadways, including arterial and side streets of North America and Europe (INRIX 2013). Data provided by the private sources are captured using GPS unit equipped vehicles, from mobile devices, sensors, or other electronic mechanisms. The archived traffic data are used to facilitate traffic management, traveler information, and planning activities for both local and long distance travelers.

The applicability of INRIX and Bluetooth detectors to accurately collect travel time on all types of facilities (in particular, urban arterial streets) is still unclear though their use has rapidly increased in recent years. The key objectives of this research, therefore, are: 1) to collect and evaluate the accuracy of estimated section-level travel time data on urban streets from a GPS equipped floating test car, INRIX and Bluetooth detectors and compare them with data obtained using manual floating test car method, 2) research and compare the ability to capture temporal variations in travel time from the selected technologies/data sources of travel time, 3) examine the correlation between travel times collected manually and using various technologies/data sources, and 4) recommend the best technology or the best combination of technologies/data sources to capture travel time on urban streets. The data collected manually are considered as the most accurate in this research (as it does not involve any technology in collecting the travel time data). It is collected for each travel time run by trained technicians exactly at the locations where travel time from other technologies and data sources are captured. Also, the trained technicians made sure there were no other factors (example, incidents) influencing the results.

LITERATURE REVIEW

Methods and technologies such as using test (or probe) vehicles, installing magnetic loops or sensors at intersections, automatically matching license plate numbers, and electronically reading vehicle identification numbers (say, at toll booths) were used to collect travel time data on freeways and arterial streets in the past (Vo 2011). However, all these methods have intrinsic disadvantages. For instance, capital and operating costs of license plate matching are low, but this method cannot provide real-time travel time or incident data (Turner 1998). Travel times by matching vehicle license plate or tag numbers at toll booths can acquire a larger sample size than test vehicle studies. However, it requires complex planning and implementation (Courage et al. 1998).

Past studies, such as those performed by Quiroga and Bullock (1999), Chu (2013), and Bel-O-Mar Regional Council (2013), show that the GPS floating test car method is an efficient method to collect accurate travel time data. Fewer staff requirements, minimal human error, detailed data collection opportunity, good accuracy, and automatic location identification procedures are some of the many benefits of using a GPS floating test car or vehicle for travel time data collection. Signal loss, retrieving the base map, necessary and updated equipment identification, limited sample, and high cost per unit of data are some of the drawbacks of this data collection method (Turner 1998).

Bluetooth detectors can be set up on the side of a street to track users' Bluetooth enabled device through its electronic identifier (Wasson et al. 2008) and collect data without causing any interruption to traffic flow. Moreover, the cost of the travel time data point from Bluetooth detectors can be as low as 1/300th of the cost of comparable floating test car data (Traffic Technology International 2013). The Bluetooth detectors are easy to install, efficient, and cost-effective considering unitary price and the number of units needed to collect data (Rivey 2013). The type of antenna and its placement affects the performance of Bluetooth detectors. Vertically polarized antennas that radiate a radio frequency signal in all directions (Porter et al. 2010), placing two omni-directional antennas (that radiate or intercept a radio frequency signal equally well in all horizontal directions) at the same location on opposite sides of the street (Malinovskiy et al. 2011), and placing the antenna at 8- to 10-feet height (Brennan Jr. et al. 2010; Vo et al. 2011; Robert et al. 2012) increases the number of Bluetooth enabled devices detected and data quality. Findings from Schneider et al. (2010) and Vo et al. (2011) indicate that placing the detectors at one to two miles apart on arterial streets would yield accurate travel time estimates. The travel time, obtained by recording MAC addresses at upstream and downstream Bluetooth detector locations (Martchouk et al. 2011), are of good quality and better than floating test car and license plate recognition system-based data gathered along freeways (Puckett and Vickich 2010; Haghani et al. 2010). While Quayle et al. (2010) and Sidhaye (2013) showed that larger datasets from the Bluetooth detector can more effectively capture performance characteristics of the arterial street than the traditional GPS floating test car method, Wasson et al. (2008) reported that data from arterial streets showed a significantly larger variance compared with data from the freeways due to the effect of traffic signals.

Private data sources such as INRIX (2013) provide a variety of mobile applications and Internet services pertaining to traffic. The real-time data from actual vehicles and mobile devices traveling through the street network are captured to provide a comprehensive, consistent, and timely measure of traffic congestion nationwide. The data are used to conduct studies at a macroscopic level. The typical INRIX data segment lengths for freeways are 1-3 miles in urban areas and 3-10 miles in rural areas. For arterial streets, typical INRIX data segment lengths are 0.5-3 miles in urban areas and 2-5 miles in rural areas (Turner 1998).

In the past, research was conducted to validate travel times obtained from various technologies/data sources such as GPS unit, INRIX, Bluetooth detectors, etc. based on corridor-level analysis and not based on section-level analysis. The characteristics of a corridor vary from one section to another section along a segment, thus affecting the travel time. This effect can be minimized only by conducting section-level analysis. Also, previous research has shown that Bluetooth detectors can be effectively used for travel time studies on freeways. Their effectiveness as a source of travel time data for urban street segments has not been very clear from the past literature. This paper focuses on a comparison of section-level run-by-run travel time data for urban streets and to address the aforementioned limitations.

METHODOLOGY

Five segments on major urban streets in the city of Charlotte, North Carolina, were selected as the study segments to collect data and compare the effectiveness of the manual floating test car method, GPS floating test car method, INRIX, and Bluetooth detectors in capturing travel time information. The selected urban streets are connected to the Uptown area. This is the central business district (CBD) with major commercial and industrial zones. Table 1 summarizes the characteristics of each selected urban street segment.

Manual travel time data were collected using the floating test car method along the selected urban street segments. For manual data collection, travel time data collection sheets were prepared for each study segment, for both inbound and outbound direction. Each paper form contained information related to intersections along each segment where the arrival times were noted. The distance from one intersection to next intersection (or location) is defined as a section.

Table 1: Characteristics of Selected Urban Street Segments

Route Number	Route Name	# Lanes	Annual Average Daily Traffic (AADT)	Speed Limit (mph)
11	N Tryon St	3	25,000-30,000	45
12	South Blvd	2	20,000-25,000	40
14	Providence Rd	2	30,000-40,000	45
20	Queens Rd	2	14,000-20,000	35
22	N Graham St	2	14,000-20,000	45

In addition, a GPS unit was placed in the floating test car. An off-the-shelf software package (PC-Travel) was used to process travel time data between the selected intersections of all five urban street segments. The computed details were exported as an Excel file.

Data were collected for two days along each study segment—from 7:00–9:00 A.M., 11:00 A.M.–1:00 P.M., 4:00–6:00 P.M. on day 1, and 7:00–10:00 A.M. and 3:00–6:00 P.M. on day 2. Different time periods were selected to capture the difference in travel time and examine the effectiveness of the selected technologies/data sources in collecting travel time data by time period.

Overall, three trained technicians participated in the field data collection during each travel time run. The first person noted the arrival time on the sheet manually; the second person captured data at the same location using a GPS unit, whereas the third person drove the vehicle at the speed of traffic (overtake as many vehicles that passed the test car). Six to 10 travel time runs (in each travel direction) based on traffic conditions were captured during each time period.

Data Collection Using Bluetooth Detectors

Six Bluetooth detectors were provided with Location ID (identifier referring to the intersection) and Group ID (identifier referring to the urban street segment) in addition to name, description, and owner information. The data from Bluetooth detectors were collected in both encrypted and plain text format.

The Bluetooth detectors were installed at selected signalized intersections along each study segment for easy access of power from the signal controller cabinet. A majority of signal control cabinets are close to traffic heading toward the Uptown area. As the objective was to compare travel time from different technologies/data sources, the signalized intersections for the installation of Bluetooth detectors were selected in such a way that the position of Traffic Message Channel (TMC) codes (points where INRIX data are available) matched with the position of these signalized intersections. Manual and GPS data were also gathered at the same points. The mounted height of the antenna to capture data using Bluetooth detectors varied between 10-12 feet along the selected urban streets (based on recommendations from past research as discussed in the Literature Review section). Data were collected using the Bluetooth detectors, continuously for at least 48 hours for each section along each study segment.

After uninstalling the Bluetooth detectors, the raw data were uploaded and processed using the Acyclica Analyzer website (https://cr.acyclica.com/). From the same website, travel times were noted by the travel time run and by time of the day with reference to the manual times obtained from the floating test car method for each section. Travel times for each section were tabulated separately for all the days the Bluetooth detector was installed. By selecting the required time period and direction of travel time run, the average travel time from all the detected Bluetooth enabled devices during that particular time period was noted.

The raw data may include outliers such as Bluetooth detections from bicyclists, pedestrians, transit system users, or customers who stopped at nearby stores/restaurants (includes coffee shops, gas stations, etc.). For an accurate estimation of travel times from Bluetooth detectors (to overcome the effect of data outliers), a filtering technique based on minimum and maximum speeds on a section was developed and incorporated. Maximum and minimum travel times were computed for each section based on these minimum and maximum speeds. The raw data with information for each detected Bluetooth enabled device were processed to then remove outliers for each section.The number of outliers is very small (at most two in a data collection hour for a section).

The default filtering procedure captures all Bluetooth enabled devices during a travel time run period. This could lead to erroneous travel time estimates. Therefore, the use of ±1.5 min, ±2.5 min, and ±5 min as data filter ranges for each travel time run was examined. These data filter ranges were applied for each travel time run. For example, if a manual run starts at 8:00:00 A.M. and ends at 8:03:00 A.M. on a particular section and data filter range is ±1.5 min, the samples (Bluetooth enabled devices) that are detected by the Bluetooth detector from 7:58:30 A.M. to 8:01:30 A.M. at the start and 8:01:30 A.M. to 8:04:30 A.M. at the end were taken into consideration for that particular travel time run. Based on these data filter ranges, the average travel times for each travel time run were estimated from Bluetooth detectors installed along the study segment and compared with travel time from other technologies/data sources.

INRIX Data Collection

INRIX data were obtained for the same days on which manual and GPS data were collected, for each selected urban street segment through the web interface.

The data from INRIX were also available for two complete days. For better comparison of technologies / data sources for travel time data collection, the travel time from INRIX was extracted for each travel time run on each data collection day. Like in the case of Bluetooth detectors, data were also filtered using ±1.5 min, ±2.5 min, and ±5 min as data filter range for each travel run.

RESULTS

As mentioned previously, data were collected and gathered along five urban street segments, for two days, during morning (AM), mid-day (Mid-day) and evening (PM) time periods.

Table 2 shows the sample sizes based on time-of-the-day. For INRIX, the sample sizes shown are not the actual counts but are equivalent to the travel time runs for which data were captured. In the case of Bluetooth detectors, the sample sizes are based on the number of detections summed up for all the sections.

The number of detections from Bluetooth detectors is lower during the morning time period and higher during mid-day and evening time periods. This may be because of higher noise levels/ disturbance, traffic signals, weather and environmental conditions, or varying traffic volumes during different time periods.

Table 2: Sample Size by Time-of-the-Day

Technology/Source		AM	Mid-day	PM
Manual/GPS		332	140	296
INRIX		332	140	296
Bluetooth (# of Detections)	Default filtering	301	3,936	6,454
	±1.5 Min Filter	63	704	1,222
	±2.5 Min Filter	83	933	1,550
	±5.0 Min Filter	122	1,458	2,426

Comparison of Travel Time Estimates by Study Segment and Time-of-the-Day

Table 3 shows travel times collected manually and the percentage difference observed from the GPS unit, INRIX, and Bluetooth detectors during mid-day and evening time periods on day 1 along South Blvd (inbound) study sections. It can be noticed from Table 3 that travel times from the GPS are very close to those collected manually except for Run 1 at 4:46 P.M. This is because the GPS travel times have been collected from the same floating test car that was used for the manual data collection. The absolute value of the percentage difference in travel time from Bluetooth detectors are observed to be greater than INRIX for 9 out of the 24 travel time runs on sections along South Blvd (Table 3).

To better assist in comparing the results, the absolute value of percentage difference in travel time from the GPS unit, INRIX, and Bluetooth detectors when compared to the manual floating test car were categorized into six different percentage range categories (0-10, 10-20, 20-30, 30-40, 40-50, and >50). The percent of travel time runs that fall in each category were summarized for each study segment. Figure 1 shows the percent of travel time runs by range of percentage difference in travel times (absolute values) for selected technologies/data sources and study segments during the morning time period.

The absolute value of percentage difference between GPS and manual travel time is less than 10% for all sections along the five segments during the morning time period (Figure 1). The figure also reveals that travel time readings from INRIX and Bluetooth detectors differ from manually collected data. The absolute value of percentage difference is observed to be reasonably high in some cases. For instance, out of the total 408 travel time runs gathered along N Graham St, more than 100 travel time runs have absolute value of percentage difference in travel time greater than 70% for the Bluetooth detectors.

Table 3: Percentage Difference in Travel Time by Travel Time Run Compared to Manual Travel Times During Mid-day and Evening Time Periods Along South Blvd

Section	Manual (Sec)	GPS (%)	INRIX (%)	Bluetooth (%)	Manual (Sec)	GPS (%)	INRIX (%)	Bluetooth (%)	Manual (Sec)	GPS (%)	INRIX (%)	Bluetooth (%)
5/29/13	Run 1 (Time) 11:15 AM				Run 2 (Time) 11:49 AM				Run 3 (Time) 12:17 PM			
1	82.5	0.6	8.7	49.0	91.1	1.0	11.8	-18.3	90.0	1.1	31.3	-27.3
2	128.3	0.6	2.0	72.1	115.8	0.2	15.0	120.3	137.5	0.4	-7.1	77.7
3	323.4	0.2	-40.5	-29.5	323.8	0.1	-35.0	-22.3	246.7	0.5	-14.6	14.2
4	126.6	0.3	-24.2	7.7	123.9	0.9	-17.2	40.0	119.8	-2.3	-22.4	50.0
5/29/13	Run 1 (Time) 4:46 PM				Run 2 (Time) 5:28 PM				Run 3 (Time) 6:20 PM			
1	150.5	16.3	-36.5	-5.3	184.0	-3.8	-49.7	1.8	173.0	1.2	-46.5	21.7
2	146.3	36.7	5.0	66.6	225.8	-0.4	-22.9	4.7	211.1	0.4	-32.4	57.1
3	244.2	-40.2	-11.1	-6.1	319.8	0.1	-46.0	-22.2	380.2	-0.1	-31.8	-28.9
4	157.9	-43.6	-16.8	-1.3	163.1	0.6	-37.1	-0.7	146.5	0.3	-50.9	-5.0

To account for the effect of traffic and examine the performance over time, the average travel time considering all travel time runs are computed for each technology/data source by time period. The percentage difference based on these averages are then computed and summarized by time period (Figure 2). In the figure, AM, MD, and PM indicate morning, mid-day, and evening time periods, respectively. The percentage differences shown in Figure 2 for GPS unit, INRIX, and Bluetooth detectors are in comparison to manually collected travel times. N Tryon St, South Blvd, and Providence Rd showed higher percentage difference during the evening time period (almost -44%, -27%, and -24%, respectively) in the case of INRIX data. The percentage differences for INRIX and Bluetooth detectors are reasonably close to each other irrespective of the time of day along Queens Rd. For N Graham St, the percentage difference for Bluetooth detectors varied by 200%, 240%, and 94% during morning, mid-day, and evening time periods, respectively.

The inaccurate travel time estimates from Bluetooth detectors could be due to outliers from the default filtering procedure. Therefore, a micro-level analysis was done by filtering the raw data obtained from the Bluetooth detectors and compared to manually collected travel times. Based on the start and end times of the travel time run, data filter ranges of ±1.5 min, ± 2.5 min, and ±5 min were tested to perform this micro-level analysis and compute absolute value of percentage differences in travel times.

Figure 3 shows the percent of travel time runs by range of percentage difference in travel times (absolute values) from Bluetooth detectors using various data filter ranges. Out of the three data filter ranges, ±1.5 min data filter range was observed to yield a reasonable sample size (though lowest of the three considered data filter ranges, as can be noted from Table 2). However, the sum of the total percent of travel time runs for ranges of percentage difference ≤40 is highest for ±1.5

min data filter range for all the five study segments. As an example, the total percent of travel time runs for N Tryon St is [(25.8% for 0-10 range of percentage difference) + (19.6% for 10-20 range of percentage difference) + (13.6% for 20-30 range of percentage difference) + (10.6% for 30-40 range of percentage difference)] = 69.6% for ≤40 range of percentage difference in the case of ±1.5 min data filter range (compared to ~65% and ~64% for ±2.5 min data filter range and ±5 min data filter range, respectively). This indicates that relatively more accurate results can be obtained using ±1.5 min data filter range.

Figure 1: Percent of Travel Time Runs by Absolute Value of Percentage Difference in Travel Time for Different Segments During Morning Time Period

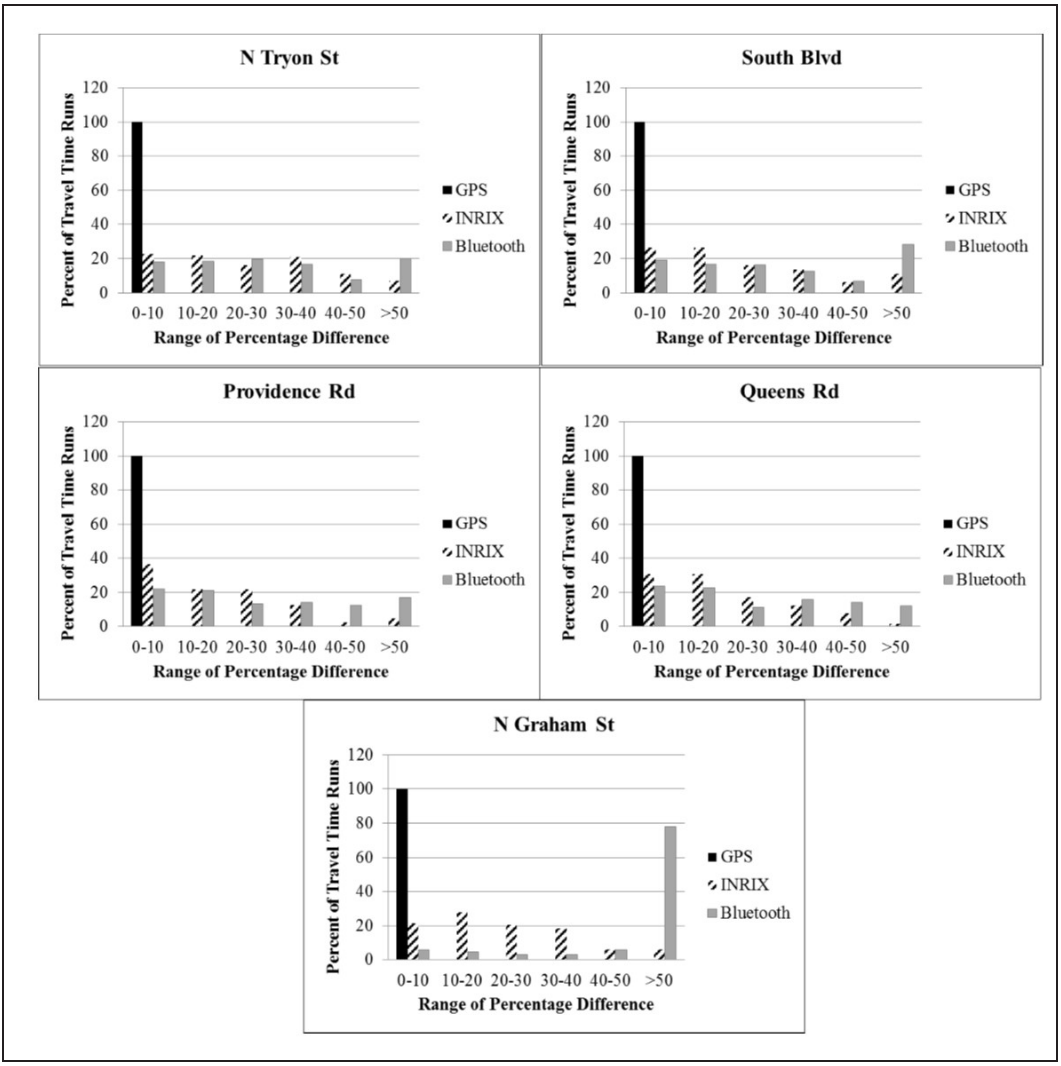


Figure 2: Percentage Difference in Average Travel Time by Time Period

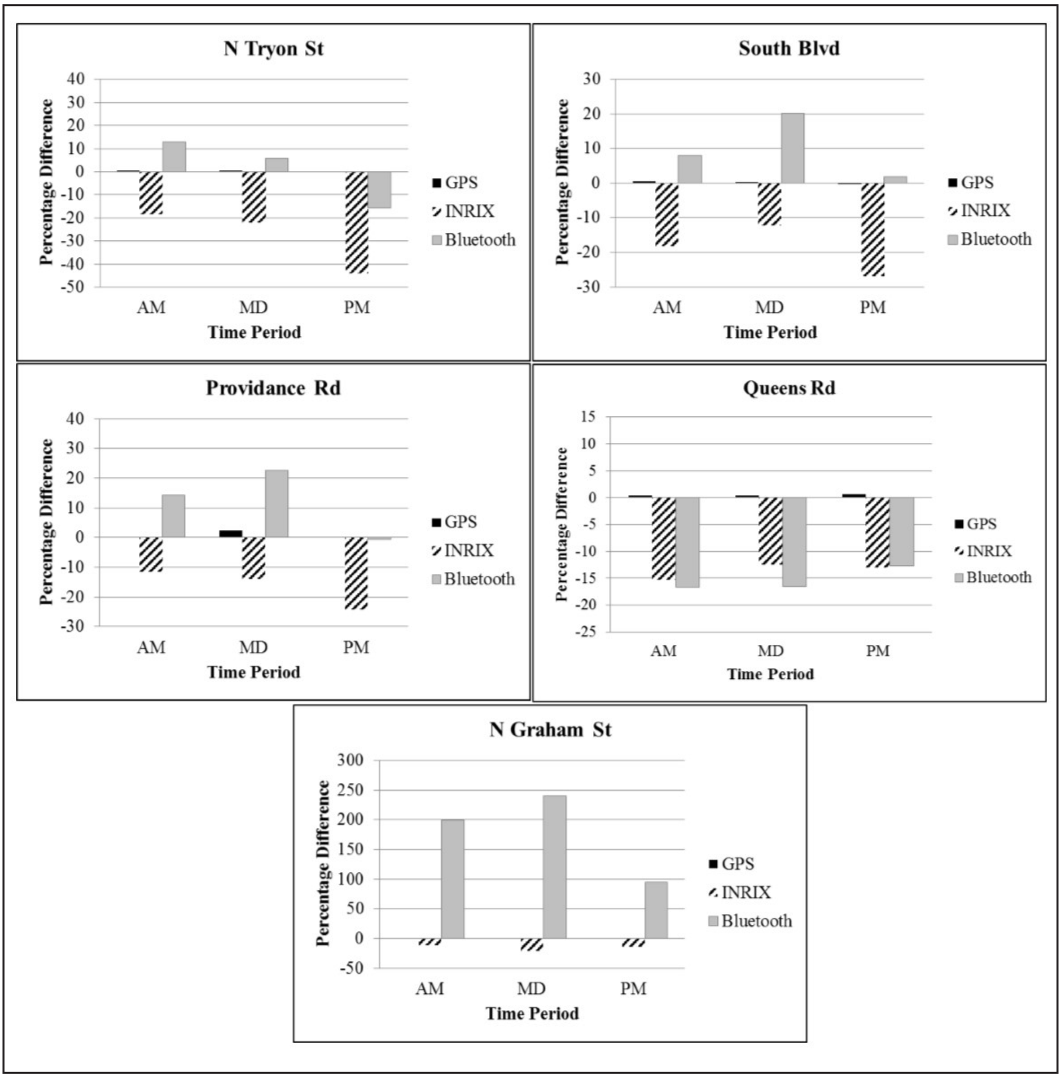
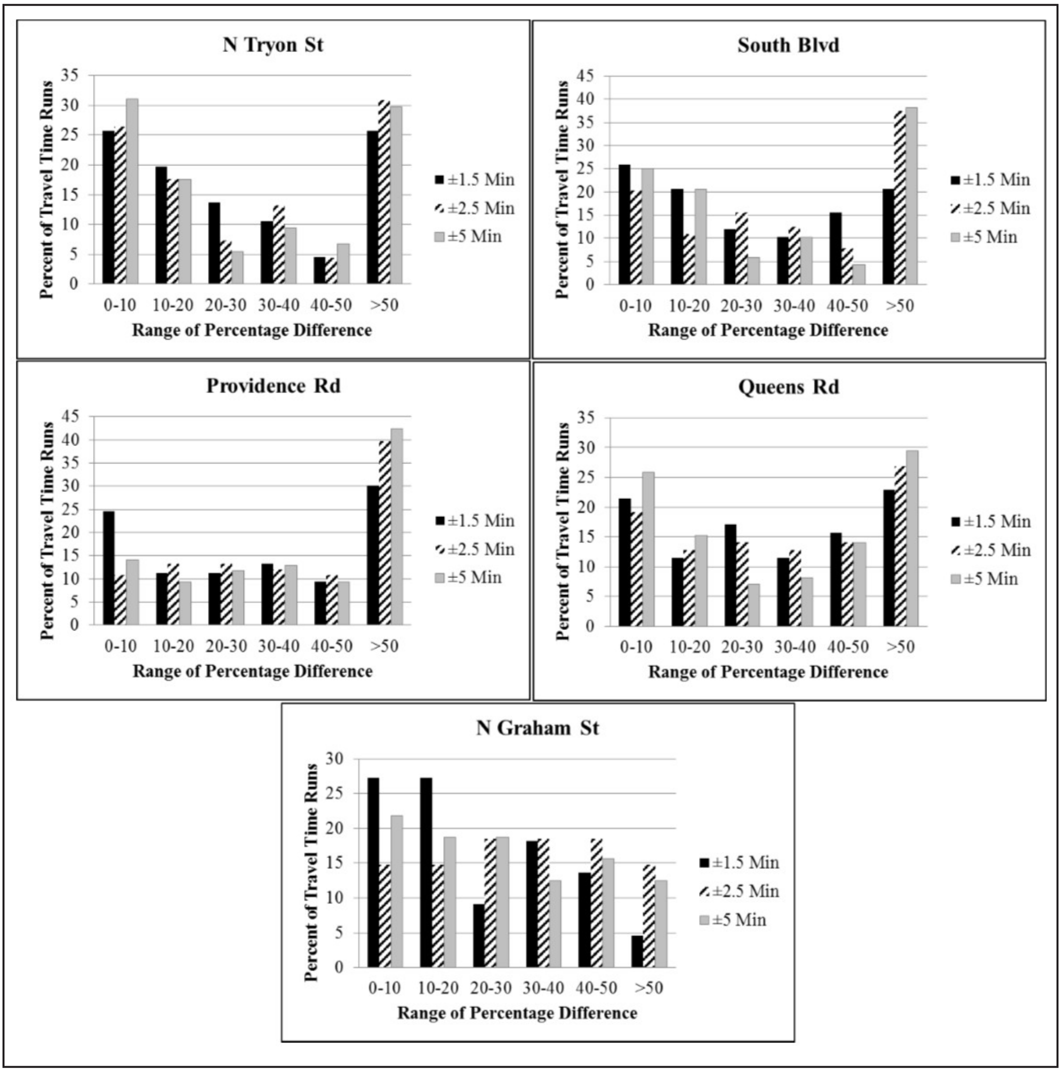


Figure 3: Percent of Travel Time Runs by Absolute Value of Percentage Difference in Travel Time from Bluetooth Detectors Using Various Data Filter Ranges



The computed absolute value of percentage difference in travel times for the selected urban street segments, based on ±1.5 min data filter range, is shown in Figure 4. The INRIX travel times were also extracted and computed based on ±1.5 min data filter range for each travel time run to be consistent with travel times from Bluetooth detectors. The absolute value of percentage difference in travel times from GPS are mostly in the 0-10 range of percentage difference, while they are widely spread in all the ranges for INRIX and Bluetooth detectors. INRIX has higher bars for percentage differences in travel time up to the 30-40 range of percentage difference while Bluetooth detectors has higher bars in the 40-50 and >50 range of percentage differences.

Figure 4: Absolute Value of Percentage Difference in Travel Times for Different Segments Using ±1.5 min Data Filter Range

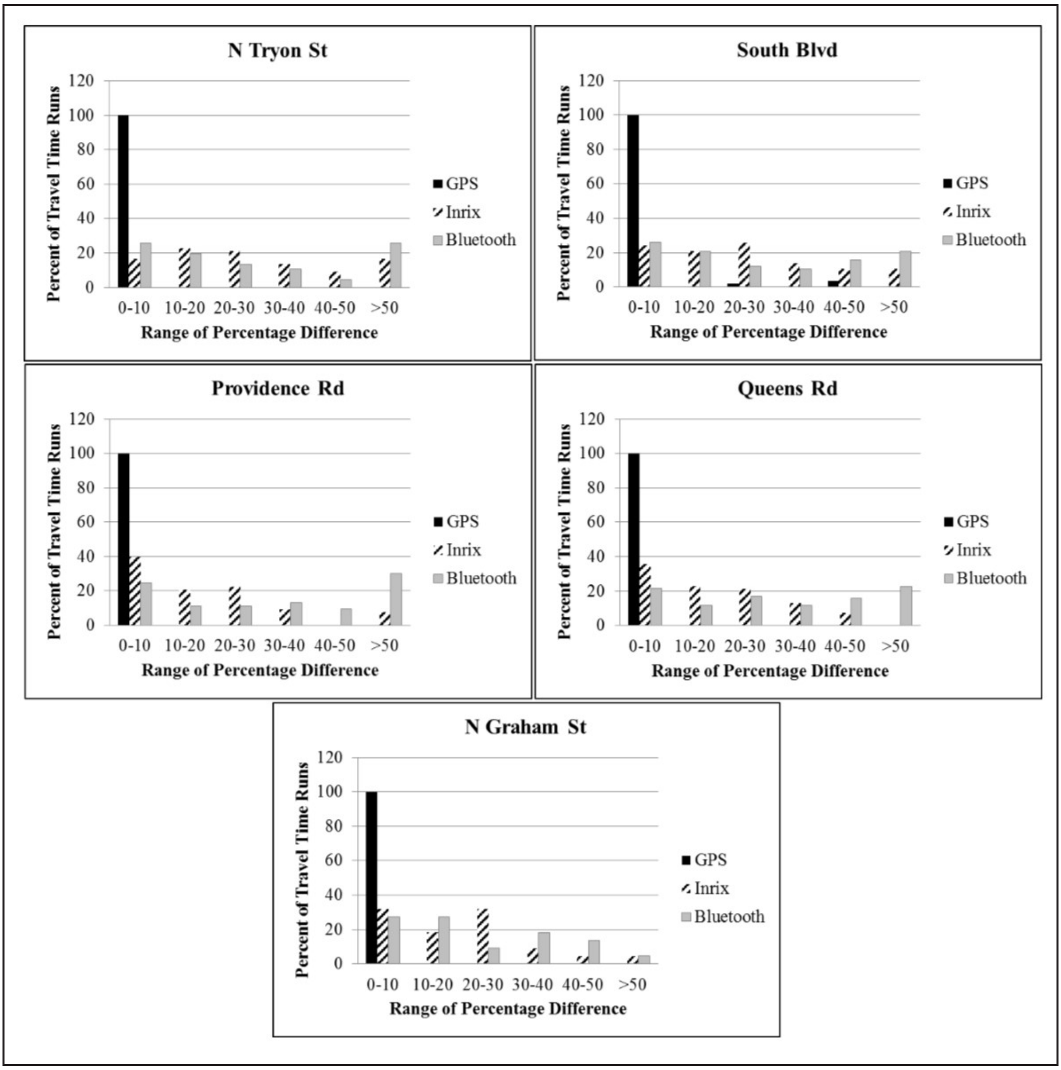


Table 4 summarizes the cumulative percent of travel time runs by absolute value of percentage difference in travel time collected along all study segments using GPS unit, INRIX, and Bluetooth detectors. Overall, the absolute value of percentage difference in travel time is ≤10% for 99.5% of travel time runs collected using GPS unit, indicating that it is the most reliable travel time data collection technology. While the absolute value of percentage difference in travel time is ≤20% for 52.7% of travel time runs obtained from INRIX (no filtering), it is ≤20% for 34.5% of travel time runs collected using Bluetooth detectors (default filtering). Using ±1.5 min data filter range did not yield significant improvements in INRIX outputs. The percent of travel time runs from Bluetooth detectors, with absolute value of percentage difference in travel time ≤20%, increased to 40.8% after using ±1.5 min data filter range. While the proposed data filtering method improved the accuracy of travel time estimates from Bluetooth detectors, it still does not match outputs from INRIX (both with no filtering and ±1.5 min data filter range).

Table 4: Cumulative Percent of Travel Time Runs by Absolute Value of Percentage Difference in Travel Time

Absolute Value of Percentage Difference in Travel Time	GPS	INRIX (No Filtering)	INRIX (±1.5 Min Data Filter Range)	Bluetooth (Default Filtering)	Bluetooth (±1.5 Min Data Filter Range)
≤10	99.5%	27.2%	28.7%	17.7%	24.3%
≤20	99.6%	52.7%	50.0%	34.5%	40.8%
≤30	99.6%	70.8%	73.2%	47.7%	54.0%
≤40	99.7%	86.7%	85.3%	60.3%	65.8%
≤50	100.0%	93.7%	91.9%	69.6%	77.2%
≤100	100.0%	100.0%	100.0%	100.0%	100.0%

Effect of Section Length on Bluetooth Detector Travel Time Estimates

Figure 5 shows the effect of the number of detections and section length (spacing between signalized intersections with Bluetooth detectors) on travel time estimates from Bluetooth detectors. The section length along the considered segments varied from 0.75 miles to 2.75 miles. Considering higher data filter ranges (±2.5 min and ±5 min) does not seem to lower the percentage difference of Bluetooth-detector-based travel time estimates when compared to manually captured travel time. The maximum percentage difference for shorter sections was observed to increase with an increase in the data filter range. However, the percentage difference tends to decrease with an increase in section length for ±1.5 min, ±2.5 min, and ±5 min data filter ranges (Figure 5) i.e., the accuracy of travel time estimates from Bluetooth detectors was observed to improve with an increase in spacing between the Bluetooth detector locations.

Statistical Analysis

To further compare the travel times obtained from GPS, INRIX, and Bluetooth with the manual travel time data, t-tests were conducted at a 95% confidence level. The results obtained from t-tests are shown in Table 5. From the results obtained, the zero is not between the upper and lower bound of 95% confidence interval. This shows a significant difference in the means at a 95% confidence level between manual and GPS, manual and INRIX, and manual and Bluetooth detector travel time estimates. However, unlike manual and INRIX or manual and Bluetooth detectors travel time estimates, the difference in means between manual and GPS travel time estimates is very low (around 0.4 seconds). The correlation coefficient between manual and GPS travel time estimates is close to 1, which indicates that manual and GPS travel times are almost the same.

The correlation coefficient between manual and INRIX travel time estimates is 0.53, which indicates a moderate correlation between the two travel time data samples. For Bluetooth detectors (default filtering) and manual travel time estimates, the computed correlation coefficient is 0.2 (very low). The lower correlation indicates that the default filtering procedure may not be accurate and that the data need further processing and analysis. The difference in the means between Bluetooth detectors based on filtering technique using start and end times proposed in this research and manual travel time was also observed to have a lower correlation as well (0.23), somewhat better when compared with the default filtering procedure. However, the mean, standard deviation and the standard error have reduced significantly when ±1.5 min data filter range was used, indicating overall improved results.

Figure 5: Relation Between Bluetooth Detector Spacing and % Difference

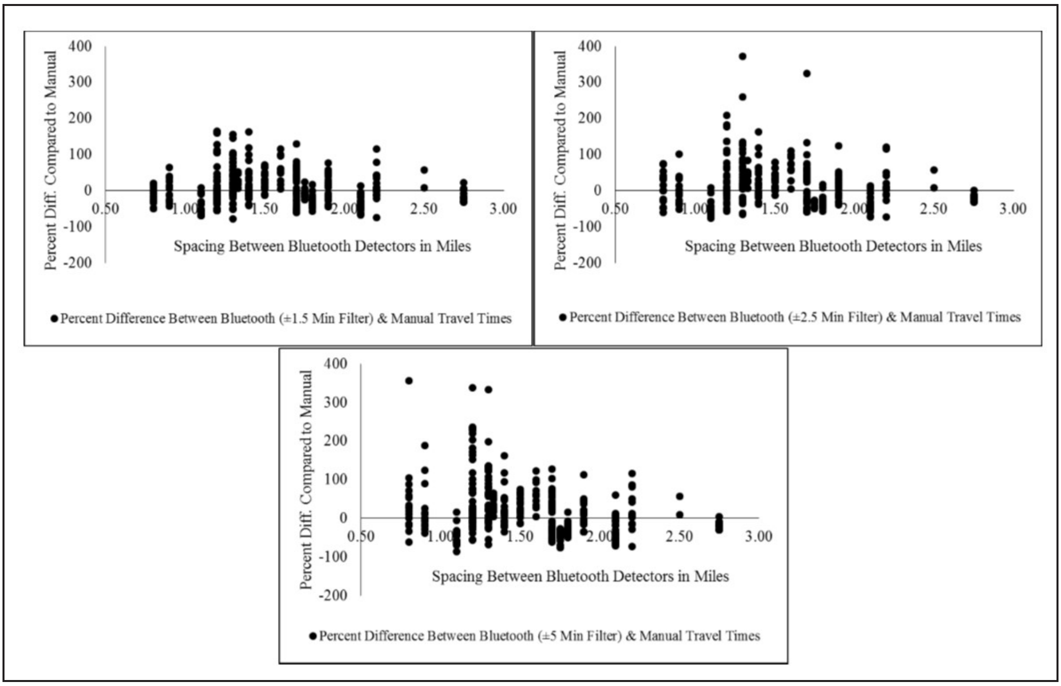


Table 5: Statistical Analyses Comparing Travel Times from Selected Technologies/Data Sources

Null Hypothesis	Paired Differences					Correlation
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval		
				Lower	Upper	
H_0: H_{Manual} - H_{GPS} = 0	-0.42	5.37	0.20	-0.81	-0.04	1
H_0: H_{Manual} - H_{INRIX} = 0	43.18	96.31	3.53	36.25	50.11	0.53
H_0: H_{Manual} - $H_{Bluetooth\ (Default)}$ = 0	-75.27	256.47	9.40	-93.73	-56.81	0.2
H_0: H_{Manual} - $H_{Bluetooth\ (\pm 1.5\ min\ data\ filter\ range)}$ = 0	15.35	113.08	7.86	0.14	30.85	0.23

Note: Alternative hypothesis H_1: Difference in travel times is not equal to 0.

On-network characteristics such as speed limit, the number of signalized and un-signalized intersections, the number of driveways, the number of turnings (left or right), the number of bus stops, traffic volume by time period, the direction of travel (toward or away from Uptown area), and time of day may play an important role in travel time differences. These characteristics were collected for all the sections along each study segment through field visits. Since each section is different from others in length, the number of signalized and un-signalized intersections, the number of driveways, the number of turnings, the number of bus stops, and the average travel time during the time period were divided by the respective section length. As the number of lanes are different, traffic volume along a section was divided by the number lanes. Statistical analysis was conducted by computing the Pearson correlation coefficients (Table 6) to examine the role of the selected variables in the percentage difference in travel time from GPS, INRIX, and Bluetooth detectors (default filtering to maximize sample size). In this research, two variables are considered to be highly correlated to each other if the computed Pearson correlation coefficient is ≤ -0.2 or ≥ +0.2 at a 95% confidence level (indicated by * in Table 6).

Table 6: Correlation Between the Percentage Difference in Travel Times from Selected Technologies/Data Sources and the Variables

On-network Characteristics	Percent Diff. between GPS and Manual Travel Time per Mile	Percent Diff. between INRIX and Manual Travel Time per Mile	Percent Diff. between Bluetooth and Manual Travel Time per Mile
Inbound	-0.04	0.01	-0.02
Outbound	0.04	-0.01	0.02
Speed Limit (35mph)	-0.02	0.01	0.17
Speed Limit (45 mph)	0.02	-0.01	-0.17
# of Signalized Intersections per Mile	-0.09	-0.08	0.16
# of Unsignalized Intersections per Mile	-0.10	-0.02	-0.12
# of Commercial Driveways per Mile	-0.05	-0.16	0.11
# of Residential Driveways per Mile	0.10	0.21*	-0.25*
# of Turnings per Mile	0.16	0.22*	-0.05
# of Bus-stops per Mile	-0.06	-0.19	0.12
# of Lanes	0.18	0.20*	-0.20*
Traffic Volume per Lane	-0.20*	-0.22*	-0.20*
AM Time Period	0.11	0.11	0.00
Mid-day Time Period	0.04	0.09	0.10
PM Time Period	-0.15	-0.21*	-0.10

* Correlation is significant at a 95% confidence level (probability value ≤ 0.05 level; two tailed test).

The percentage difference between GPS and manual travel time per mile is highly correlated to the traffic volume per lane at a 95% confidence level. The negative sign for traffic volume per lane indicates that an increase in traffic volume leads to a decrease in the percentage difference between GPS and manual travel time.

The percentage difference between INRIX and manual travel time per mile is highly correlated with the number of residential driveways per mile, the number of turnings per mile, the number of lanes, traffic volume per lane, and evening time period at a 95% confidence level. The negative sign for the traffic volume per lane indicates that an increase in traffic volume value leads to a decrease in the percentage difference between INRIX and manual travel time. Likewise, the negative sign for the evening time period indicates that the percentage difference between INRIX and manual travel time per mile would be lower during the evening time period. The positive sign for the number of residential driveways per mile, the number of turnings per mile, and the number of lanes indicate that an increase in their values leads to an increase in the percentage difference between INRIX and manual travel time.

The percentage difference between Bluetooth and manual travel time per mile is highly correlated with the number of residential driveways per mile, the number of lanes, and traffic volume per lane at a 95% confidence level. The negative sign indicates that an increase in their value leads to a decrease in the percentage difference between Bluetooth and manual travel time.

CONCLUSIONS AND RECOMMENDATIONS

This paper presents an analysis and evaluation of the quality and accuracy of travel time estimates obtained from a GPS unit, INRIX, and Bluetooth detectors by comparing it with manual data. A GPS unit is the most reliable travel time data collection technology for urban street segments. The travel times from INRIX are more promising when compared to the travel times from the Bluetooth detectors. The Bluetooth detectors showed more samples in higher percentage difference range than INRIX. These findings were supported by t-tests conducted at a 95% confidence level.

Based on the start and end times of the run, data filter ranges of ±1.5 min, ±2.5 min, and ±5 min were tested to perform micro-level analysis of the raw sample from Bluetooth detectors and examine the percentage differences in travel times. Out of the three data filter ranges, ±1.5 min data filter range yielded better results but the lowest number of detections. The travel times from INRIX, however, are more promising than those obtained from Bluetooth detectors even after filtering data using the proposed method (based on minimum and maximum travel time for each section and data filter range).

The relationship between the spacing of locations at which data are captured using Bluetooth detectors indicate that the percentage difference in travel time estimates decreases with an increase in the spacing between the Bluetooth detectors.

The ability to capture accurate travel time data using the selected technologies/data sources seems to increase with an increase in traffic volume (which could be associated to a higher number of samples in the case of INRIX and Bluetooth detectors). Time of day seem to play a role in the number of samples captured (detection rate) using Bluetooth detectors. The numbers of detections are lower during the morning time period when compared with the evening time period (though the placement of Bluetooth detectors is mostly in signal control cabinets close to traffic heading toward the downtown area). The cause of difference in detections by time of day merits investigation and further research.

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Disclaimer

The views, opinions, findings, and conclusions reflected in this paper are the responsibility of the authors only and do not represent the official policy or position of the USDOT/OST-R, NCDOT, UMD, INRIX, or any other state, or the University of North Carolina at Charlotte or other entity. The authors are responsible for the facts and the accuracy of the data presented herein. This paper does not constitute a standard, specification, or regulation.

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A Simplified Method for Performance Evaluation of Public Transit Under Reneging Behavior of Passengers

by Md. Kamrul Islam, Upali Vandebona, Vinayak V. Dixit and Ashish Sharma

This paper develops a model based on the Markov Chain technique to evaluate performance of a public transport route. The model addresses a special situation where a passenger left behind by a bus leaves the system without any further waiting to make an alternative travel arrangement. Such reneging behavior is indicative of an infinite penalty associated with further waiting from a passenger viewpoint. Apart from the theoretical derivations for the various attributes of interest, numerical examples to analyze the system performance (such as expected number of passengers served, expected number of abandoned passengers, and expected amount of unused space on the transit system) are presented. This provides insights for optimum selection of fleet size and size of vehicles

INTRODUCTION

Two basic problems often faced by analysts of transportation systems are related to estimation of vehicle size and frequency of service. In the case of public transit systems, the use of smaller buses with a relatively high service frequency lowers the average waiting time and increases operating speed, but is not suitable for high passenger demand conditions as it costs more to operate per seat provided. On the other hand, comparatively larger buses are usually associated with lower operating cost to operators, but lead to low service frequencies and long average waiting time for passengers. From the operator perspective, it is desirable to use large vehicles that maximize productivity. From the passengers' perspective, the frequency of service is the matter of concern. This poses a dilemma to transit designers in selection of service configuration to meet user needs and desired service levels in terms of service frequency.

The analysis in this paper offers insights to the problem faced by transit system designers; namely with regard to fleet size as well as what should be the size of the vehicles that should be part of the fleet. To address this, a stochastic model using Markov Chain Technique is formulated for a bus transit system with multiple stops, where carriers with a regular headway serve all waiting passengers under a capacity constraint. Markov Chain is a method used to model sequential events of bus operation at a stop where randomly arrived passengers wait for a bus and board the bus depending on space availability after alighting of passengers. This paper sheds light on the performance of transit using the following metrics: number of passengers served by the system, number of passengers that were unable to use the service because of space unavailability, and number of unused space throughout the transit operations.

LITERATURE REVIEW

There were a number of studies performed on bus size and frequency related to urban public transport systems with the aim of improving system performance and enhancing efficiency.

Jansson (1980) paid significant attention to operating cost and user cost while arguing that previous models underestimated user cost and overestimated operator cost. He proposed a model that minimizes total social cost, which includes operator cost, passenger waiting time, and travel time during peak capacity conditions. He concluded that the vehicle size required to minimize social cost is smaller than the vehicle size found in practice, where the number of vehicles is set for a given vehicle size to achieve an average occupancy rate (the mean occupancy rate is the ratio of the mean passenger flow to the product of the service frequency and the bus size). Oldfield and Bly (1988) provided an analytical model to determine optimal bus size, which considered elastic demand that is affected by trip cost. They showed that the optimal size varies with the square root of demand and with the unit cost to the power of 0.1 to 0.2. In a case study in the United Kingdom for typical urban operating conditions, they found that the optimal bus size lies between 55 and 65 seats for a monopoly service.

Jansson (1993) included the variability of value of time to optimize the vehicle size, frequency, and journey price simultaneously. However, because it required large amounts of data, this model was found to be difficult to implement compared with other models. Lee et al. (1995) developed a model that is able to find the bus size for different periods of day in addition to optimal bus size for each route. They also attempted to find suitable conditions to use one bus or alternative uses for a mixed-size fleet. They determined the threshold ratio of peak demand to off-peak demand for multiple-route operation is 1.92 and showed that mixed-fleet operation is preferable on multiple route operation in case of high variation in demand between peak and off-peak period. Rietveld et al. (2001) have extended Mohring's (1972, 1976) basic "square root model" for frequencies and derived a general formulation under an alternative regime of welfare and profit optimization for frequency, vehicle size, and cost of building a railway system. It was observed that in rail transport, the average occupancy rates were low. Chien (2005), with the objective to minimize total cost, developed a methodology integrating both analytical and numerical techniques to optimize headway, vehicle size and passenger route choice for a feeder bus service. The methodology is then applied to analyze a non-stop feeder bus service connecting a selected rail station and a recreation center (Sandy Hook, NJ). It was shown that the optimal fleet size is a function of the demand multipliers. If the demand multiplier is less than 0.7, the optimal fleet size is three buses. The optimal fleet size is four and five buses if the demand multiplier is between 0.7 and 1.1, and greater than 1.1 but less than 1.6, respectively. Dell'Olio et al. (2008) have presented a model to solve the problem of optimizing frequencies and bus size on a transit network consisting of 15 routes. They claimed that their model can designate different types of buses on each route taking into account the reciprocal influence of each route in addition to optimization of the capacity of the bus. However, their model differs from the more commonly held idea that smaller buses are more profitable in a majority of cases.

These earlier studies did not consider the situation where passengers are unwilling to wait for the next bus when they have been unable to board an earlier bus. The current study considers such situations, where buses are full, the transit operators lose a proportion of passengers. This deteriorates the level of service of the transit system.

For the objective of estimating the expected number of passengers served by transit systems, allowing for lost passengers, a queuing theory technique known as the Markov Chain method has been applied. In queuing theory, serving more than one customer at a time is a case known as bulk service. The service capacity is referred to as variable capacity, as it is not the same at all instances of service. In a transportation system analogy, customers are passengers and servers are vehicles, respectively. Bulk service for a single station was first addressed by Bailey (1954) and Downton (1955) applying imbedded Markov Chain technique for a transportation system when the average number of passengers that can be served was constant. Jaiswal (1961) extended Bailey's model for a series of stations where number of passengers served were not constant, rather based on the number of passengers waiting at a stop and vehicle capacity. Arguing that these models are very complex to solve and numerical answers to these models are difficult to find, Giffin (1966) developed a model for a transit system with a series of stations where the simplification was made in assuming there are no en-route departures of customers and all customers remain onboard the vehicle until it reaches the terminal. A. Grosfeld-Nir and Bookbinder (1995) and Lam et al. (2009) considered departure of passengers from buses at on-route destinations but did not link with the performance measures of transit systems. This paper demonstrates how a Markov Chain technique can be utilized to calculate numerical answers to a model bulk service transit system of multiple stops served by a fixed-size vehicle fleet.

MODELING FRAMEWORK

This section presents a description of operation of a bus route and the associated notations along with the modeling framework used to evaluate performances of bus transit systems.

Description of A Bus Route Operation

The operation of bus transit in a route that contains multiple stops is illustrated with the aid of the schematic diagram shown in Figure 1 (a) and Figure 1 (b). From the point of view of bus operation, empty buses are dispatched from the dispatch station and travel along the route allowing passengers to alight and board at stops. This process of serving, boarding, and alighting passengers continues stop after stop. The bus movement is presented as a trajectory diagram in Figure 1(a). The vertical axis shows the distance travelled by buses along the route stopping at designated bus stops, and the horizontal axis indicates the time. Inclined lines between two stops show bus travel from one stop to the next stop. Inclined lines between two stops show bus travel from one stop to the next stop. The dotted lines between two inclined lines show the time spent at stops allowing mainly for boarding and alighting of passengers. As shown in Figure 1 (b), there are five events related to passengers. These events are (a) passengers arrive at a bus stop, (b) passengers board a bus upon arrival if space is available, (c) passengers wait for a bus, (d) passengers leave a stop if space is not available, and (e) a bus departs with passengers for next stop.

Figure 1 (a): Trajectory of Buses Along a Route for Regular Headway of Buses

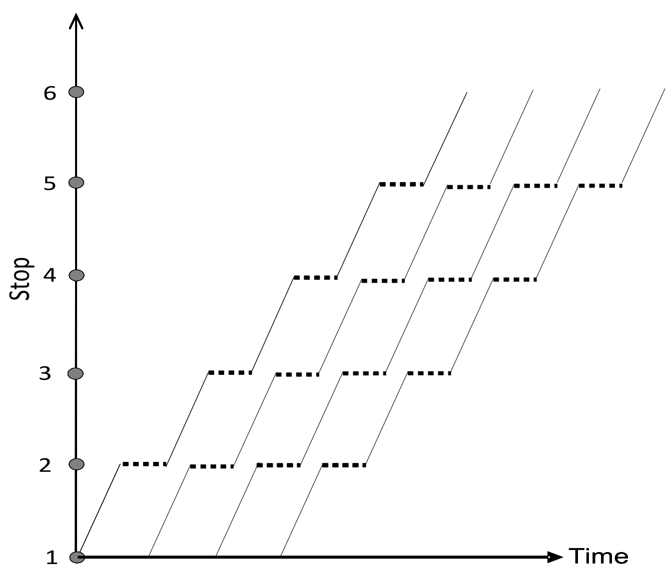
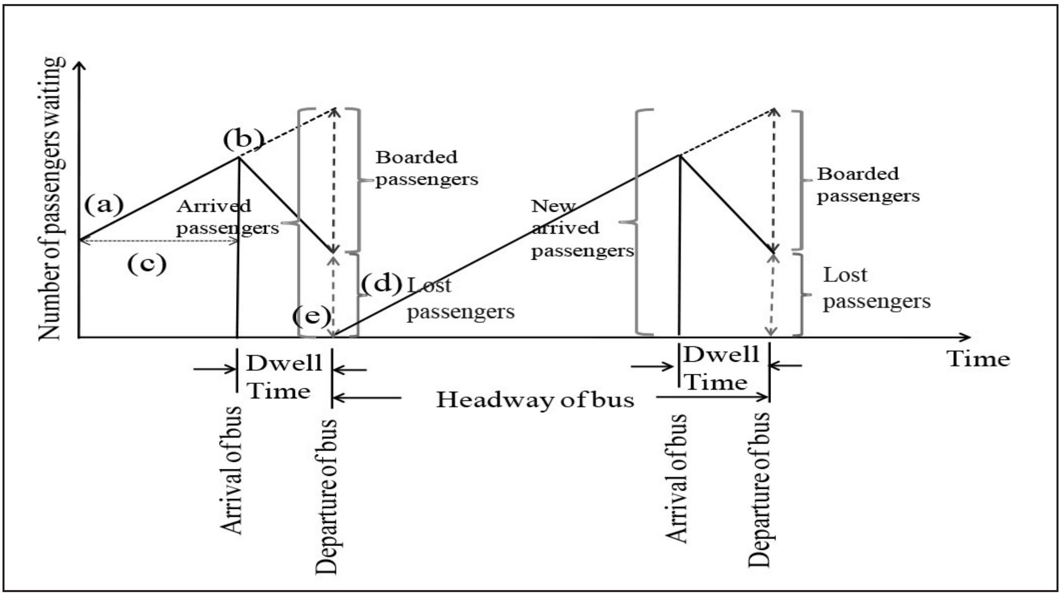


Figure 1 (b): Schematic Presentation of Dynamic Interaction Between Bus and Passengers at Stops



Assumptions

The following assumptions are made in the model formulated to describe the bus operation in Figure 1(a).

a) *Operational:*
   - Bus size: Buses dispatched in this service are assumed be of the same size.
   - Service process: Buses serve passengers up to their passenger capacities after passengers alight from bus at given stop. If there is no passenger boarding at a stop, buses skip the stop. It should be noted that no time stop is considered here.
   - Capacity of stop: The capacity of the bus stop to accumulate arriving passengers is assumed to be infinite.
   - Time table: To simplify the model, buses are assumed to arrive at stops according to a fixed timetable and early or late arrivals of buses are not allowed.
   - Headway of bus: Bus headways are assumed to be less than 12 minutes to justify the adoption of random arrival of passengers at stops. Evidences from several empirical studies demonstrated that this assumption is reasonable. Jolliffe and Hutchinson (1975) provided a behavioral explanation of the association between bus and passenger arrivals at a bus stop. They presented passenger arrival pattern in three categories: (i) proportion of passengers (q) arrive coincidentally with the bus (see and run to stop), (ii) proportion of passengers (1-q) who arrive at stop at optimal time based on published timetable and experience, and (iii) proportion of passengers (1-q)(1-p) who arrive randomly. Bowman and Turnquist (1981) used the term "unaware" of schedule for the passengers who arrive at stops randomly. Moreover, they reported that 12 to 13 min. headways is transition from random to coordinated passenger arrivals at stops as concluded by Okrent (1971). O'Flaherty and Mangan (1970) also suggested 12 min. in Leeds as the transition. Furthermore, Seddon and Day (1974) showed by empirical research that passengers arrive at stops randomly for headway at less than 10-12 minutes. Fan and Machemehl (2009) identified 11-minute vehicle headway as the transition from random passenger arrivals to non-random arrival.

- Number of alighting passengers: No passenger disembarks from a bus at the first stop, as the bus arrives empty at the first stop. At other stops, except the last one, the number of alighting passengers depends on the arrival occupancy. Passenger alighting probability is assumed to be the same during the period of study. Passenger behavior is assumed to be independent of each other. Thus, the number of alighting passengers at each stop is assumed to follow a binomial distribution as suggested by Andersson and Scalia-Tomba (1981). At the last stop, all on-board passengers alight to ensure the bus is empty.
- Alighting and boarding process: It is assumed that boarding of passengers on a bus starts after the completion of alighting of passengers. A fraction of onboard passengers alight upon arrival at a stop according to the above assumption. Also, a bus picks up all passengers while adhering to a capacity constraint.
- Boarding and alighting times: For simplicity, boarding and alighting times are assumed to be negligible.
- Travel time: Travel time between stops is assumed constant and remains unchanged during the operation period.

b) *Demand :*

- Arrival of passengers: It is assumed that passengers arrive randomly at a stop according to a Poisson process. The number of passengers waiting is a function of passenger arrival rate at a stop and the time interval between two consecutive arrivals of buses. Furthermore, passenger arrival at one stop is independent of arrivals at any other stop. It is assumed that passenger demand does not change over the period of interest.
- Passenger waiting behavior: It is assumed that an alternative mode of transportation is available for "impatient passenger." An impatient passenger is defined as a person reluctant to wait for another bus when he/she is denied entry to the first bus to arrive due to inadequacy in space. Hence, passengers rejected to be served by the next bus are considered lost from the system.

This kind of model can be an approximation for transit operators serving suburbs where the population may have a low tolerance to waiting time. For example, passengers who look for an alternative mode of transportation to be on time at work during rush hour (i.e., 6.00 am to 9.00 am) can be considered impatient passengers. Also, this analysis can be viewed as a particular situation of a large system where there is substantial one-way traffic from suburban areas to the city center. Another scenario where the analysis applies is when passengers wait for a bus on a street just outside their homes (where they have a personal auto immediately available). If the bus has no capacity to accept passengers, then they would travel by their autos.

Notations: The following notations are adopted in the formulations

Table 1: Notations

N	Total number of stops
V	Number of buses provided per hour
n	Index number of stops to be served
λ_n	Passenger arrival rate at stop n
d_n	Alighting proportion of passengers at stop n
H_n	Headway of bus at stop (i.e., Time between two consecutive buses at stop n)
x_n	Number of passengers on bus leaving stop n
p_{jn}	Probability of j number of passengers on a bus leaving stop n
L_{e_n}	Distance between two stops n and $n+1$
C	Bus size in terms of seats and standing passengers allowed
g_{kn}	Probability that k passengers arrive at stop n in the time interval of H_n and given by $\dfrac{e^{-\lambda_n H_n}(\lambda_n H_n)^k}{k!}$

Mathematical Formulation for the First Stop

Important performance measures for a bus transit system can be developed from the probability distribution of space available on buses as they progress along a fixed route. This probability distribution can be obtained by carefully monitoring the four events mentioned in the previous section.

Consider P_n as the probability vector of number of onboard passengers on a bus leaving stop n and p_{in} indicates each element of the vector where value of i ranges from 0 to C. This means the probability vector P_n has $C+$ *1 element*, which can be represented as ($p_{0n}, p_{1n}, p_{2n}\cdots\cdots\cdots p_{Cn}$).

The first stop, the first entry of the probability vector, p_{01}, indicates the probability of no onboard passenger when the bus leaves stop 1. For example, in this particular case of stop 1, when no passenger arrives between the two consecutive buses, there will be no passengers waiting, and therefore no passengers will be onboard after stop 1. Thus, the probability of no passenger arriving at the stop, (or probability of no onboard passenger in the bus departing the first stop) can be derived as $g_{01} = e^{-\lambda_n H_n}\frac{(\lambda_n H_n)^0}{0!} = e^{-\lambda_n H_n}$. Other entries $p_{11}, p_{21}\cdots\cdots\cdots\cdots p_{C\text{-}1,1}$ can be found in a similar way by varying the value of k from 1 to C-1 in the expression $e^{-\lambda_n H_n}\frac{(\lambda_n H_n)^k}{k!}$ respectively. The last entry, p_{C1}, can be found by simply applying total law of probability as $1-\sum_{i=0}^{C-1} e^{-\lambda_1 H_1}\frac{(\lambda_1 H_1)^i}{i!}$ or by summing the probability of passenger arrivals as $\sum_{i=C}^{\infty} e^{-\lambda_1 H_1}\frac{(\lambda_1 H_1)^i}{i!}$, since no passengers alight at the first stop, the probability vector of the number of onboard passengers leaving the first stop p_1 can be found as follows:

$$(1)\quad p_i^1 = \begin{cases} e^{-\lambda_1 H_1} \dfrac{(\lambda_1 H_1)^i}{i!} & for\ 0 \le i < C \\ 1 - \sum_{j=0}^{C-1} e^{-\lambda_1 H_1} \dfrac{(\lambda_1 H_1)^i}{i!} & for\ i = C \end{cases}$$

Since passengers can alight at stops other than the first, the method to find the entries of the probability vector of onboard passengers on the buses at other stops $p_{01}, p_{11}, p_{21}, \ldots\ldots, p_{C1}$ is different from above and is discussed in the next section.

Mathematical Formulation for the Second and Subsequent Stops

When a bus approaches the second stop, the number of available spaces in the bus is reduced by the number of passengers picked up at the first stop. However, the number of available spaces on the bus at the second stop can increase if one (or more) onboard passengers alight at the second stop. Then the waiting passengers at the second stop are allowed to board the bus until the bus is full. Passengers left behind in the event of inadequate capacity are considered lost from the system, as mentioned earlier. Since passenger arrivals at stops and alighting are random, passenger boarding and alighting at a stop can be modeled as a stochastic process. Thus, there are two sets of probability arrays required to describe the algebra related to transit route operation:

i. A probability vector representing the number of onboard passengers at a stop after the alighting process has completed.
ii. A probability vector representing the number of onboard passengers at a stop after the boarding process is completed.

Details of these vectors are described below:

Probability vector representing the number of onboard passengers at a stop after the alighting process has completed upon arrival at the second stop. If there are i passengers on board a bus approaching the second stop, the state of the process is defined as E_i. Here, i could be any value between 0 to C, i.e., there will be a possibility that there are no onboard passengers, only one passenger on board, two passengers on board, three passengers on board, and up to a maximum of C number of passengers on board the approaching bus. If any of the passengers alight at the second stop and there are still some of the j passengers remaining on board, the state E_i will be changed to E_j. In other words, the process makes a transition from state E_i to state E_j. This transition can be represented by a "Transition Probability Matrix," which is described further.

Now, let us consider, A_n is a one-step transition matrix related with alighting of passengers on a bus arriving at stop n and $a_{ij\,n}$ is the cell entry for row i, column j of the matrix A_n. The $a_{ij\,n}$ represents the conditional probability that j passengers will remain on board after *(i-j)* number of passengers alight at stop n. In other words, the conditional probability that j number of passengers will remain on board after alighting at stop n given that the bus approached from stop *(n-1)* to stop n with i onboard passengers. These quantities can be denoted as A_2 and $a_{ij\,2}$ for the second stop. In the event of a bus approaching the second stop empty, i.e., there are no onboard passengers approaching the second stop, probability of alighting zero passengers is one. Thus, the first entries in the first row of matrix A^2, $a_{00\,2}$ is 1 and 0 for other entries in the first row.

If $(i\text{-}j)$ passengers alight at the second stop, i onboard passengers will be reduced from i to j. If the fraction of onboard passengers alighting at the second stop is d_2, then $(d_2)^{i-j}$ is the probability of $(i\text{-}j)$ passengers alighting at the second stop and $(1 - d_2)^{i-(i-j)} = (1 - d_2)^j$ is the probability of not alighting $(i\text{-}j)$ passenger at the stop. According to the principle of binomial distribution, $\binom{i}{i-j}(d_2)^{i-j}(1-d_2)^j$

is the probability of alighting *(i-j)* passengers from i number of onboard passengers at stop 2. Then, for $i \geq j$, the entries for $a_{ij\,2}$ are $\binom{i}{i-j}(d_2)^{i-j}(1-d_2)^j$. Since, a transition from i onboard passengers to some number greater than j is not possible; thus, for $i < j$, the entries for $a_{ij\,2}$ are zero.

Let us consider P_2' is the probability vector of onboard passengers after the alighting process has completed at the second stop, then P_2' can be readily obtained by multiplying P_1 (the probability vector of onboard passenger departing the first stop) by A_1 (transition probability matrix of passenger alighting at the second stop), i.e., $P_2' = P_1 A_1$.

Probability vector representing the number of onboard passengers at a stop after the boarding process is completed: When the alighting process at the second stop is finished, if space is available, the bus is allowed to pick up waiting passengers. If, after the alighting process, there are k passengers remaining on board, the process is said to be in state E_k. Here, k could be any value between zero to C, i.e., there is also a possibility of having onboard passengers anywhere from zero to a maximum of C that remained on board the bus. Additional boarding of passengers transforms the state from E_k to E_l. Therefore, another transition probability matrix is defined whose elements are the conditional probability that (*l-k*) number of waiting passengers at the second stop are allowed to board the bus given that the bus already has k onboard passengers after the alighting process has finished. Now, consider B_n as a one step transition probability matrix associated with waiting passengers boarding at bus at stop n ($n \geq 2$) and $b_{kl\,n}$ as a conditional probability that (*l-k*) new passenger will board the bus given that it has already k passengers on board after the alighting process has finished. This is the cell entry for row k, column l of the matrix B_n.

In general, k passengers on board the bus will go to l, if (*l-k*) new passengers board the bus at the second stop. If λ_2 is the arrival rate of passengers at the second stop, then the probability of arrival of (*l-k*) passengers is $g_{(l-k)2} = e^{-\lambda_2 H_2} \cdot \frac{(\lambda_2 H_2)^{(l-k)}}{(l-k)!}$. Hence, the entries of the matrix B^2 for each bus is given by,

$$
(2) \quad b_{kl2} = \begin{cases} e^{-\lambda_2 H_2} \dfrac{(\lambda_2 H_2)^{(l-k)}}{(l-k)!}, & \text{for } 0 \leq l < C \\ 1 - \displaystyle\sum_{l=0}^{C-1} e^{-\lambda_2 H_2} \dfrac{(\lambda_2 H_2)^{(l-k)}}{(l-k)!} & \text{for } l = C \end{cases}
$$

In addition, for a bus the transition from k onboard passengers to a number lesser than k is clearly impossible. For this reason, $b_{kl\,2} = 0$ *for* $l < k$.

The probability vector of onboard passengers in a bus leaving the second stop (denoted by p_2) can be readily obtained by multiplying p_2 (the probability vector of onboard passengers after completion of passenger alighting at the second stop) and B_2 (the transition probability matrix of passengers boarding at the second stop), i.e., $P_2 = P_2' B_2 = P_1 A_2 B_2$.

Since the system is Markovian, using the Chapman Kolmogorov Equations (Ross 2003), the probability vector for the number of onboard passengers in the bus at any stop n, P_n for $n \geq 1$, can be found as $p_n = p_{n-1} A_n B_n$. In such an approach, the probability statements regarding the onboard passengers leaving a stop can be derived.

PERFORMANCE MEASURES

Once it is possible to calculate the probability vector of onboard passengers leaving a stop, then it is easy to calculate the number of passengers served, number of lost passengers, the load factor, and the unused space on a bus along a route. These performance measures are derived below.

Expected Number of Passengers Served Along a Transit Route

The revenue earned by transit operators mostly comes from the number of passengers. Therefore, the expected number of passengers served along a complete transit route is an important performance measure. To evaluate this measure, the expected number of passengers remaining on a bus at a stop after alighting of others can be found as $\sum_{i=0}^{C} x_{in} p_{in-1} A_n$. x^n is the number of onboard passengers on a bus leaving stop n. It ranges from zero to C. Since passengers are allowed to board the bus after the alighting process has ended and the bus leaves the stop, the expected number of passengers on a bus leaving a stop is $\sum_{i=0}^{C} x_{in} p_{in-1} A_n B_n$. Hence, it is possible to find the expected number of passengers served at a stop from the difference between these two quantities, i.e., expected number of passengers served per bus at stop n,

(3)
$$E(S_n) = \left(\sum_{i=0}^{C} x_{in} p_{in-1} A_n B_n - \sum_{i=0}^{C} x_{in} p_{in-1} A_n \right) = \left(\sum_{i=0}^{C} x_{in} p_{in} - \sum_{i=0}^{C} x_{in} p'_{in} \right)$$

This expression gives the expected number of passenger served at an individual stop. The number of total served passengers (TSP) per bus along a transit route can be calculated by summing the number of passengers served at each individual stop as $\sum_{k=1}^{N} E(S_k)$.

Expected Number of Abandoned Passengers Along a Transit Route

For any given configuration of transit systems, the number of passengers unable to board a bus due to shortage of spaces is another measure of effectiveness. On average, the system will be in equilibrium in that the expected number of passengers arriving for service by each bus at a stop will be the sum of the number of passengers served at a stop and the expected number of passengers turned away from a stop. i.e.,

Expected number of passengers requesting service at a stop = Expected number of passengers served at a stop + Expected number of abandoned passengers at a stop.

(4) Expected number of abandoned passenger per bus at a stop,
$$E(Ab_n) = \lambda_n H_n - E(S_n)$$

This expression provides the expected number of abandoned passengers at an individual stop among the system of N total stops. The number of total abandoned passengers (TAP) per bus along a transit route can be calculated by summing the number of passengers lost at each individual stop as $\sum_{k=1}^{N} E(Ab_k)$.

Number of Total Unused Capacity in Bus Along a Transit Route

When service demand is low compared with the supply, some bus spaces remain unused during the service period, and transit operators can calculate the amount of unused capacity in buses defined as the capacity remaining after the passenger boarding process is finished and buses begin leaving a stop. These unused spaces can be calculated by subtracting the number of passengers onboard from the bus size, i.e.

(5) $E(U_n) = \mathrm{C} - E(S_n)$

In the case of a bus fully congested, no unused spaces are left, i.e, number of unused spaces on bus is zero. The number of total unused capacity (TUC) per bus along the complete route can be found by summing the expected unused spaces in buses at each stop as $\sum_{k=1}^{N-1} E(U_k)$.

Moreover, the variance of these measures can be calculated at each stop as follows:

(i) Variance of served passengers per bus at stop n

(6) $$\mathrm{var}(s_n) = \left(\sum_{i=0}^{C} x_{in}^2 p_{in} - \left(\sum_{i=0}^{C} x_{in} p_{in} \right)^2 - \sum_{i=0}^{C} x_{in}^2 p_{in}^{'} + \left(\sum_{i=0}^{C} x_{in} p_{in}^{'} \right)^2 \right)$$

(ii) Variance of abandoned passengers per bus at a stop:

(7) $$\mathrm{var}(L_n) = \lambda_n H_n - \mathrm{var}(s_n)$$

Work Utilization Coefficient

Another performance indicator namely "Work Utilization Coefficient (WUC)" is adopted from Vuchic (2005) as the output or quantity of offered or utilized service on a transit line expressed as *"transportation work W"*. When all buses of a fleet run on entire lengths of routes, *offered work* W_0, expressed in space-kilometer during one hour is:

(8) $$W_0 = V \times C \times \sum_{m=1}^{N-1} L_{e_m} \; ; \quad (W_0 \; in \; spaces - km/h)$$

Passenger-kilometer traveled along the transit route is called *Utilized work* W_u. The procedure to calculate this value is shown below.

Let us consider a matrix, "passengers-kilometer matrix," denoted by *PK* of dimension (m×n) is constructed, where *m* is the origin stop of a passenger and *n* is destination stop and pk_{mn} is the element of passengers-kilometer matrix indicates the value of passenger-distance travelled from origin stop m to destination stop *n* where *m* =1, 2…..*N* and *n* = 1, 2, 3……*N*. The matrix *PK* can be presented as follows:

(9) $$PK = [pk_{mn}] = \begin{cases} 0 & for \;\; m \geq n \\ E(S_m) d_{m+1} L_{e_m} & for \;\; n = m+1 \; and \; n \neq N \\ E(S_m) d_n (n-m) L_{e_m} \prod_{r=m+1}^{n-1} (1-d_n) & for \;\; m+1 < n < N \end{cases}$$

Formulation of each element of the matrix *PK* is explained here. In general, no passengers alight at the same stop they board the bus. This formulation neglects those passengers who board in error and cannot get down at the same stop. Thus, the entries in the main diagonal of the matrix *PK* are zero, i.e, $pk_{mn} = 0$; for $m = n$. Furthermore, since it is obviously impossible that the numerical value of a destination stop n less than the origin stop m, the entries below the main diagonal are zero. i.e, $pk_{mn} = 0$; for $m > n$.

In the event of passengers alighting at a stop immediately after their origin stop, the passenger-distance travelled can be found straightforwardly by multiplying the distance between two stops (L_e) by number of passengers alighting at the stop. Number of passengers alighting can be calculated by multiplying the onboard passenger in a bus leaving the origin stop $E(S_m)$ by the alighting proportion at the destination stop d_n. Thus, for $n= m+1$ and $n \neq N$, the entries of the matrix *PK* are $E(S_m)d_{m+1}L_{e_m}$ for $n= m+1$ and $n \neq N$.

In the case of a passenger alighting at a stop other than that immediately following the origin stop, the entries are $E(S_m)d_n(n-m)L_{e_m}\prod_{r=m+1}^{n-1}(1-d_n)$ for $m + 1 < n < N$. Then, total passenger-kilometers (TPK) can be found by summing all the elements of the PK matrix as follows:

$$(10)\quad TPK = \sum_{m=1}^{N}\sum_{n}^{N} pk_{mn} = \sum_{m=1}^{N-1} E(S_m)d_m + L_{e_m} + \sum_{m=1}^{N-1}\sum_{n=m+2}^{N} E(S_m)d_n(n-m)L_{e_m}\prod_{r=m+1}^{n-1}(1-d_n)$$

Now, WUC can be defined as the ratio of *utilized work* to the *offered work* as per Vuchic (2005) as:

$$(11)\quad WUC = \frac{W_u}{W_o} = \frac{TPK}{V \times C \times \sum_{m=1}^{N-1} L_m} \qquad (WUC\ in\ passenger-km/sp-km)$$

Ratio of Lost Work to Demanded Work (Lw/Dw)

A performance measure, the "Ratio of Lost work to Demanded work (L_w/D_w)" (Islam et al. 2014), is used to investigate the effect of bus size and frequency of service on the performance of a transit system. Here, "Demanded Work (D_w)" is defined as passenger-km that is demanded by passengers to travel along a route based on their origin and destination. However, some passengers may leave the system in case of space unavailability on the bus without further waiting. The passenger-km anticipated by abandoned passengers is termed as "Lost Work (L_w)." Thus, the ratio of lost work to demanded work (L_w/D_w) reflects the amount of lost transportation work in relation to demanded transportation work that awaits for service in the system. Mathematically, the demanded work can be found by replacing $E(S_m)$ by $E(\lambda_m H_m)$ (i.e., number of arrivals at stop m between two consecutive buses) in Equation 12 as follows:

$$(12)\quad D_w = \sum_{m=1}^{N-1} E(\lambda_m H_m)d_{m+1}L_{e_m} + \sum_{m=1}^{N-1}\sum_{n=m+2}^{N} E(\lambda_m H_m)d_n(n-m)L_{e_m}\prod_{r=m+1}^{n-1}(1-d_n)$$

Similarly, the lost work (L_w) can be found by replacing $E(S_m)$ by $E(\lambda_m H_m)$ (i.e., number of abandoned passengers at stop m per bus) in Equation 13 as follows:

$$(13)\quad L_w = \sum_{m=1}^{N-1} E(Ab_m)d_{m+1}L_{e_m} + \sum_{m=1}^{N-1}\sum_{n=m+2}^{N} E(Ab_m)d_n(n-m)L_{e_m}\prod_{r=m+1}^{n-1}(1-d_n)$$

The term "Ratio of Lost work to Demanded work (L_w/D_w)" is used here to investigate the adequacy of supplied capacity in response to demand for service, whereas the term "Work Utilization Coefficient (WUC)" indicates utilization of supplied capacity to the system. Analytically, the higher the value of the ratio L_w/D_w reflects the higher amount of lost transportation work and vice versa. For the hypothetical bus route presented in the fifth section, the values of WUC and L_w/D_w for different sizes of buses against service frequency is shown in Figure 4.

NUMERICAL EXAMPLES

The way in which a transit system designer can use the developed model is illustrated here by a series of examples. The impacts of simple policy decisions are also described. A numerical example is presented using the same demand data from Hickman (2001). Suppose an operator wants to examine the role of bus size and number of buses on a route with 10 stops, where each stop has infinite waiting room and stops are equally spaced. It is assumed that passengers arrive at all stops following the Poisson distribution with mean arrival rate specified in column 2 of Table 2. Table 2 also shows the proportion of passengers who alight at stops. Since empty buses start their journeys from the first stop, no passengers alight there. However, passengers alight at the second through the ninth stop, if these are their destinations and all remaining passengers alight upon the arrival of a bus at the tenth stop. To investigate the role of bus sizes on transit system performance,s bus capacity is increased in a stepwise manner from 20-passenger bus to 60-passenger bus. In addition, the bus headways are assumed to be less than 12 minutes as mentioned earlier. In this analysis, bus capacity includes standing passenger spaces and available number of seats. With such a fixed configuration, a transit designer will be confronted with two basic problems, determining bus size and fleet size.

Table 2: Parameters of Example Bus Route (Hickman 2001)

Stop	Arrival Rate (passenger/minutes)	Alighting Proportion
1	0.75	0
2	1.5	0
3	0.75	0.1
4	3	0.25
5	1.5	0.25
6	1	0.5
7	0.75	0.5
9	0	0.75
10	0	1

Numerical analysis of performance measures of the transit system with respect to passengers served by the system and those abandoned due to unavailability of space on buses as a function of different service frequencies are shown in Figures 2 and 3.

Based on the figures, it is observed that the number of passengers served by the system increases as the bus size and frequency increases. This also implies that as the bus size and frequency increase, the number of abandoned passengers decreases. However, unused capacity increases with an increase in bus size and frequency. This suggests that when a transit agency runs large buses, the number of passengers that can be accommodated on the bus increases for a given service demand, and cuts down the number of abandoned passengers.

Figure 2: Passengers Served Per Hour by Different Sizes of Buses Against Service Frequency

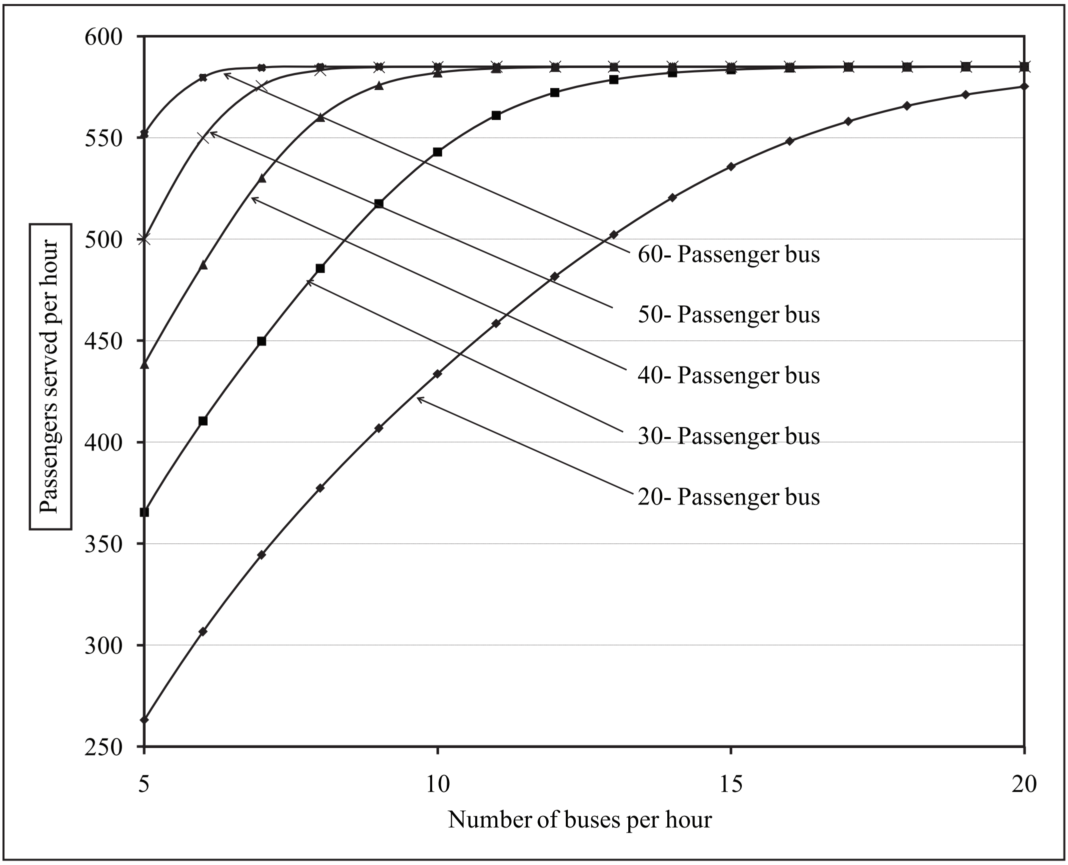


Figure 3: Abandoned Passengers per Hour by Different Sizes of Buses Against Service Frequency

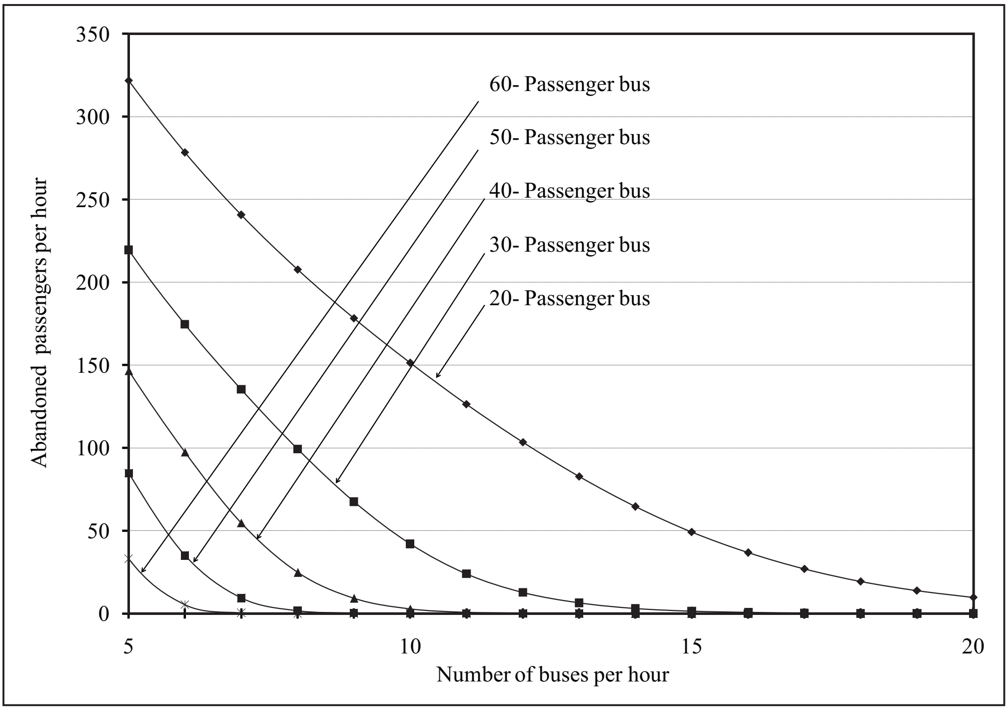


Figure 4 (a): Work Utilization Coefficient for Different Sizes of Buses Against Service Frequency

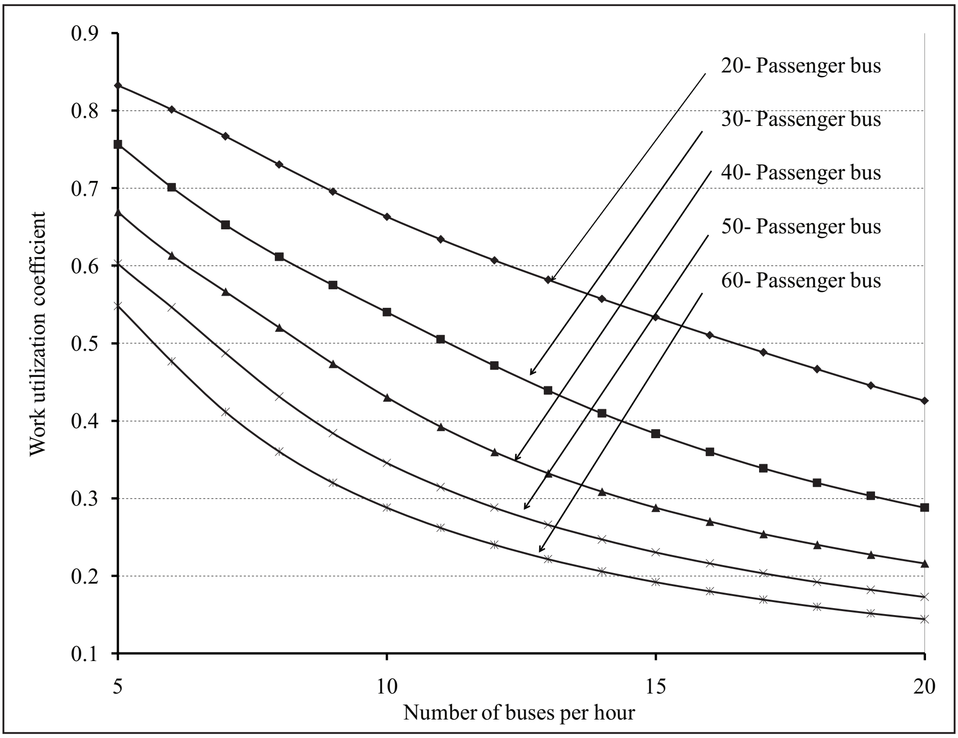
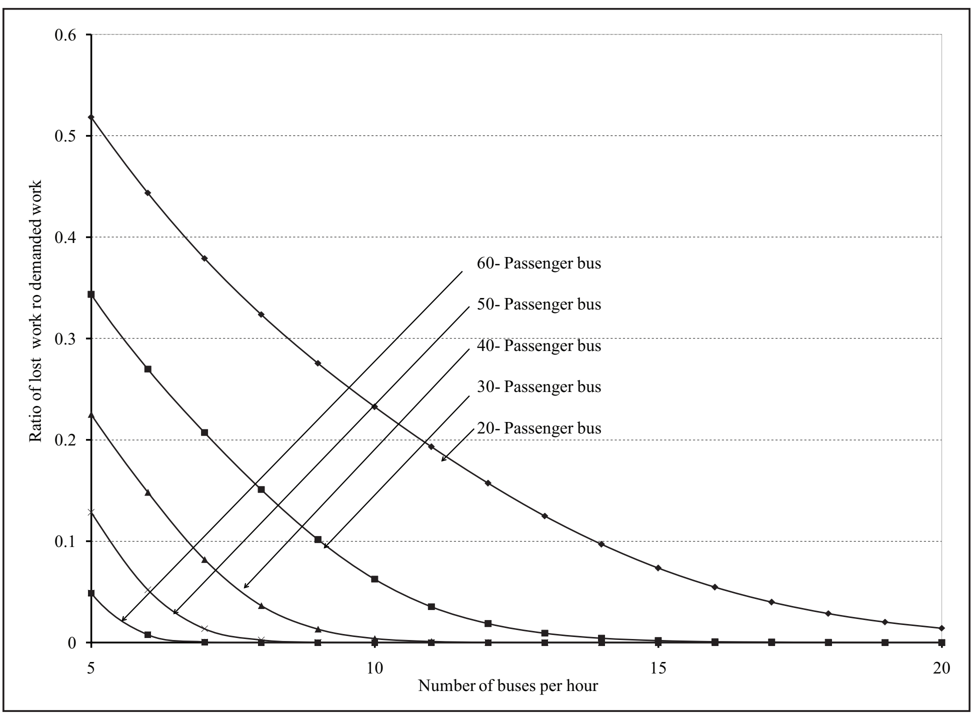


Figure 4 (b): Ratio of Lost Work to Demanded Work for Different Sizes of Buses Against Service Frequencies



The utilization of system capacity is shown in Figure 4 (a) and (b) using the WUC and the ratio of lost work to demanded work (L_w/D_w), respectively. It is observed that both WUC and L_w/D_w decrease with increases in bus size and frequency. A decrease in L_w/D_w indicates that the amount of lost work will be reduced if large sizes of buses with higher frequency are supplied [Figure 4 (b)]. However, in such cases, WUC will be reduced [Figure 4 (a)] indicating lower utilization of systems, which is not desirable to transit operators. Thus, the problem of the transit system designer is to select the appropriate total system capacity, which trades off between bus size and frequency.

Figure 5: Comparison of Policy to Examine System Behavior by Providing a Few Larger Buses or Number of Smaller Buses

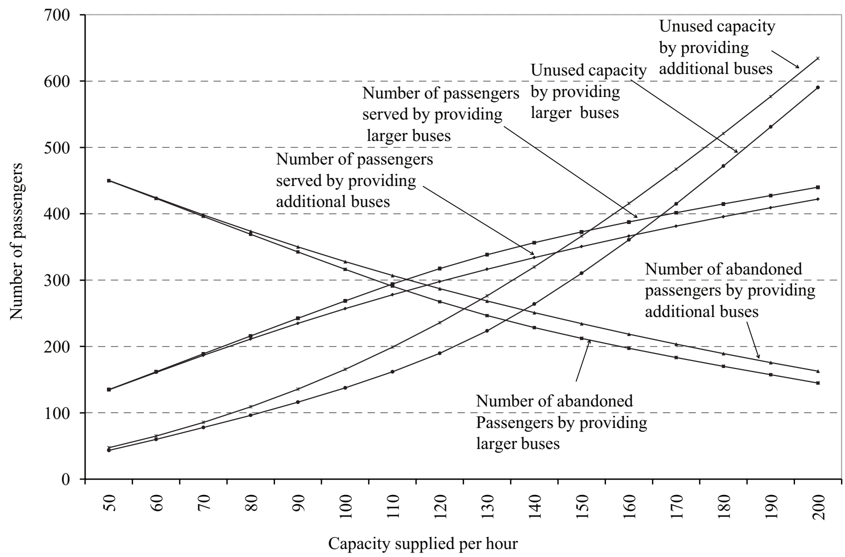


Figure 5 shows the trade-off between providing larger or smaller buses as a function of spaces supplied per hour to the system. If it is assumed that the transport planner has the freedom to use any number of buses of a particular size, then the same level of system capacity can be achieved by providing a small number of large buses at a smaller frequency or a large number of smaller buses with a high frequency. For example, a total system capacity of 100 spaces per hour can be supplied by five 20-passenger buses per hour. The effect of such policy choice is explored graphically using the numerical example in Figure 5. It is observed that there is a smaller number of abandoned passengers as well as lower unused capacity when there are a smaller number of large buses as compared with a larger number of small buses. Therefore, it can be said that under the assumptions made here, the best operating strategy is to select the largest bus size. Moreover, in Figure 5 the intersection points between the curves representing unused capacity and abandoned passengers seem that they should indicate a "best" policy for this application. That is, they identify several "optimal" points with respect to unused capacity and abandoned passengers. Looking at this figure, supplying between 125 and 140 capacity per hour would result in an optimal trade-off between unused capacity and abandoned passengers. Hence, this figure indicates possible strategies for selecting bus sizes based on unused capacity and abandoned passengers. Thus, it can be viewed as a simple application of the proposed models.

Figure 6 (a): Standard Deviation of Passengers Served Per Bus by Different Sizes of Buses Against Service Frequency at Stop 5

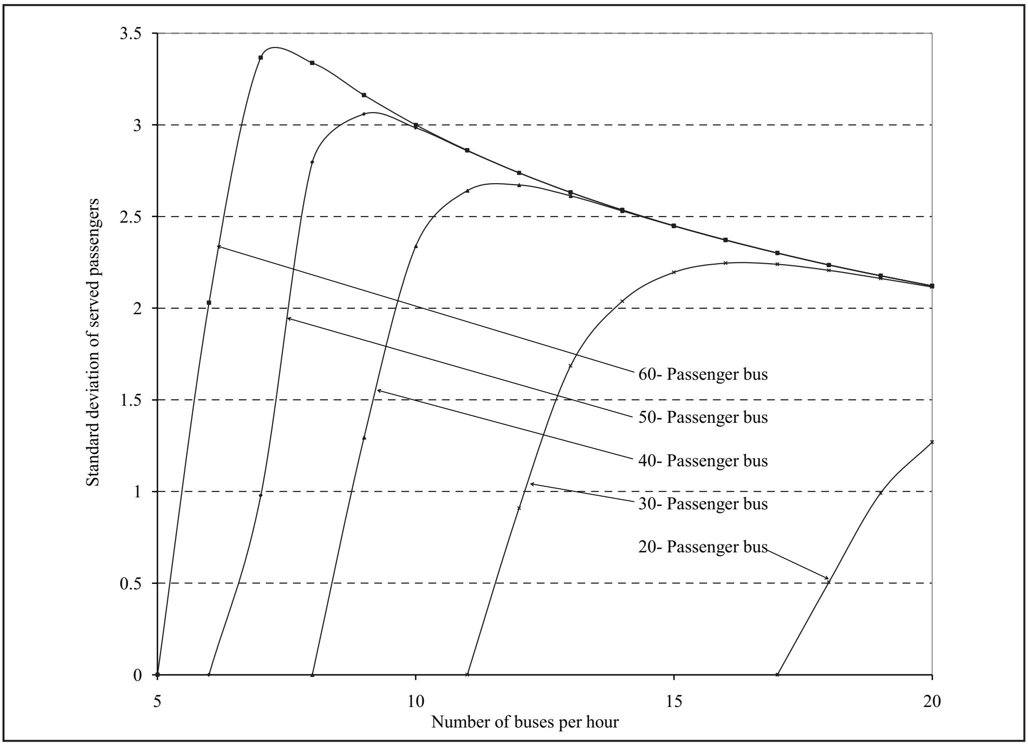
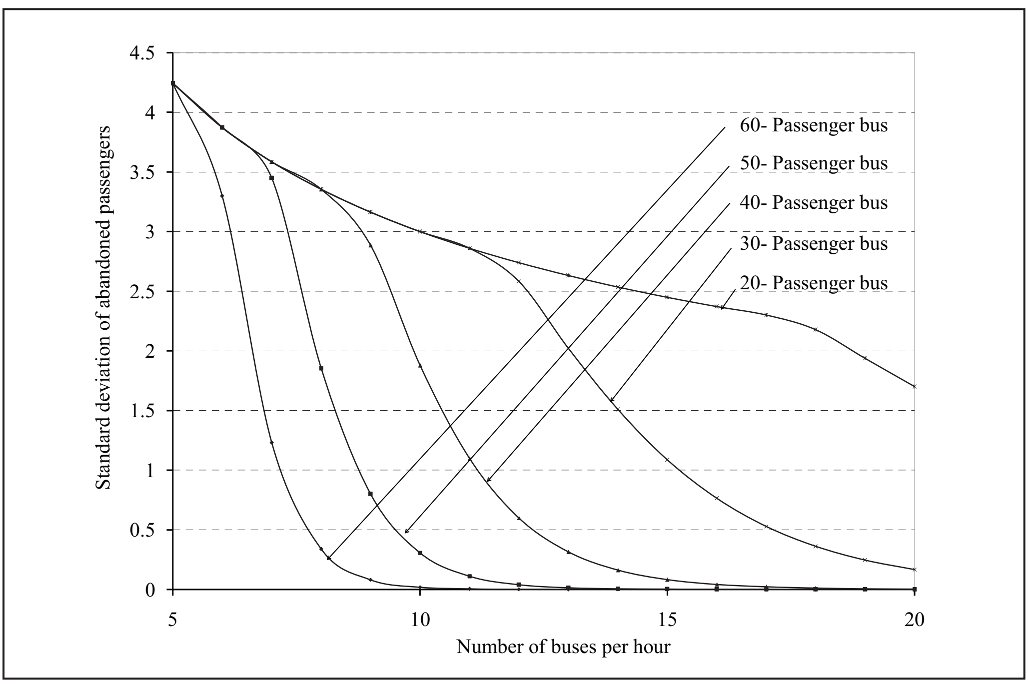


Figure 6 (b): Standard Deviation of Abandoned Passengers per Bus for Different Sizes of Buses Against Service Frequency at Stop 5



In addition to the above performance measures, transit operators are interested in the variance of passengers served, as well as the variance of abandoned passengers as performance indicators. Figure 6 (a) and 6 (b) show the variance of served passengers and variance of abandoned passengers for different sizes of bus and frequency at stop 5, which is the stop with maximum load on the route.

Figure 6 (a) shows that for a 20-passenger bus, the variation of served passengers at this stop is zero for frequencies between five to 17 buses per hour. This indicates that a 20-passenger bus will be full with respect to its carrying capacity, and passengers will be abandoned during the operation for most service times. Similarly, zero variance of served passengers for other bus sizes and frequencies signifies inability to satisfy passenger demand along the route. The figure shows that there is a point for each bus size after which the variance of served passengers decreases with an increase in bus frequency. Figure 6 (b) shows that variance of abandoned passengers decreases with the increase in bus size and frequency. The lower variance of abandoned passengers indicates the high probability of receiving transit service and vice versa.

CONCLUSIONS

In this paper, passenger reneging behavior is modeled in relation to bus sizes and frequencies used in transit operation. Passengers are described as "impatient" when they leave stops without further waiting, once they are unable to board a bus due to capacity constraints. This behavior can be seen as an approximation of a particular situation where substantial one-way suburban commuters look for an alternative mode of transportation at rush hour to be on time at the workplace. Another situation where this analysis applies is the possibility of balking when a passenger waiting for a bus on a street outside his/her home has a vehicle ready to use in case of inability to board the preferred bus. Using the Markov Chain technique, the stochastic elements of the bus transit system and its performance measures are derived. This model is then demonstrated using numerical examples to illustrate the impacts on transit policy. This model can be viewed as a simplified means to evaluate transit system performance under different levels of supply and demand. This simplified model is able to provide practitioners quantitative insights to problems regarding vehicle sizes and frequencies quickly and effectively.

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Traffic Impact Analysis (TIA) and Forecasting Future Traffic Needs: Lessons from Selected North Carolina Case Studies

by Srinivas S. Pulugurtha and Rakesh Mora

The focus of this paper is to conduct an evaluation of selected traffic impact analysis (TIA) case studies, review current practice, and recommend procedures that could be adapted to better forecast and plan future traffic needs. Lessons from the evaluations indicate that considering regional traffic growth rate, peak hour factor (PHF), heavy vehicle percentage, and other off-site developments would yield relatively better TIA forecasts. Incomplete development with vacant parcels was observed at several case sites, possibly due to the state of the economy. Therefore, conducting analysis assuming multiple "build out" years (say, three and five years based on the magnitude of the development) as complete build out years would help state and local transportation agencies plan and better allocate resources based on the need.

INTRODUCTION

Growth in population has led to increased travel demand that rapidly exceeded the designed capabilities of roads, leading to record levels of congestion (USDOT 2015). Long-term projections indicate that population, passenger-miles traveled, and traffic congestion are expected to continue rising (Cambridge Systematics, Inc. 2004). State and local transportation agencies are increasingly motivated to understand the impact of this growth and need to improve methods used in estimating future traffic conditions (CNT 2012).

Past studies primarily focused on the benefits of treatments pertaining to operational and safety performance of roadways near new developments (Levinson et al. 1996; Vargas and Reddy 1996; Parsonson et al. 2000; Bared and Kaisar 2002; Dissanayake and Lu 2003; Eisele and Frawley 2003; Eisele et al. 2004). However, the literature documents no formal evaluation to determine if the improvements and access scenario for new developments provided the traffic operational outcomes that had been forecasted in TIA studies before implementation. The difference in "what was forecasted to happen?" and "what is happening right now?" could be attributed to aspects such as incomplete or delayed development, using default peak hour factor (PHF) - defined as the ratio of peak hour traffic volume divided by four times the peak 15-minute traffic volume (Roess et al. 2004), using the default heavy vehicle percentage, and considering the traffic growth rate that may not be applicable to that area. Also, no research was done to analyze and evaluate the effectiveness of the methods used in TIA studies and suggest procedures to improve accuracy of the forecasts.

Most of the TIA guidelines provided by state and local transportation agencies incorporate adjacent traffic growth. However, inaccurate growth numbers would not yield precise results. Moreover, examining possible causes of traffic problems due to the off-site developments would help better identify appropriate solutions to serve traffic.

Traffic volume, delay, and level-of-service (LOS) are the measures of effectiveness (MOEs) typically considered in TIA studies. Considering other MOEs, such as the number of stops and 50th percentile queue length, would not only provide more insights on operational performance of intersections but also help in identifying suitable and appropriate solutions to improve traffic performance (e.g., use reduced signal cycle length or increase the number of left-turn lanes if queue length for left-turn traffic of an approach is very high). These MOEs typically are provided as outputs by Synchro® (Trafficware 2013) traffic simulation software, which is normally used by consultants in TIA forecasts.

Treatments such as traffic signals and additional lanes are used to reduce delays and crash risk at such locations by managing driveways, turning movements, and median openings between the two travel directions. These treatments not only help reduce the number of conflict points on roadways but also ensure a smooth flow of traffic. Though there is an improvement in traffic operation at intersections with such implemented treatments, it could affect the operational performance at adjacent intersections along the corridor. The literature documents no research on examining the effect of TIA recommendations at intersections adjacent to new developments.

The forecasted LOS outcomes from the TIA reports are often the sole basis for driveway (and even rezoning and site plan) approvals. Consequently, decision makers continue to authorize and conduct business on a preliminary study without detailed knowledge concerning the interim or ultimate performance of the development that accessed the road network. This often results in state and local transportation agencies re-engaging themselves in a defensive and re-active posture, investing limited funds to fix operational and safety problems following the opening of a major development (shopping centers, activity centers, power centers, schools, and other traffic generators) or a subsequent phase of a major development. Therefore, there is a need to research and evaluate the effectiveness of operational improvement treatments such as increasing driveway/intersection spacing, limiting median openings, adding new traffic signals, and adding turn lanes that are typically recommended in the TIA study. Lessons and the outcomes will be useful in addressing operational problems not only at new residential and commercial developments but also in retrofitting existing locations based on identified issues.

The objectives of this research paper are: 1) to conduct an evaluation of selected TIA case studies and 2) recommend a procedure (based on lessons learned) that could be adopted to conduct similar review assessments for flagged or random sites in the future so as to improve operational performance. Further, this research aims to find answers to questions such as:

1. What was expected to happen and what is happening now?
2. Which evaluation methods need to be adopted so as to yield better forecasts?
3. How do the TIA recommendations affect operational performance at intersections near and adjacent to the development?
4. What are the most/least effective treatments that would help improve traffic operations at TIA sites?

The answers to the above questions (findings from this research) will help state and local transportation agencies adopt accurate methods and implement treatments that benefit the transportation system users. The outcomes from this research are expected to contribute to significant business improvements and yield improved knowledge and practices with regard to what works, what does not work, and what departments of transportation (DOTs) or local transportation agencies can do to improve operational performance of roadways.

LITERATURE REVIEW

A TIA study assesses the impact of a proposed development on its street network depending on the characteristics of the development. The study provides recommendations to mitigate the negative impact of the development and also to enhance the performance of the road network surrounding the development. Edwards (Unknown Year) outlined the major benefits of a TIA study. They are listed as follows.

1. Forecast additional traffic and distribution/assignment associated with the new development based on acceptable local practices.
2. Determine the improvements/modifications/restrictions that are necessary to accommodate the new development.

3. Assist communities in land use decision making and in allocating scarce resources to areas that need improvement.
4. Identify potential problems with the proposed development that may influence a developer's decision to pursue it.
5. Reduce the negative impact of a development and ensure that the transportation network can accommodate the development.
6. Provide direction to community decision makers/developers of expected impacts and protect the community investment in the street system.

Not performing a TIA study may lead to failure in estimating the impact of development, which in turn can increase the number of conflicts, delay, and reduce the LOS on the roads. Similar to symptoms of poor access management (Stover and Koepke 2000), increase in crash rates, poor traffic flow, numerous brake light activations by drivers in the through lanes (indicators of delay and stops), increase in congestion, unaesthetic strip development, and neighborhoods disrupted by traffic and pressure to signalize more locations, widen an existing street, or build a bypass are some of the ill-effects observed in absence of an appropriate TIA study.

Analytical methods and operational tools are important to solve traffic engineering problems due to their efficiency in modeling and simulating real-world data and traffic performance. Some of the tools that are used to analyze various traffic facilities and scenarios are TRANSYT-7F™ (Wallace et al. 1984), CORSIM™ (FHWA 1996), Synchro® (Trafficware 2013), and VISSIM (PTV 2014). Bared and Kaisar (2002) used TRANSYT-7F™ and CORSIM™ to determine optimum signal setting and to represent geometric designs with variation in traffic flow at an intersection. Eisele and Frawley (2003) used VISSIM to quantify travel time, speed, and delay along the corridors. Synchro® was used to optimize the signal timings and results were incorporated into VISSIM for evaluation of the model in their study.

Muldoon and Bloomberg (2008) of the Oregon Department of Transportation (ODOT) suggested vital recommendations for the TIA process. The recommendations included more attention to the selection of apt land use code from the Institute of Transportation Engineers (ITE) Trip Generation Manual (ITE 2012), assumptions pertaining to pass-by trips (not produced or attracted to the development), seasonal variation of traffic, evaluation of alternate modes of transportation, traffic growth rates in the concerned area, future/horizon year analysis, and safety analysis. The study did not include any discussion on methods or tools for improved forecasts.

Treatments are typically recommended in TIA studies to accommodate access, improve traffic operations, and minimize the impact of the proposed new development. They include installing traffic signals, median treatments, adding lanes (left, right, and other), and unsignalized access points.

Traffic signals account for most of the delay experienced by motorists on the road network (Levinson et al. 1996). A traffic control signal should not be installed unless an engineering study indicates that installing a traffic control signal will improve the overall safety and/or operation of the intersection (FHWA 2003). Closely spaced signals along a corridor result in increased travel delay, frequent stops, and increased fuel consumption with excessive vehicular emissions.

Median treatments, between both travel directions, are considered as one of the most effective practices, as they play a vital role in controlling operational and safety aspects on roadways. Pedestrian and vehicular safety can be improved through the use of medians. They are generally classified into three types (TRB 2003): undivided median, two-way left-turn lanes (TWLTL), and raised median.

Widening roads is generally expected to improve the operational performance, and hence, often a very common recommendation in the TIA studies. Dunay et al. (2000) observed counter-intuitive results that adding lanes makes traffic worse. Their article documented the suspected paradox that the highways built around New York City in 1939 were generating greater traffic problems than those that existed prior to 1939. Moreover, they mentioned that adding lanes or even double-decking the roadways would have no more than a cosmetic effect on traffic problems.

Unsignalized access points increase the number of conflicts on driveways. These conflict points slow down vehicles and even increase crash rates, especially where left turns must cross two or more lanes of opposing traffic. As stated in AASHTO (2001), driveways are effectively the same as intersections and should be designed consistent with their intended use. The numbers of crashes are disproportionately higher at driveways than at intersections; therefore, their design and location merit special consideration.

Overall, the literature documents articles and reports on TIA recommended treatments and operational/safety effects due to the implementation of these treatments. No research or documented evidence was found on the evaluation of both the effectiveness of TIA reports and operational performance of adopted recommended treatments. Addressing questions such as "what was expected to happen and what is happening now?" and comparing the two will serve as valuable inputs when conducting future TIA studies. In addition, developing and using accurate and proven methods to forecast the effects will help make better decisions and contribute to improved transportation system performance.

RESEARCH METHOD

The research method adopted involves the following four steps:

1. Select TIA case studies
2. Identify measures of effectiveness (MOEs)
3. Collect data
4. Conduct operational evaluation using selected methods
5. Analyze effectiveness of treatments

Select TIA Case Studies

The focus of this step is to identify TIA case studies for evaluation such that they are geographically distributed throughout the state of North Carolina. They also should represent different levels of urbanization (urban and suburban areas) and land use within their vicinity.

Identify Measures of Effectiveness (MOEs)

MOEs pertaining to operational aspects of a roadway (such as stops, queue length, delay, and LOS) are selected and used to conduct analyses of data and evaluate the effectiveness of forecasted methods. The LOS categories are defined as follows (TRB 2010).

Intersection Delay (sec/veh)	LOS
≤10	A
> 10-20	B
> 20-35	C
> 35-55	D
> 55-80	E
> 80	F

Collect Data

Published TIA reports (based on studies conducted prior to the construction of the development) comprising operational data (traffic volume, stops, queue length, delay, and any other appropriate data) "before" construction of the development and forecasted "after" construction of the development were collected for each selected case study. These reports also have details of future traffic conditions with and without the development, and whether the existing system will be able to accommodate the additional traffic generated by the development at the site.

In addition, traffic volume, the number of stops, queue length, and delay along with geometric conditions were collected to represent conditions during the "build" condition (year) at the selected intersections (or locations) near each TIA site. Due to resource limitation, the number of stops, queue length, and delay were only collected for left-turning traffic and through traffic, while traffic volume and geometric conditions were captured for the entire intersection. The exclusion of queue length and delay for right-turning traffic was not expected to have notable effect on the considered MOEs as right-turning vehicles (generally low in number) are allowed to turn right on red at more than 99% of signalized intersections in North Carolina.

The day of the week and durations for data collection were determined based on the duration of data collection used in collected TIA reports. Accordingly, data were collected for one day during the morning peak hours (7 AM - 9 AM) and evening peak hours (4 PM - 6 PM) in this research. Trained observers were used to collect the data in the field. Both manual and video data collection methods were adopted.

Conduct Operational Evaluation Using Selected Methods

The evaluation of operational performance and forecasting methods was conducted using three different methods. Traffic volume, geometric conditions, and MOEs for "no build" condition and forecasted for "build" condition are from TIA reports, while MOEs computed using traffic volume and geometric condition data collected during the study year (2009) for the "build" condition are from this research effort. The PHF, heavy vehicle percentage, traffic growth rate, and current signal timing information specific to the intersections at the site were used to compute MOEs in this research. Default driver and vehicle related characteristics were used for analysis.

Method 1: Study the Operational Performance Before and After the Development at the Site. In this method, the traffic volume and selected MOEs in the TIA reports for the "no build" condition are compared with the same MOEs computed using traffic volume and geometric conditions data collected during 2009 for the "build" condition. These MOEs are computed using Synchro® traffic simulation software. This method helps in studying the effect of the new development with recommended treatments at intersections near and adjacent to the development.

Method 2: Study the Effectiveness of Methods to Forecast the Operational Effects Due to the Development. This method helps in studying the effect of methods used to forecast traffic needs due to a new development. MOEs for the "build" condition forecasted in the TIA reports are compared with the same MOEs for the "build" condition computed using traffic volume and geometric conditions data collected during 2009. These MOEs are computed using Synchro® traffic simulation software.

Method 3: Study the Effectiveness of the Research /Traffic Simulation Software. The selected MOEs, such as the number of stops and delay collected in the field during 2009 for the "build" condition, are compared to the same MOEs computed using Synchro® traffic simulation software (considering traffic volume and geometric conditions data collected during 2009) for the "build" condition. This method identifies the effectiveness of the adopted TIA procedure in replicating the real-world data and operational performance. It also provides insights to obtain better estimates of traffic conditions in the future.

Analyze Effectiveness of Treatments

Analysis was carried out to compare intersection delay under "no build" conditions during 2009 and "build" conditions during 2009. This helps to examine if there was an increase or decrease in intersection delay after the development with the deployed treatments ("build" condition during 2009) when compared with the projected study year "no build" condition.

ANALYSIS & RESULTS

Six TIA case studies in the state of North Carolina were selected for data collection, analysis and evaluation. Table 1 shows information pertaining to location, type, build-out year, percent of development completed as of spring 2010, and level of urbanization of all six TIA sites selected for this research. The first four sites are in the Charlotte region, while the last two sites are in the Raleigh area.

For illustration purpose, WT Harris Boulevard Primax Site is discussed in detail in this paper. MOEs are summarized at intersection level (not by approach and turning movement). Readers are referred to the study conducted for the North Carolina Department of Transportation (NCDOT) for analysis of sites pertaining to all case studies (Pulugurtha and Mora 2010).

Table 1: Selected TIA Case Study Sites and Their Characteristics

Site	Type of Development	TIA Study/Start Build Year	Anticipated Full Build Out Year	% Completed at the time of this Research	Level of Urbanization
WT Harris Boulevard Primax	Commercial	2004	2009	75	Urban
Mountain Island Square	Mixed Land Use	2004	2009	60	Sub-urban
Cato Property	Residential	2004	2010	95	Sub-urban
University Pointe	Commercial	2005	2010	70	Urban
Midway Plantation	Commercial	2005	2007	95	Urban
Retail Development at Youngsville	Commercial	2005	2008	75	Sub-urban

Primax Properties, LLC, proposed a commercial development located on an approximately 549,000 square feet vacant area in the southeast quadrant of E. WT Harris Boulevard (NC 24) / Rocky River Road (SR 2828) intersection in Charlotte. The property was planned to be completed in 2009 ("build out" year). Following are the intersections that are under the area of influence of the site (as indicated in the WT Harris Boulevard Primax site TIA report). The type of intersection control, whether existing or proposed and near or adjacent to the development, are shown in parentheses.

1. E. WT Harris Boulevard (NC 24) / Rocky River Road (SR 2828) (existing; signalized; near)
2. E. WT Harris Boulevard (NC 24) / Grier Road (SR 2976) (existing; signalized; adjacent)
3. Rocky River Road (SR 2828) / Grier Road (SR 2976) (existing; signalized; adjacent)
4. Rocky River Road (SR 2828) / Proposed Access A (unsignalized; proposed; near)
5. E. WT Harris Boulevard (NC 24) / Proposed Access B (unsignalized; proposed directional crossover; near)

The operational performance at intersections 1, 2, and 3 was evaluated using the three different methods. Traffic data were collected from TIA reports and in the field (using manual and video data collection methods) to compute MOEs such as the number of stops, delay, and LOS at these intersections using Synchro® 6.0 traffic simulation software. Table 2 summarizes traffic data by approach and turning movement from TIA reports (both before development and forecasted) and observed in the field (year 2009).

Table 2: Traffic Volume Before, Forecasted, and Observed After Development (WT Harris Boulevard Primax Site, Charlotte, North Carolina)

Approach	Turning Movement	Morning Peak Hour			Evening Peak Hour		
		Before (2004)	Forecasted (2009)	Observed (2009)	Before (2004)	Forecasted (2009)	Observed (2009)
E. WT Harris Blvd / Rocky River Rd*							
Eastbound	L	14	51	53	25	101	77
	T	53	94	82	238	348	72
	R	71	82	11	57	66	22
Westbound	L	102	153	115	23	122	77
	T	143	192	31	44	76	31
	R	619	938	718	105	265	318
Northbound	L	27	91	36	36	102	43
	T	1,710	2,014	1,607	1,253	1,524	1,378
	R	22	28	10	30	44	84
Southbound	L	59	209	102	435	771	726
	T	1,064	1,338	1,047	1,631	1,974	1,623
	R	9	24	41	22	37	52
E. WT Harris Blvd / Grier Rd							
Eastbound	L	34	70	42	43	71	82
	T	65	151	113	339	513	317
	R	196	227	148	289	335	306
Westbound	L	379	638	344	105	248	286
	T	382	554	327	95	173	132
	R	15	17	69	28	32	52
Northbound	L	236	277	213	208	245	205
	T	1,769	2,120	1,651	1,262	1,525	1,411
	R	130	247	220	441	688	486
Southbound	L	25	91	75	25	87	119
	T	1,130	1,339	1,010	1,130	1,807	1,574
	R	39	64	39	39	79	56
Rocky River Rd / Grier Rd							
Eastbound	L	95	276	133	653	1,132	771
	R	1	1	19	15	17	50
Northbound	L	6	7	13	9	10	7
	T	175	369	194	731	1,140	674
Southbound	T	753	1,193	703	175	378	352
	R	821	1,306	850	152	415	364

L, T and R above indicate left-turn, through and right-turn movements, respectively.

* indicates intersection is closest to the development/site

Traffic volume (shown in Table 2) increased considerably (more than the general 3% annual growth of traffic on the roads) at all the three study intersections after the development at the TIA site. Moreover, the forecasted traffic volumes involve very large errors relative to the observed traffic volumes.

Method 1: Study the Operational Performance Before and After the Development

Table 3 shows the total number of stops, intersection delay, and intersection LOS for "no build" condition from TIA reports and computed using traffic volume and geometric conditions data collected during 2009 for the "build" condition.

The number of stops and intersection delay increased from 2004 ("no build" condition) to 2009 ("build" condition) at all the three intersections near the site during the evening peak hours, but only at one intersection near the site during the morning peak hours. The cause can be attributed to site traffic/off-site development growth, changes in signal timing patterns, and, use of PHFs and heavy vehicle percentages from field observations for the "build" condition. The increase in intersection delay could also be due to construction of two new access points near the new development.

Table 3: Delay and LOS Before and After Development (WT Harris Boulevard Primax Site, Charlotte, North Carolina)

Intersection	Morning Peak Hour			Evening Peak Hour		
	# Stops	Delay (sec/veh)	LOS	# Stops	Delay (sec/veh)	LOS
TIA Reports - 2004 (No Build Condition)						
WT Harris Blvd / Rocky River Rd*	1,635	26.6	C	2,593	37.7	D
WT Harris Blvd / Grier Rd	3,696	50.2	D	2,333	32.2	C
Rocky River Rd / Grier Rd	635	12.6	B	1,259	35.6	D
Computed from Field Counts - 2009 (Build Condition)						
WT Harris Blvd / Rocky River Rd*	1,892	34.2	C	3,061	38.9	D
WT Harris Blvd / Grier Rd	3,027	49.9	D	3,888	72.0	E
Rocky River Rd / Grier Rd	554	7.0	A	1,516	40.4	D

* indicates intersection is closest to the development/site

Method 2: Study the Effectiveness of Methods to Forecast the Operational Effects of the Development

The MOEs for the "build" condition forecasted in the TIA reports were compared with the MOEs for the "build" condition using traffic volume and geometric conditions data collected during 2009 and computed using Synchro® traffic simulation software (Table 4). The total number of stops, intersection delay, and intersection LOS are shown in the table. The results were used to evaluate "what was expected to happen and what is happening now?"

The computed delays for the "build" condition from TIA reports during the morning peak hour are slightly lower than the computed delays from field counts for two of the three study intersections. The forecasted delay at the intersection next to the development, E. WT Harris Boulevard/Rocky River Road intersection, during the evening peak hour was higher than the current delay, while the delay at E. WT Harris Boulevard/Grier Road was lower than observed delay. The delay at the Rocky River Road/Grier Road intersection was higher during the morning peak hour and lower during the evening peak hour than the observed delay.

Table 4: Delays and LOS - Forecasted vs. Computed (WT Harris Boulevard Primax Site, Charlotte, North Carolina)

Intersection	Morning Peak Hour			Evening Peak Hour		
	# Stops	Delay (sec/veh)	LOS	# Stops	Delay (sec/veh)	LOS
Forecasted from TIA Reports - 2009 (Build Condition)						
WT Harris Blvd / Rocky River Rd*	3,310	32.3	C	4,571	63.7	E
WT Harris Blvd / Grier Rd	4,683	42.8	D	4,567	50.0	D
Rocky River Rd / Grier Rd	1,296	24.8	C	2,053	26.0	C
Computed from Field Counts - 2009 (Build Condition)						
WT Harris Blvd / Rocky River Rd*	1,890	34.2	C	3,071	38.9	D
WT Harris Blvd / Grier Rd	3,027	49.9	D	3,888	72.0	E
Rocky River Rd / Grier Rd	554	7.0	A	1,516	40.4	D

* indicates intersection is closest to the development/site

The total number of stops from TIA reports (forecasted) are higher than those computed from field counts, at all three study intersections, during both morning and evening peak hours.

The difference in forecasted and computed number of stops, delay, and LOS for the "build" condition could be due to 1) the use of PHFs and heavy vehicle percentages from field observations, and, 2) existing signal timing patterns that are different than those used in the TIA. In addition, the planned completion year of the proposed development is 2009. However, field visits indicate that only 75% of the proposed development was complete by the spring of 2010. Overall, differences in what was expected to happen are observed based on analysis.

Method 3: Study the Effectiveness of Research/Traffic Simulation Software

The number of stops and delay observed directly from the field were compared to those computed from the Synchro® analysis to examine the effectiveness of the research or traffic simulation software in forecasting traffic condition. As stated previously, these data were only collected for left-turning and through traffic. Since the research has incorporated factors that are omitted in the TIA study, results from this method suggest consideration of additional factors to better forecast future needs. The observed average delay and computed average delay are shown in Table 5.

Table 5: Delays and LOS - Observed vs. Computed (WT Harris Boulevard Primax Site, North Carolina)

Intersection	Morning Peak Hour			Evening Peak Hour		
	# Stops	Delay (sec/veh)	LOS	# Stops	Delay (sec/veh)	LOS
Observed in the Field - 2009 (Build Condition)						
WT Harris Blvd / Rocky River Rd*	806	35.0	C	1,344	39.0	D
WT Harris Blvd / Grier Rd	1,588	45.0	D	2,574	44.0	D
Rocky River Rd / Grier Rd	301	7.0	A	1,971	33.0	C
Computed from Field Counts - 2009 (Build Condition)						
WT Harris Blvd / Rocky River Rd*	1,561	34.2	C	2,882	38.9	D
WT Harris Blvd / Grier Rd	2,872	49.9	D	3,426	72.0	E
Rocky River Rd / Grier Rd	301	7.0	A	1,486	40.4	D

* indicates intersection is closest to the development/site.

The observed total number of stops is lower than the computed number of stops for two of the three study intersections. The observed delay at E. WT Harris Boulevard/Rocky River Road intersection are close to the computed delay during the morning and evening peak hours. At E. WT Harris Boulevard/Grier Road intersection and Rocky River/Grier Road intersection, the observed delays are close to the computed delays during the morning peak hour, while the observed delays are lower than the computed delays for two intersections during the evening peak hour. The estimates had an effect on LOS at these two intersections during evening peak hours.

The difference in observed and computed number of stops for two of the study intersections could be attributed to exclusion of right-turning traffic in the field for capturing these MOEs. The relatively high difference between observed and computed delay during evening peak hours for WT Harris Boulevard/Grier Road intersection could be due to unusually high right-turning traffic for one of the approaches or inability of the traffic simulation software to forecast accurately for the observed traffic volume conditions. The difference in delays was observed to be marginal for the other two intersections or durations.

Summary of Results for All TIA Case Study Sites

As shown in Table 1, the “build-out” year varied from 2007 to 2010 for the selected TIA sites. However, the percent of development completed varied from 60% to 95% as of spring 2010.

Table 6 compares the PHF, heavy vehicle percentage, and traffic growth rate for all the sites. These are additional factors considered in this research. Both default values assumed and used by consultants who prepared TIA reports and actual observations from the field are shown in the case of PHFs and heavy vehicle percentages. The computed PHFs based on observed traffic data at the selected intersections of TIA sites varied from 0.87 to 0.97, while consultants used a default value of 0.90. Likewise, heavy vehicle percentages varied from 0% to 5% at the selected intersections of TIA sites, while consultants used a default value of 2%.

In general, traffic volumes forecasted at the selected TIA sites in the TIA reports are observed to be higher than those observed in the field (Table 2). The percent difference is high though the forecasted and observed right-turn traffic volumes differed by a low value. The numbers of stops from the TIA also followed a similar pattern as traffic volume. The difference in results obtained could be attributed to assumed default growth rate (3%), which did not reflect the real-world scenario. In reality, the growth rates varied from -9% to +25% at the selected intersections of TIA sites.

Table 6: Observed PHF, Heavy Vehicle Percentage, and Growth Rate

Site	Intersection	Time period	PHF	Heavy Vehicle (%)	Traffic Growth Rate
WT Harris Boulevard Primax	E. WT Harris Blvd / Rocky River Rd	AM	0.89	2.0	0.0
		PM	0.92	1.2	3.0
	E. WT Harris Blvd / Grier Rd	AM	0.95	3.8	-1.0
		PM	0.96	2.0	5.0
	Rocky River Rd / Grier Rd	AM	0.95	2.0	1.0
		PM	0.92	2.0	5.0
Mountain Island Square	Brookshire Blvd / Mt. Holly Huntersville Rd	AM	0.93	1.0	0.0
		PM	0.93	0.6	14.0
	Mt. Holly Huntersville Rd / Callabridge Ct	AM	0.96	2.0	-6.0
		PM	0.94	0.0	5.0
Cato Property	Tom Short Rd / Ballantyne Commons Pkwy	AM	0.86	3.0	10.0
		PM	0.94	0.0	5.0
	Tom Short Rd / Ardrey Kell Rd	AM	0.97	4.0	17.0
		PM	0.95	1.0	15.0
	Ardrey Kell Rd / Providence Rd	AM	0.96	2.0	11.0
		PM	0.92	1.0	2.0
	Providence Rd / Allison Woods Dr	AM	0.93	1.0	3.0
		PM	0.91	0.5	3.0
University Pointe	North Tryon St (US 29) / McCullough Dr	PM	0.96	1.0	2.0
	North Tryon St (US 29) / The Commons at Chancellor Park Dr	PM	0.96	0.6	N/A
Midway Plantation	Knightdale Blvd (US 64) / Southbound Off Ramp	AM	0.95	5.0	-9.0
		PM	0.94	2.0	-3.0
	Knightdale Blvd (US 64) / Northbound On Ramp	AM	0.89	5.0	-3.0
		PM	0.89	1.0	12.0
	Knightdale Blvd (US 64) / Site Drive #1 (Hinton Oaks Blvd)	AM	0.90	4.0	1.0
		PM	0.94	1.0	12.0
	Knightdale Blvd (US 64) / Site Drive #3 (Wide Waters Pkwy)	AM	0.94	4.0	0.0
		PM	0.87	2.0	25.0
Retail Development at Youngsville	US 1 / NC 96	AM	0.92	2.0	-2.0
		PM	0.92	2.0	0.0
	US 1 / Mosswood Blvd	AM	0.94	2.0	-3.0
		PM	0.91	2.0	-2.0

Note: 0.9, 2% and 3% were assumed as PHF, heavy vehicle % and growth rate in selected TIA studies.

Effectiveness of Treatments

Analysis was conducted to compare delay at intersections near each site before and after the development with the deployed treatments, and to study if there was an increase or decrease in the intersection delay due to deployed treatments. The treatments installed at the six TIA sites included additional right-turn or left-turn lane, additional approach/leg (convert three-legged intersection to four-legged intersection), installation of traffic signal, access points, and un-installation of directional (provision of left turns in one direction only) crossovers. Table 7 summarizes treatments implemented after development, at the time of this research, at each TIA case study site.

Table 7: Summary of Treatments by TIA Case Site

Treatment	WT Harris Primax	Mt. Island Square	Cato Property	University Pointe	Midway Plantation	Retail Development at Youngsville
Additional right turn lane	X			X		
Additional left turn lane	X	X	X	X	X	
Traffic signal Installation		X		X		
Reducing cycle length			X			
Increasing cycle length			X			
Additional approach/leg	X		X	X		X
Access points	X		X		X	
Uninstallation of directional crossover*				X		

* Provision for left-turns in one direction only.

The "no build" condition data were projected to the year 2009 so as to reflect the growth in traffic and for easy comparison. The projections were based on a pre-approved 3% traffic growth rate recommended for use in TIA by NCDOT. The delay based on the projected data was then compared to operational performance based on 2009 field data (Table 8). An increase in delay, in particular, during evening peak hours was observed at most of the study intersections. These trends seem to be similar and consistent irrespective of the type of treatment and development. Also, an increase in delay and decrease in operational performance was observed at adjacent intersections in addition to the intersection near the site. As expected, a decrease in the effect was observed with an increase in distance of an intersection from the development.

Table 8: Change in Intersection Delay for 2009 "No Build" and "Build" Conditions at Intersection Near and Adjacent to TIA Case Site

Site	Intersection	Delay	
		AM	PM
WT Harris Boulevard Primax	E. WT Harris Blvd / Rocky River Rd*	I	I
	E. WT Harris Blvd / Grier Rd	D	I
	Rocky River Rd / Grier Rd	D	I
Mountain Island Square	Brookshire Blvd / Mt. Holly Huntersville Rd	I	I
	Mt. Holly Huntersville Rd / Callabridge Ct*	I	I
Cato Property	Tom Short Rd / Ballantyne Commons Pkwy*	I	I
	Tom Short Rd / Ardrey Kell Rd	I	I
	Ardrey Kell Rd / Providence Rd	I	I
	Providence Rd / Allison Woods Dr		
University Pointe	North Tryon St (US 29) / McCullough Dr		D
	North Tryon St (US 29) / The Commons at Chancellor Park Dr*		I
Midway Plantation	Knightdale Blvd (US 64) / Southbound Off Ramp	D	D
	Knightdale Blvd (US 64) / Northbound On Ramp	I	I
	Knightdale Blvd (US 64) / Site Drive #1 (Hinton Oaks Blvd)	I	I
	Knightdale Blvd (US 64) / Site Drive #3 (Wide Waters Pkwy)*	I	I
Retail Development at Youngsville	US 1 / NC 96*	I	I
	US 1 / Mosswood Blvd	D	I

Note: "I" indicates an increase and "D" indicates decrease in intersection delay.
* indicates intersection is closest to the development/site.

CONCLUSIONS

Traffic volume and MOEs such as the number of stops and delay at intersections near the development generally increased after the development was built. This can be attributed to general growth of traffic and traffic generated by the new development. It was also observed that other off-site developments aggravated traffic problems at some intersections. Traffic generated by these off-site developments was either under-estimated or not considered in the TIA. The MOEs were generally over-estimated when conducting TIA. The computed ratios tend to be very high for lower values (say, low right-turn traffic volume along an approach) than when compared to those with higher values.

Field observations at the study intersections yielded very different PHFs and heavy vehicle percentages than default values. While using default PHF and heavy vehicle percentage values (0.9% and 2%, respectively) would yield conservative forecasts if PHF is greater than 0.9 and heavy vehicle percentage is less than 2%, it may not be appropriate or suitable when PHF is lower than 0.9 or heavy vehicle percentage is greater than 2%. Therefore, where appropriate, lower PHFs or higher heavy vehicle percentages than default values are recommended for use.

The cycle lengths and signal phasing/timing parameters used in TIA are different from what was observed in the field under current conditions. This had an effect on "what was forecasted to happen?" and "what is happening right now?" It is therefore recommended that suggested TIA guidelines be considered while designing signal timing and phasing for TIA (in addition to analysis based on existing signal phasing and timing data). This would also assist in easy comparison and effective evaluation of treatments after the deployment.

A pre-approved default growth rate of 3% was used in projecting future traffic in most of the TIA reviewed as a part of this research. The growth rate may vary based on changes to land use characteristics, off-site developments, and the type of facility. Therefore, considering traffic growth rate within the vicinity of the site will yield better estimates.

In most of the TIA reports, traffic conditions were forecasted using three years as the time frame for completion of construction. Several proposed developments and improvements were not complete (vacant parcels and incomplete implementation of transportation projects possibly due to the state of the economy) at the time of this research (though the complete build out year was 2009 for most case sites were considered). The percent of development completed at the selected study sites varied from 60% to 95%. It would help if consultants carry out analysis with multiple build-out years (say, three and five years based on the magnitude of the development) and present analysis for the same. For instance, a development was scheduled for full build out in three years. If the construction was delayed due to unforeseen conditions (such as a fall in the economy), it would allow the decision makers to plan and implement treatments based on the status of construction ("build" condition).

As stated before, incomplete development was observed during 2009 at several case sites. However, the observed MOEs are higher in value than the forecasted MOEs even with partial development at most of the sites considered in this research. Collecting and analyzing data under "ground-zero" conditions prior to start of construction of the development in addition to collection and analysis of data at regular intervals (say, every year) throughout the construction of the development would help better understand the operational effects of new developments. On the other hand, since uncertainty may prevail during the project construction, it would better help the decision makers if a range of MOE forecasts is available from the TIA study depicting the best/worst case scenarios. This would also help identify, plan, and deploy treatments at suitable times over the project duration in the future.

TIA studies do not generally include safety evaluation of the site. Including safety evaluation would help better understand the effect of the development and treatments on crashes at intersections near the site. Further, data collected for one day are normally used in TIA. Collecting and using data for multiple days would eliminate the variability that can lead to any biased results. Using average day data observed from multiple days or average results from analysis done for multiple days would yield more realistic outputs.

Overall, it can be concluded that ignoring the PHFs, heavy vehicle percentages, local growth rates, and off-site developments would not yield the best results. Some results obtained (example, decrease in traffic volume) in this research may seem counter-intuitive in nature. However, lessons learned from this research serve as valuable inputs to DOTs in making decisions or adopting policies that would lead to use of better methods for forecasting the impacts of new developments.

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Disclaimer

The contents of this paper reflect the views of the authors and not necessarily the views of the University. The authors are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of either the North Carolina Department of Transportation or the Federal Highway Administration at the time of publication. This report does not constitute a standard, specification, or regulation.

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Intrarailroad and Intermodal Competition Impacts on Railroad Wheat Rates

by Michael W. Babcock and Bebonchu Atems

The issue addressed in this paper is more fully understanding the relationship of intrarailroad competition and rail rates for wheat in the largest wheat producing states, which are Idaho, Kansas, Minnesota, Montana, North Dakota, Oklahoma, South Dakota, Texas, and Washington. The overall objective of the study is to investigate railroad pricing behavior for wheat shipments. The rate model was estimated with OLS in double-log specification utilizing the 2012 STB Confidential Waybill sample and other data.

The research found that the distance from origin to destination and the total shipment weight had the expected negative relationships with railroad wheat rates and were statistically significant. The distance from origin to the nearest barge loading location had the expected positive relationship to railroad wheat rates and was also significant. The weight of each covered hopper car and the Herfindahl-Hirschman Index were both non-significant. However, the study used other data to determine that intrarailroad competition for wheat shipments within states appears to be present in most states.

INTRODUCTION

Railroads were the most heavily regulated transportation mode prior to passage of the Staggers Rail Act in 1980. Deregulation gave the railroads price flexibility that was previously unavailable. Prices between variable cost and 180% of variable cost were not subject to regulatory review. The Staggers Act set time limits for ICC decisions regarding abandonments and mergers. Thus, Class I railroads were able to quickly abandon or sell unprofitable branch lines. Mergers reduced the number of Class I railroads from 40 in 1980 to seven today.

Generally, deregulation has benefited both the railroads and the shippers. For the railroad industry, the average rate of return on investment increased from less than 3% in the 1970s to 4.4% for the 1980s, 7.64% in the 1990s, and 8.21% in the 2000s (Association of American Railroads [AAR], various years). For the 2010 to 2013 period, the rate of return on investment averaged 12.09% (AAR 2014). The average railroad rate of return on shareholders' equity rose from 2.44% in the 1970s to 7.37% in the 1980s, 9.51% in the 1990s, and 9.38% in the 2000s (AAR, various years). For the 2010-2013 period, the rate of return on shareholders' equity averaged 13.94% (AAR 2014).

Gallamore (1999) analyzed the relationship between deregulation and innovation in the rail industry. Using a before-and-after analysis, he pointed out that railroads stagnated under the final decades of ICC regulation but have significantly recovered as indicated above by the improved financial performance after 1980.

According to Grimm and Winston (2000), the net annual benefits to shippers were more than $12 billion (in 1999 dollars) in the first decade following passage of the Staggers Act. Shippers have benefited from 20 years of declining rail rates (inflation adjusted revenue per ton-mile) as well as the preservation of rural area branch lines sold or leased to short line railroads (Prater 2010).

Railroads are important for transporting agricultural commodities to domestic processing locations and export ports. These shipments involve large scale movements of low value, bulk commodities over long distances. Compared with other major grains (and soybeans), railroads are a particularly valuable mode for transporting wheat, moving 51% of all wheat shipments in 2013

(Sparger and Marathon 2015). According to Prater (2010), nine of the top 10 wheat producing states are more than 150 miles from barge transportation on the Mississippi River, which provides the most significant intermodal competition to railroads for long distance shipments of grain to export ports. Wheat shippers in the Great Plains states do not have a cost effective transportation alternative to railroads since barge loading locations are not directly accessible, and trucks are not competitive for hauling shipments over long distances. Therefore, intramodal competition for wheat shipments is expected to be a significant factor in rail rates. Table 1 contains Class I railroad route mileage for the nine major wheat producing states in 2013.

The data in Table 1 indicate the railroad mileage of some states is dominated by a single Class I railroad. For example, 88.1% of the rail miles in Idaho are UP miles. The BNSF has 94.1% of the Montana rail miles, 78.1% of the North Dakota miles, and 75.4% of the Washington miles. These states all have regional and local railroads that act as bridge carriers for the Class I railroads and, as such, they provide little direct intrarailroad competition. However, depending on the state railroad network, non-Class I railroads may contribute to intrarailroad competition.

Unlike Idaho, Montana, North Dakota, and other states are characterized by a Class I duopoly of roughly equal size firms. For example, in Kansas the BNSF has 44.3% of the Class I rail miles and the UP has 55%. In Minnesota the BNSF has 36.4% and the CP (Canadian Pacific) has 38.9% of the state's rail miles. In Oklahoma the BNSF and UP have 43.9% and 49.7% of the Class I rail miles, respectively. The BNSF and UP have respective shares of 40.5% and 52% of Texas Class I miles. This group of states would be expected to have lower rail wheat rates than the previous group due to greater intrarailroad competition. The degree of intrarailroad competition varies among states as should the level of railroad wheat prices. Potentially, intrarailroad competition could vary within states as well.

The overall objective of this research is to investigate 2012 railroad pricing behavior for the shipment of wheat. Specific objectives include: (1) measure the impact on railroad wheat rates of the intensity of intramodal competition, (2) develop a model to measure the impact of railroad costs, intramodal competition, and intermodal competition on rail wheat rates in the nine major wheat production states, (3) identify and measure the major cost determinates of railroad wheat rates, and (4) examine the hypothesis that railroad intramodal competition varies within a state with implications for intrastate variation in railroad wheat rates.

WHEAT PRODUCING STATE RAIL SYSTEMS

Tables 2-10 contain the railroad route mileage of nine states by class of railroad. Idaho has two Class I railroads, but the UP has 88.1% of the Class I miles. Idaho also has 10 Class III railroads, which collectively account for 714 miles for 41.7% of total Idaho rail miles.[1] However, Idaho has no CRDs (Crop Reporting Districts) for wheat that are served by at least two Class I railroads.

Table 3 contains Kansas rail mileage, with BNSF and UP accounting for the great majority of Class I miles. Kansas has 11 Class II and III railroads, which as a group account for 40.5% of Kansas railroad mileage.

Table 4 indicates that Minnesota has more Class I rail mileage than non-Class I. CP and BNSF are the dominant Class I railroads, but UP and CN (Canadian National) have significant track mileage as well. Minnesota has 10 Class II and III railroads, which account for only 17% of the total Minnesota rail system.

As indicated by the data in Table 5, the BNSF is the dominant railroad in Montana, accounting for 63.2% of the Montana rail network. Montana has two Class II and three Class III railroads that as a group account for 36.8% of total Montana rail miles.

Table 1: Class I Railroad Mileage by State, 2013

State	BNSF	% of Total	UP	% of Total	KCS	% of Total	CN	% of Total	CP	% of Total	Total
Idaho	118	11.9%	877	88.1%	-	-	-	-	-	-	995
Kansas	1,237	44.3	1,535	55.0	18	0.6	-	-	-	-	2,790
Minnesota	1,686	36.4	665	14.4	-	-	479	10.3	1,804	38.9	4,634
Montana	2,003	94.1	125	5.9	-	-	-	-	-	-	2,128
North Dakota	1,714	78.1	-	-	-	-	-	-	482	21.9	2,196
Oklahoma	1,037	43.9	1,173	49.7	150	6.4	-	-	-	-	2,360
South Dakota	889	59.8	-	-	-	-	-	-	598	40.2	1,487
Texas	4,929	40.5	6,336	52.0	908	7.5	-	-	-	-	12,173
Washington	1,633	75.4	532	24.6	-	-	-	-	-	-	2,165
Total	15,246	49.3	11,243	36.4	1,076	3.5	479	1.5	2,884	9.3	30,928

Source: State Department of Transportation

BNSF – Burlington Northern Santa Fe; UP – Union Pacific; KCS – Kansas City Southern; CN – Canadian National; CP – Canadian Pacific

Table 6 reveals that BNSF is the dominant Class I railroad in North Dakota, but CP has about 500 miles as well. North Dakota has two Class II and two Class III railroads that collectively constitutes 35.4% of the North Dakota rail system.

Table 7 indicates that Oklahoma has two Class I railroads (BNSF and UP) of roughly equal size. Oklahoma has more (18) Class III railroads than any of the other eight states (except Washington, which also has 18) and account for 35.1% of the Oklahoma railroad network.

Table 8 reveals that South Dakota has two Class I railroads, with BNSF accounting for about 60% of the Class I miles and UP the other 40% of the South Dakota rail system. South Dakota has seven Class III railroads, which account for 19.5% of the South Dakota railroad network.

Texas has significantly more rail miles than any of the other eight states (Table 9). UP has 52% of the Class I rail miles, followed by BNSF (40.5%) and KCS (7.5%). Texas has two Class II railroads and eight Class III railroads that together accounty for 12.8% of the Texas railroad system.

Table 10 displays Washington rail miles, which indicate that the BNSF is the dominant Class I railroad in Washington with 75% of the rail miles; UP accounting for the remaining 25%. Washington has 18 Class III railroads, accounting for 35.9% of the Washington railroad network.

Table 2: Idaho Railroad Mileage by Class of Railroad, 2013

Class I	**Miles**
Burlington Northern Santa Fe (BNSF)	118
Union Pacific (UP)	877
Subtotal	995
Local Railroads (Class III)	
Montana Rail Link	33.5
Bountiful Grain and Craig Mountain	126.6
St Maries River	72.3
Boise Valley	42.1
Eastern Idaho	264.5
Great Northwest	4.3
Idaho Northern Pacific	101.3
Pend Oreille Valley	25.7
Washington and Idaho	19.1
U.G. Government	24.3
Subtotal	714
Grand Total	1709

Source: *2013 Idaho Statewide Rail Plan*. Idaho Department of Transportation.

Table 3: Kansas Railroad Mileage by Class of Railroad, 2013

Class I	**Miles**
Burlington Northern Santa Fe (BNSF)	1,237
Union Pacific (UP)	1,535
Kansas City Southern (KCS)	18
Subtotal	2,790
Regional Railroads (Class II)	
Kansas and Oklahoma Railroad	753
Local Railroads (Class III)	
South Kansas and Oklahoma Railroad	305
KYLE Railroad	417
Cimarron Valley Railroad	183
Nebraska, Kansas, and Colorado Railroad	122
Garden City Western Railroad	45
V&S Railway	25
Blackwell Northern Gateway Railroad	18
Blue Rapids Railroad	10
Boothill and Western Railroad	10
Missouri and Northern Arkansas Railroad	8
Subtotal	1,143
Grand Total	4,686

Source: *2011 Kansas Statewide Rail Plan*. Kansas Department of Transportation, pp. 40 and 52.

Table 4: Minnesota Railroad Mileage by Class of Railroad, 2013

Class I	**Miles**
Burlington Northern Santa Fe (BNSF)	1,686
Union Pacific (UP)	665
Canadian National (CN)	479
Canadian Pacific (CP)	1804
Subtotal	4,634
Regional & Local Railroads (Class II & Class III)	
Minnesota Northern Railroad	257
Twin Cities and Western Railroad	234
Progressive Rail Inc.	97
Minnesota Prairie Line	94
Otter Tail Valley Railroad	72
St Croix Valley Railroad	66
Northern Plains Railroad	51
Minnesota Southern Railroad	42
Red River Valley and Western	32
Minnesota, Dakota and Western	6
Subtotal	951
Grand Total	5,585

Source: *2014 Minnesota Statewide Rail Plan,* Minnesota Department of Transportation, 2014.

Table 5: Montana Railroad Mileage by Class of Railroad, 2013

Class I	**Miles**
Burlington Northern Santa Fe (BNSF)	1,939
Union Pacific (UP)	125
Subtotal	2,064
Regional Railroads (Class II)	
Montana Rail Link	475
Dakota, Missouri Valley and Western	540
Subtotal	1,015
Local Railroads (Class III)	
Central Montana Rail Line	84
Mission Mountain Railroad	42
Butte, Anaconda and Pacific Railroad	63
Subtotal	189
Grand Total	3,268

Source: Montana State Department of Transportation, 2014.

Table 6: North Dakota Railroad Mileage by Class of Railroad, 2013

Class I	**Miles**
Burlington Northern Santa Fe (BNSF)	1,700
Canadian Pacific (CP)	484
Subtotal	2,184
Regional Railroads (Class II)	
Dakota, Missouri Valley and Western Railroad	424
Red River Valley and Western Railroad	427
Subtotal	851
Local Railroads (Class III)	
Northern Plains Railroad	297
Dakota Northern Railroad	48
Subtotal	345
Grand Total	3,380

Source: North Dakota Public Service Commission, *2013 Annual Report*.

Table 7: Oklahoma Railroad Mileage by Class of Railroad, 2013

Class I	**Miles**
Burlington Northern Santa Fe (BNSF)	1,037
Union Pacific (UP)	1,173
Kansas City Southern (KCS)	150
Subtotal	2,360
Local Railroads (Class III)	
South Kansas and Oklahoma Railroad	275
Grainbelt Corportation	176
Kiamichi Corportation	158
Arkansas-Oklahoma Railroad	118
Farmrail Corporation	161
Wichita, Tillman and Jackson Railroad	85
South Kansas and Oklahoma Railroad	67
Arkansas, Todd and Ladd Railroad	47
Texas, Oklahoma, and Eastern	41
Blackwell Northern Gateway Railroad	18
Cimarron Valley Railroad	35
Tulsa-Supulpa Union Railroad	23
Sand Springs Railroad	20
Tulsa Port of Catoosa	16
Western Farmers Electric Coop Railway	14
Public Service of Oklahoma Railroad	10
Northwestern Oklahoma Railroad	5
Port of Muscoge Railroad	5
Subtotal	1,274
Grand Total	3,634

Source: *Oklahoma Statewide Freight and Passenger Rail Plan*, Oklahoma Department of Transportation, 2014.

Table 8: South Dakota Railroad Mileage by Class of Railroad, 2013

Class I	**Miles**
Burlington Northern Santa Fe (BNSF)	889
Canadian Pacific (CP)	598
Subtotal	1,487
Local Railroads (Class III)	
D&I Railroad	54.2
Dakota, Missouri Valley, Western Railroad	56.4
Dakota Southern Railroad	168.5
Sisseton Milbank Railroad	37.1
Sunflour Railroad	19.4
Ellis and Eastern Railroad	14.3
Twin Cities and Western Railroad	10.7
Subtotal	361
Grand Total	1,848

Source: *2014 South Dakota Statewide Railroad Plan,* South Dakota Department of Transportation.

Table 9: Texas Railroad Mileage by Class of Railroad, 2013

Class I	**Miles**
Burlington Northern Santa Fe (BNSF)	4,929
Union Pacific (UP)	6,336
Kansas City Southern (KCS)	908
Subtotal	12,173
Regional Railroads (Class II)	
Texas Northeastern Railroad	665
Texas Pacifico Transportation	391
Subtotal	1,056
Local Railroads (Class III)	
Fort Worth and Western Railroad	276
West Texas and Lubbock Railroad	107
Texas Northeastern Railroad	104
Blacklands Railroad	66
Farmrail Corp. Railroad	59
Brownsville and Rio Grande Railroad	42
Kiamichi Railroad	40
Georgetown Railroad	30
Subtotal	724
Grand Total	13,953

Source: Texas Department of Transportation.

Table 10: Washington Railroad Mileage by Class of Railroad, 2013

Class I	**Miles**
Burlington Northern Santa Fe (BNSF)	1,633
Union Pacific (UP)	532
Subtotal	2,165
Local Railroads (Class III)	
Palouse River and Coulee City Railroad	169
Cascade and Columbia River Railroad	148
Kettle Falls International Railroad	142
Eastern Washington Gateway Railroad	108
Puget Sound and Pacific Railroad	108
Washington and Idaho Railroad	87
Columbia Basin Railroad	86
Central Washington Railroad	80
Great Northwest Railroad	69
Port of Pend Oreille Railroad	61
Portland, Vancouver, Junction Railroad	33
Patriot Woods Railroad	29
Royal Slope Line	26
Yakima Central Railroad	21
Western Washington Railroad	18
Port of Seattle Railroad	11
Port of Chehalis Railroad	10
Columbia and Cowlitz Railroad	9
Subtotal	1,215
Grand Total	3,380

Source: Washington Department of Transportation.

STATE WHEAT PRODUCTION

Table 11 contains average annual wheat production for each of the nine states during the 2009-2013 period. Kansas, North Dakota, Montana, and Washington had the largest production with 341.5, 310.2, 193, and 146.2 million bushels, respectively. Collectively, the nine states averaged 1,463.3 million bushels of wheat per year.

Table 11: Total Average Wheat Production, 2009-2013 (Thousands of Bushels)

State	Average Production	Production Rank
Idaho	103,654	7
Kansas	341,500	1
Minnesota	75,438	9
Montana	192,953	3
North Dakota	310,186	2
Oklahoma	105,459	6
South Dakota	107,270	5
Texas	80,460	8
Washington	146,200	4
Total	1,463,310	

Source: US Department of Agriculture, National Agricultural Statistics Service

Wheat production data indicate likely origin areas for rail wheat shipments. Total annual wheat production varies greatly in all nine states. For example, total Idaho wheat production increased by 18.2% between 2009 and 2011, before plunging 16.3% in 2012 (relative to 2011) and then recovering by 6.7% in 2013 (relative to 2012). Idaho wheat production is concentrated in the North and East CRDs.

Since Kansas is the leading producer of wheat in the U.S., it has significant production throughout the western two-thirds of the state. However, the Central and South Central CRDs have the largest wheat production in the state. Total Kansas wheat output fell 25.2% between 2009 and 2011, rose 38.2% in 2012, and then fell by 16.5% in 2013.

Montana wheat production is concentrated in the North Central and Northeast CRDs, accounting for, on average, 77.2% of total state output. Total Montana wheat production displayed an "up, then down" pattern. Production rose 21.9% from 2009 to 2010, then fell 18.8% in 2011, followed by an 11.3% gain in 2012 and a 4.2% increase in 2013.

North Dakota has wheat production in all nine of its CRDs. However, the Northwest plus the Northeast districts, on average, account for 38.7% of the state's wheat production. Total North Dakota wheat output plummeted 46.9% between 2009 and 2011, soared 69.7% in 2012, but then in 2013 declined 19.2% to its lowest level of the five-year period.

Oklahoma wheat production is concentrated in the West Central, Southwest, and North Central CRDs, which account for 72.6% of average Oklahoma wheat output. Total Oklahoma wheat production increased 59.5% in 2010 (relative to 2009), then dropped by 41.8% in 2011. Production in 2012 more than doubled the 2011 production, increasing by 119.9%, but declined in 2013 by 31.9%.

Average wheat production in South Dakota is concentrated in the Central and North Central CRDs, accounting for about 46% of total output. Total production declined 18.9% between 2009 and 2011, and fell another 26% between 2011 and 2013. Wheat production in 2013 was only 60% of the 2009 output.

Texas wheat production, on average, is concentrated in the Northern High Plains and the Blacklands CRDs, which account for 59.2% of Texas output. Total production rose 108.2% in 2010 compared with the depressed production of 2009. Production in 2011 decreased 61.3%, rose 94.3% in 2012, and then declined by 29% in 2013.

Washington wheat production is located almost entirely in the East Central and Southeast CRDs, which together constitute 86% of average wheat output. Total production increased 36.4% between 2009 and 2011 and then declined by about 13% in both 2012 and 2013.

LITERATURE REVIEW

Numerous studies have examined the relationship of railroad industry competition and rail pricing in agricultural markets. Many of the previous studies investigated the impact of deregulation after the passage of the Staggers Rail Act of 1980. A significant amount of the literature is regional in scope motivated by the fact that regional railroad networks vary, resulting in regional variation in intrarailroad and intermodal competition.

Several studies analyzed changes in intramodal competition and rail prices in grain transport following passage of the Staggers Act of 1980. These include Adam and Anderson (1985), Babcock et al. (1985), Chow (1986), Fuller et al. (1987), and MacDonald (1987) (1989a) and (1989b). In general, these studies found that rail wheat rates declined in nearly all corridors in the 1981-1985 period. Grain rates on movements by rail to the Great Lakes, Gulf of Mexico, and the Pacific Coast declined by large percentages.

Wilson and Wilson (2001) documented the rail rate changes that occurred as a result of deregulation in the 1972-1995 period. They use a nonlinear regulatory adjustment mechanism to represent the annual effects of deregulation over time and saw that the largest effects occurred shortly after deregulation. Over time, the total effects of deregulation continue to reduce rail rates but at a slower rate.

Wilson and Wilson found that in 1981, the effect on rail rates of the Staggers Act was a decrease of 10.6%, 9.9%, 1.8%, 13.7%, and 8.4% for barley, corn, sorghum, wheat, and soybeans, respectively. These initial effects grew over time at a decreasing rate. By 1995, the long-term percent reduction in rail rates resulting from deregulation was 52%, 46%, 55%, 52%, and 42% for barley, corn, sorghum, wheat, and soybeans, respectively. Thus, rail deregulation had relatively small initial effects on rail rates but eventually developed into larger long-term effects.

Harbor (2008) took a comprehensive look at competition within the U.S. railroad industry. She found that the further a shipment originates from water competition, the higher the rail rates. For instance, corn shippers located 100 miles from a barge loading point pay 18.5% higher rates than those located 50 miles from water. Soybean shippers located 100 miles from water have rail rates 13.4% higher than shipments originating 50 miles from barge loading points.

Harbor (2008) concludes that a movement from a monopoly to a duopoly causes corn rail rates to decline by 23.1% at 25 miles from water, 16% at 50 miles away, and 9.6% at 100 miles from water. She also found that a movement from a duopoly to a triopoly causes rail rates for corn to decline an additional 14.2% at 25 miles from water, an additional 10.1% at 50 miles away, and an additional 15.7% at 100 miles from water.

Some studies have focused on the issue of railroad wheat rates in the northern Great Plains states, especially Montana and North Dakota. Bitzan et al. (2003) provided insight into inter- and intra-commodity rail rate differentials observed since rates were deregulated in 1980. The study found that the benefits of railroad deregulation were not distributed evenly across or within commodities, favoring grain producers in regions with higher levels of intermodal competition.

The study concluded that as the number of railroads serving a market decreases or that distance to the nearest water competition rises, rail rates increase. Thus, states dominated by a single railroad and also distant from water competition will have relatively high rail rates. The authors found that the northern, southern, and Central Plains states had higher rail rates than the Eastern Corn Belt.

Koo et al. (1993) examined railroad pricing behavior in shipping grain from North Dakota to domestic and export destinations by using an econometric technique with cross sectional data from 1984 to 1989. The authors found that cost factors play an important role in the variation of rail rates; distance, volume, and weight per car all have significant effects on North Dakota rail rates. They also observed that North Dakota's primary grain commodities (wheat and barley) experience higher rates than corn and soybeans because wheat and barley are not heavily produced in water competitive regions.

Kwon et al. (1994) investigated the ability of railroads to practice differential pricing in a competitive and unregulated transportation market. They also measured the determinants of rail differential pricing in the Kansas wheat transportation market. Using data from the second half of the 1980s the authors found that railroads practice differential pricing in the unregulated Kansas wheat transportation market. This is the case for both the intra-Kansas and Kansas export wheat transportation markets, although the determinants of railroad differential prices are different in the two markets.

In 2007, Montana lawmakers appropriated $3 million for research into rail issues facing Montana, including rates and service. Cutler et al. (2009) note that Montana is distant from ports and population centers and, combined with the bulk nature of the commodities, means that motor carrier intermodal competition is ineffective. Thus, nearly 100% of Montana wheat is shipped by rail to the PNW (Pacific Northwest).

Cutler et al. (2009) found that in 2006, Montana and North Dakota wheat shippers paid higher average rail rates on a per-car basis and a per-ton basis than wheat shippers in other nearby states. They also found that the average revenue to variable cost ratio (R/VC) for Montana wheat shipments to the PNW was 253% in 2006, well above the averages for all other states with significant railroad wheat shipments.

Marvin Prater et al. (2010) examined the sufficiency of rail rate competition in rural areas and the impact of intramodal competition on rail rates. They found that rail competition for grain and oilseed shipments generally decreased in the 1988-2007 period. Also, revenue to variable cost ratios (R/VC) increased in most CRDs and the ratios were related to the number of railroads competing in the CRD.

Recent data are inconclusive on whether North Dakota and Montana wheat rail rates are higher than other states. In the 1988-2007 period, Prater et al. (2010) found that in the case of revenue per ton, Montana and North Dakota had the smallest increases of the 10 states evaluated. Iowa, Nebraska, Kansas, and South Dakota had the largest increases.

For revenue per ton-mile, Colorado, Kansas, Indiana, and Missouri had the largest increases, while Montana, North Dakota, and Illinois had the smallest increases. In fact, North Dakota revenue per ton-mile actually decreased in the 1988-2007 period.

For R/VC ratios, the states with the largest increases were Kansas, Missouri, Colorado, and Nebraska. Montana's R/VC ratio remained virtually unchanged. North Dakota and Indiana had the least increase in R/VC ratios in the 1988-2007 era.

USDA (2013) provided average grain and oilseed tariff rates per ton-mile by state for the 2006-2010 period for 36 states. The rates ranged from 2.5 cents (South Dakota) to 9.8 cents (Michigan) per ton-mile. Montana and North Dakota had rates of 3.3 and 3.4 cents, respectively. Montana had the 7th lowest rate and North Dakota had the 8th lowest rate. The study didn't supply rates for wheat separately.

Babcock et al. (2014) estimated an empirical model of intrarailroad competition involving Montana, North Dakota, and Kansas using OLS (robust standard errors) and double log specifications.

Equations were estimated for Kansas-Montana data, North Dakota-Kansas data, and the Kansas, Montana, and North Dakota data for both estimation methods.

For the Kansas-Montana estimation, the total shipment weight and the distance from Montana wheat origins to Portland were the most significant. Average Montana wheat rail rates were about the same as Kansas. For the Kansas-North Dakota estimation, the total shipment weight and the distance to Portland from North Dakota wheat origins were the most significant factors. North Dakota average rail wheat rates were higher than Kansas average rail wheat rates.

The hypothesis of the study was that the greater intrarail competition in Kansas relative to Montana and North Dakota would result in higher railroad wheat prices in Montana and North Dakota than Kansas. The hypothesis was confirmed for North Dakota but not for Montana.

MODEL

The model in this study is a variant of the model published in Koo et al. (1993) where equilibrium prices of rail transport of agricultural products are determined by the demand for and supply of rail service. The demand for an individual railroad's service (Q_d) is a function of the price of the railroad's service (P_1), the price of other railroads' transport service (P_2, P_3…), the prices of other modes of transport (A_1, A_2…), and other factors affecting the demand for rail transport (S). Thus, the demand function is equation (1).

(1) $Q_d = f(P_1, P_2, P_3 \ldots A_1, A_2, S)$

The supply of a railroad's service (Q_s) is a function of the price of the railroad's service (P_1), the price of other modes of transport (A_1, A_2…), and cost factors such as distance (d), shipment volume (v), and other variables that affect the cost of rail transport (C). Thus, the supply function is equation (2).

(2) $Q_s = f(P_1 \ldots A_1, A_2, d, v, C)$

In equilibrium $Q_d = Q_s$ so equations (1) and (2) can be combined to form the equilibrium condition. Thus, the equilibrium price equation for railroad (1) is as follows:

(3) $P_1 = f(P_2, P_3 \ldots, A_1, A_2, d, v, S, C)$

If the prices of other railroads (P_2, P_3) are defined as intramodal competition (iac) and the prices of other modes (A_1, A_2…) are defined as intermodal competition (ioc), then equation (3) can be rewritten as follows:

(4) $P_1 = f(iac, ioc, d, v, S, C)$

The empirical model for this study is based on equation (4). As discussed above, intermodal competition is likely to be minimal for rail shipments of wheat since the shipments are long distance movements to domestic processing centers and export ports making truck competition ineffective. The average distances from Great Plains origins to barge loading locations is 364.6 miles (Montana), 381.9 miles (North Dakota), 219.9 miles (Kansas), 276.7 miles (Texas), 214.8 miles (South Dakota), and 186.4 miles (Oklahoma). These distances render barge competition to be minimal to nonexistent.

The only significant source of competition is intrarailroad competition. Thus, the empirical model is as follows:

(5) $RATE = b_0 + b_1 CARWT + b_2 DIST + b_3 TSW + B_4 BARGE + b_5 HHI + e_1$

RATE – Railroad rate in dollars per ton-mile for the shipment
CARWT – Weight of covered hopper (pounds)
DIST – Distance in rail miles between origins and destinations
TSW – Total shipment weight (tons)
BARGE – Distance from origins to barge loading locations
HHI – Herfindahl-Hirschman Index

In terms of hypothesis testing, CARWT, the weight of the rail car, is expected to have a negative relationship with the change in rail rates per ton-mile (RATE). This is because operating costs such as switching cost per car, labor costs, clerical costs, and various other costs are fixed per car, so the costs per car decrease as car weight increases. Thus, the change in rail rates per ton-mile falls as car weight increases.

The expected sign of the distance between origins and destinations (DIST) is negative. A large amount of railroad costs are fixed with respect to distance such as loading and clerical costs, insurance, interest, taxes, and managerial overhead. As these fixed costs are spread over more miles, the costs per mile decrease at a decreasing rate, so the change in rail rate per ton-mile falls as distance increases.

The variable for total shipment weight TSW reflects (a) the number of cars in the shipment and (b) the tons in the shipment. Since the empirical model includes the commodity CARWT, the weight of the shipment reflects the impact on rail rates of increased cars in the shipment. Because a large share of rail costs are fixed with respect to weight, railroads also realize economies of weight. Therefore, the change in rail rates per ton-mile are expected to decrease at a decreasing rate as weight per shipment increases.

Next, intermodal competition is proxied by highway miles to barge loading locations. Longer distances to water access points reduce the feasibility of truck-barge competition for rail wheat shipments. Thus, the theoretically expected sign of BARGE, the distance from origins to barge loading locations, is positive since greater distances to water ports are likely to give greater pricing power to the railroads.

Finally, the Herfindahl-Hirschman Index (sum of squared market shares of each railroad in the CRD) is used to measure intrarailroad competition. The higher the index the greater the rail market concentration in the CRD. The maximum value of the index is 10,000 when one firm has a monopoly in the market. The index approaches zero when a market consists of a large number of firms of about equal size. The theoretically expected sign of the HHI is positive. As the index increases rail market concentration increases, leading to less intrarailroad competition and higher railroad wheat transport prices.

DATA

The principal data source for this study is the 2012 Confidential Waybill Sample compiled annually by the Surface Transportation Board (STB). The sample contains shipment data from a stratified sample of waybills submitted by freight railroads to the STB. Data obtained from the Confidential Waybill Sample include:

1. Revenue per ton and revenue per ton-mile
2. Rail car code, i.e., C113 is a 268,000-pound loaded covered hopper car, and C114 is a 286,000-pound fully loaded covered hopper car

3. Distance in rail miles from origin to destination
4. Origin and destination state
5. Originating and termination railroad
6. Total shipment weight (obtained by multiplying the cars in the shipment by the tons shipped)

U.S.D.A. AMS (Agricultural Marketing Service) classified the waybill wheat shipment data for the nine states by CRD, which are regions of five to 14 counties. The number of CRDs for the nine wheat producing states are as follows:

Idaho	4
Kansas	7
Minnesota	6
Montana	7
North Dakota	9
Oklahoma	5
South Dakota	7
Texas	7
Washington	5
Total	57

USDA AMS personnel also calculated the shortest distance from the center of each CRD to the closest barge loading location using GPS.

EMPIRICAL RESULTS

Table 12 displays the mean, standard deviation, maximum, and minimum values of the variables. The mean car weight is 279,694 pounds with a minimum value of 268,000 and a maximum of 286,000 pounds. The mean distance of the shipment from origin to destination is 853 miles with the minimum and maximum values of 29 and 2,719 miles, respectively. The mean weight of the shipment is 385,021 tons with a minimum of 62 tons and a maximum of 1,533,753. For distance of origin CRD to the nearest barge loading location, the mean, minimum, and maximum values are 302, 7, and 552 miles, respectively. The mean of the Herfindahl-Hirschman Index was 7,347 with minimum and maximum values of 3,197 and 10,000.

The empirical model was estimated in double log specification (denoted as Ln) and the results are displayed in Table 13. Variables Ln DIST and Ln TSW have the theoretically expected negative signs and are highly significant (p value of $< .001$). Ln BARGE has the expected positive sign and is statistically significant (p value of $<.001$). The results for Ln CARWT had an unexpected positive sign, but the coefficient was non-significant. This could be due to a lack of variation in CARWT since the model contained only two car weights (268,000 and 286,000 pounds), the only car sizes and types for rail wheat shipments.

The results for Ln HHI were surprising since it had an unexpected sign, but the coefficient was non-significant. The non-significance of HHI is likely not due to multicollinearity since the partial correlation coefficients with the other explanatory variables are quite low. The correlation between Ln HHI and Ln CARWT, Ln TSW, Ln DIST, and Ln BARGE are 0.179, 0.09, 0.02, and 0.09, respectively. The lack of variation in HHI may have contributed to the lack of significance since nearly 40% of the 57 CRDs in the analysis were served by only one railroad.

There is the possibility that intrarailroad competition may no longer be a factor determining the level of railroad rates for wheat. The analysis is cross-sectional using data for 2012. It is possible that the underlying effect of HHI will be better captured using panel data analysis. This should be investigated for the years 2011, 2013, and 2014. In addition, further research should investigate the importance of intrarailroad competition in determining railroad rates for corn and soybeans for the years 2011 through 2014.

Table 14 lists the number of "single carrier" shipments; that is, CRDs served by one Class I railroad. Idaho and North Dakota have the most "single carrier" shipments while Kansas, Minnesota, and Texas have the fewest. As indicated previously, the UP has 88.1% of the Idaho Class I rail mileage while the BNSF has 78.1% of the North Dakota mileage. In contrast, the UP and BNSF have roughly equal shares of the Class I rail miles in Kansas and Texas. Minnesota is served by four Class I railroads and no single railroad has more than 39% of the state rail mileage.

Table 12: Variable Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
RATE	5.764	4.322	0.0323	57.029
CARWT	279,694	8,589	268,000	286,000
DIST	853	443	29	2,719
TSW	385,021	558,852	62	1,533,753
BARGE	302	124	7	552
HHI	7,347	1,997	3,197	10,000

RATE - Revenue per ton mile x100, measured in cents per ton-mile
CARWT - measure in pounds
DIST - measured in miles
TSW - measured in tons
BARGE - measured in miles
HHI – index number, sum of rail squared market shares in a CRD

Table 13: Model Results

Variable	Coefficient	t-statistic	p-value
Ln CARWT	0.002157	0.08	0.936
Ln DIST	-0.0422	-30.52*	0.000
Ln TSW	-0.00223	-7.67*	0.000
Ln BARGE	0.00666	4.35*	0.000
Ln HHI	0.00327	-1.18	0.238
Constant	0.324074	0.98	0.328
Observations	2001		
F-statistic	243.15		
R^2	0.38		
Root MSE	0.03411		

*statistically significant at .01 level

Table 14: Number of Shipments from CRDs That Have One Class I Railroad

State	Number of Monopoly Shipments	Rank of States*
Idaho	128	9
Kansas	0	1
Minnesota	10	2
Montana	21	4
North Dakota	103	8
Oklahoma	36	5
South Dakota	47	6
Texas	11	3
Washington	64	7

*The lower the rank number the greater the intrarailroad competition. Fewer CRDs served by only one railroad.

Previous studies have indicated that the presence of two railroads in a grain transportation market results in lower rail transportation rates than a monopoly (MacDonald (1987, 1989a, and 1989b) and Harbor (2008). Table 15 indicates that a majority of the CRDs are served by at least two Class I railroads. More specifically, none of the four Idaho CRDs are served by more than one Class I railroad but all seven Kansas CRDs are served by at least two Class I railroads. Four of the six Minnesota CRDs have at least two Class I railroads, but only three of the seven Montana CRDs have more than one Class I railroad. Seven of the nine North Dakota CRDs are served by two to three Class I railroads, but only three of the five Oklahoma CRDs have this characteristic. Next, five of seven South Dakota CRDs have two to three Class I railroads, and five of the six Texas CRDs also have more than one Class I railroad. Four of the five Washington CRDs are served by a single carrier, leaving only one that is served by more than one railroad.

The Herfindahl-Hirschman Index values (HHI) indicate substantial variation in intrarailroad competition within states, although it may no longer be a factor determining rail tariff rates for wheat during 2012. Table 16 contains the high and low HHI values of CRDs in each state and a percentage difference between them. Idaho has no variation and Washington only 6.2%. However, the other seven states have very large percentage differences ranging from Oklahoma (87.8%) to Minnesota (212.8%). Thus intrarailroad competition within states appears to be significant.

Table 15: Intrarailroad Competition by State and CRD

State	CRD	Competing Railroads
Kansas	2010	UP, BNSF, Kyle
Kansas	2020	UP, BNSF
Kansas	2030	BNSF, UP
Kansas	2040	UP, BNSF
Kansas	2050	UP, BNSF
Kansas	2060	BNSF, UP
Kansas	2080	UP, BNSF
Minnesota	2710	BNSF, UP
Minnesota	2740	BNSF, UP, TCWR
Minnesota	2750	CPUS, UP
Minnesota	2760	CPUS, BNSF, UP
Montana	3020	BNSF, CP
Montana	3030	BNSF, CP
Montana	3070	BNSF, UP
North Dakota	3810	BNSF, CPUS
North Dakota	3820	BNSF, CPUS
North Dakota	3830	BNSF, CPUS
North Dakota	3840	BNSF, CPUS
North Dakota	3850	BNSF, CPUS, RRVW
North Dakota	3860	BNSF, CPUS
North Dakota	3890	BNSF, CPUS
Oklahoma	4010	BNSF, UP, ATLT
Oklahoma	4020	UP (ATLT), BNSF
Oklahoma	4030	UP, BNSF
South Dakota	4610	BNSF, CPUS
South Dakota	4620	BNSF, CPUS
South Dakota	4630	BNSF, TCWR, CPUS
South Dakota	4650	BNSF, CPUS
South Dakota	4660	BNSF, CPUS
Texas	4811	BNSF, UP
Texas	4821	BNSF, UP
Texas	4822	BNSF, UP
Texas	4840	BNSF, UP, KCS
Texas	4870	BNSF, KCS
Washington	5330	BNSF, UP

BNSF - Burlington Northern Santa Fe
UP - Union Pacific Railroad
Kyle - Kyle Railroad
TCWR - Twin Cities and Western Railroad
CPUS - Canadian Pacific (US)
RRVW - Red River Valley and Western Railroad
ATLT - AT&L Railroad
KCS - Kansas City Southern Railroad

Table 16: Intrastate Variation in Herfindahl-Hirschman Indexes of Crop Reporting Districts (CRD)

State	Low	High	High-Low % Difference
Idaho	10,000	10,000	0
Kansas	4,839	9,279	91.80%
Minnesota	3,197	10,000	212.80%
Montana	5,008	10,000	99.70%
North Dakota	5,001	10,000	100%
Oklahoma	5,326	10,000	87.80%
South Dakota	3,834	10,000	160.80%
Texas	4,643	10,000	115.40%
Washington	9,417	10,000	6.20%

CONCLUSION

This study examined 2012 rail transportation of wheat in the nine major wheat producing states. Potential competition in this market is intramodal (railroad vs railroad) and intermodal (railroad vs truck-barge). Truck competition is not effective in this market since the shipments involve relatively low value, large shipment sizes, and are shipped over long distances. The rail networks (and thus potential intramodal competition) vary among the nine states. For example, the railroad network in Idaho, Washington, Montana, and North Dakota are largely dominated by a single Class I railroad. However, the rail networks of Kansas, Minnesota, Oklahoma, and Texas are characterized by a Class I duopoly or triopoly of roughly equal size rail firms. The latter group of states would be expected to have lower railroad wheat rates than the former group of states due to greater intrarailroad competition. Also, potentially intrarailroad competition could vary within states as well.

Intermodal competition could also vary among the nine states since the distance to the nearest barge loading location varies by state. For example, Minnesota wheat shippers are closer to barge loading locations than Montana shippers. Thus, the overall objective of the study was to investigate railroad pricing behavior for the shipment of wheat. Specific goals were to (1) measure the impact on railroad wheat rates of the intensity of intramodal competition, (2) develop a model to measure the impact of railroad costs, intrarailroad competition, and intermodal competition on wheat rates in the major wheat production states, (3) identify and measure the major cost determinants of railroad wheat rates, and (4) examine the hypothesis that railroad intramodal competition varies within a state with implications for intrastate variation in railroad wheat rates.

The model was estimated in double log specification. The distance of the shipment from origin to destination (DIST) and the total shipment weight (TSW) have the expected negative sign and were highly significant. This indicates that rail cost variables have an impact on rail wheat rates, which are lower for long distance shipments and total shipment weights (more cars in the train). Distance to barge loading locations (BARGE) had the expected positive sign and was highly significant. Thus, despite the relatively long distances of most of the nine states from barge loading locations, intermodal competition in the form of truck-barge combinations can influence railroad rates.

The Herfindahl-Hirschman Index (HHI) had an unexpected sign but was non-significant, indicating that intramodal competition was no longer significant in the determination of rail tariff rates for wheat during 2012. When the number of shipments from CRDs served by one Class I railroad is compared, Idaho and North Dakota have the most "single carrier" shipments while Kansas, Minnesota, and Texas have the fewest. Thus, the degree of intrarailroad competition varies by state.

Previous studies have found that the presence of two railroads of roughly equal size in a grain transportation market results in lower rail rates. For wheat, a total of 35 CRDs (61% of the total CRDs) are served by at least two Class I railroads. The presence of intrarailroad competition varies by state. For example, Idaho had no CRDs served by at least two Class I railroads while all seven of the Kansas CRDs were served by at least two Class I railroads.

Not only varying among states, the HHIs indicate there is substantial variation of intrarailroad competition within states. For example, when comparing the high and low HHI of CRDs in each state, it was found that Idaho has no variation and Washington has only a 6.2% difference between the high and low HHI. However, the other seven states have a very large percentage difference in HHI ranging from 87.8% (Oklahoma) to 212% (Minnesota). These differences imply that intrarailroad competition is present within states.

Overall, the study found that railroad cost factors, such as distance shipped and total shipment weight, and intermodal competition are important determinants of 2012 railroad wheat rates. The HHIs were not significant, but other evidence implies that intrarailroad competition is present within states.

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Endnotes

1. The Surface Transportation Board (STB) defines Class II railroads as those with operating revenue of $37.4 million or more and less than the Class I threshold of $467.1 million. Class III railroads are those with operating revenue less than $37.4 million. These thresholds are adjusted annually for inflation (AAR, Railroad Facts, 2014, p. 3).

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Disclaimer

The opinions and conclusions expressed do not necessarily represent the views of USDA or AMS.

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Northern Plains Grain Farm Truck Marketing Patterns

by Kimberly Vachal

A survey of farm operators in the Northern Plains Region was conducted to gather information about on-farm storage and truck markets. The objective of the study is to provide information about farm truck grain marketing patterns in the Northern Plains. There is no other source for this information. It should be complementary to other farm-to-market information and national commodity flow publications. Farmers may use the results for their own investment and productivity assessments. Local and regional planners and policy makers can use the information in calibrating travel demand and freight flow models for investment and asset management choices.

INTRODUCTION

Agriculture, including traditional grain markets and value-added activities such as food processing, biofuels production, and specialty grains, plays a large role in the economy of North Dakota and neighboring states. The 2012 Agricultural Census shows that farms in these states had crop sales of $32 billion (U.S. Department of Agriculture 2014a). In terms of private income for 2013, North Dakota generated 14.5% of its state gross domestic product from agriculture. That figure was similar in surrounding states: 15.3% in South Dakota, 7.4% in Montana, and 5.0% in Minnesota. The share of economic activity attributed to agriculture in these states is far greater than the role of agriculture in the nation's overall economy at 1.8% (U.S. Department of Commerce 2015).

Farm-generated truck movement is defined as the initial movement of grain from field to market delivery point in the distribution chain. It is especially important to understand the transportation patterns and trends for these farm truck shipments in making investment and policy decisions related to rural and agriculture-centric economies. National commodity transport data sources, such as the Commodity Flow Survey and Freight Analysis Framework, do not account for this farm-generated grain traffic (BTS 2010, Donnelly 2010). The objective of this study is to partially fill the information gap for the farm truck inventory and grain marketing patterns in the Northern Plains. Collecting truck and trip information directly from farm operators is optimal for understanding patterns and trends in farm-generated grain traffic. This traffic is not otherwise inventoried in national data sources, so it is the responsibility of individual states or other entities to collect and/or estimate farm-generated grain traffic. Findings should be unique and complementary to other farm-to-market studies (Baumel 1996, Tolliver et al. 2005, Tun-Hsiang and Hart 2009) and national commodity flow publications.

METHOD AND DATA

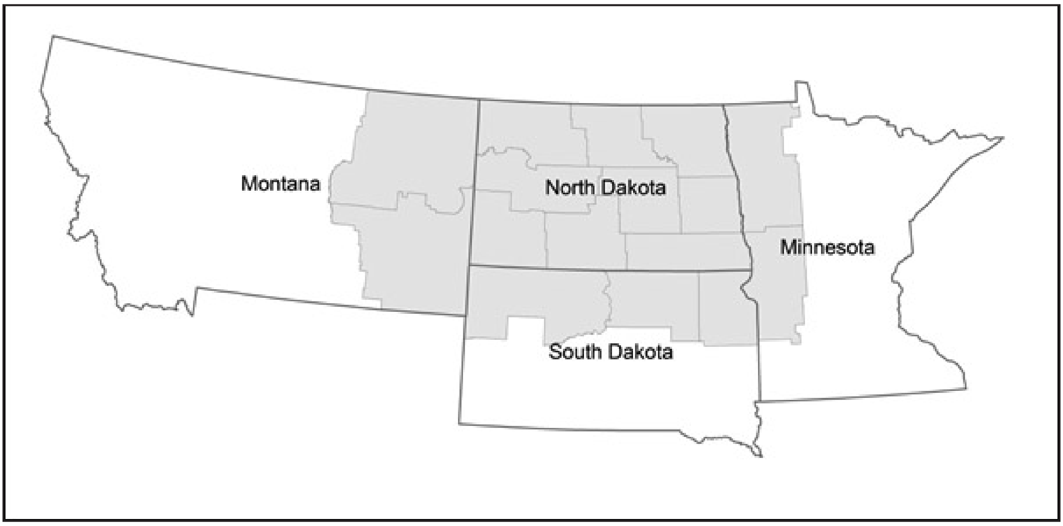
The survey method was used to collect the data needed for the study. The Upper Great Plains Transportation Institute (UGPTI) at North Dakota State University worked with the North Dakota Office of the Agricultural Statistics Service (NDASS) and the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture to complete a survey of farmers in the region. The UGPTI was the lead agency in drafting the survey instrument and compiling survey results.

Mail and Phone Surveys

The survey process was a two-phase system. A stratified non-probability quota sample was used to select the farmers from the population for the survey. An initial mail survey was distributed to a sample of farmers in the NASS contact database. A follow-up phone survey of non-respondent farmers within that initial survey sample was completed to fulfill the sample size requirement. The number of surveys collected, overall and from within each of the state strata, was deemed sufficiently large to approximate random selection so generalizations could be made about the larger population within the budget and time constraints. Although random influences cannot be ruled out within this sample technique, confidence intervals are shown since the large regional sample is assumed to have normal probability distributions.

The sample was designed to collect data for a representative sample of corn, wheat, and soybean farms in North Dakota and the adjacent crop reporting districts (CRDs) from Montana, South Dakota, and Minnesota (Figure 1). The farms surveyed may produce one or all three commodities. The sample for the survey was derived from the larger population of farms that reportedly grew at least one of the major wheat, corn, and soybean crops based on the 2013 County Agricultural Production Survey (CAPS). This group is defined as the eligible farm population that was made up of the potential survey candidates. CAPS is a federally required submission used for federal farm program management at all jurisdictions. A random sample of 6,000 farms was drawn from the eligible population.

Figure 1: Farm Truck Survey Geography



Survey Responses

The survey was mailed to these 6,000 farmers in the survey region in June 2014. The agency received 623 responses from the mailed surveys. A month after the mailing, a phone survey of randomly selected non-respondent farmers was conducted. All survey efforts resulted in 3,005 valid responses for a response rate of 50%. Stratification of respondent figures by state and commodity show that a sufficient number were received to develop statistically robust results for farm-generated grain traffic.

Survey Results

The 3,005 survey responses were queried to create a profile of the farm truck fleet in the Northern Plains. This region is heavily involved in agriculture, with three of the states dedicating 60% of their land use to crop production. The highest shares were in North Dakota and South Dakota, where 87% and 88% of the land is in crop production, respectively. Montana has about 63% of its land area in crop production. Minnesota has the lowest share of its land in crop production, at 47%. The sample respondent group included a good representation of crops across the region (Table 1).

Table 1: Respondents Reporting Crop Production, by State and Commodity

State	Wheat	Corn	Soybean
Minnesota	38%	71%	57%
Montana	80%	13%	<1%
North Dakota	70%	55%	27%
South Dakota	26%	80%	47%
Overall	51%	61%	37%
n=3,005			

The respondent farm size averaged 750 harvested acres of corn, soybeans and wheat in 2013. The harvested acres for the three commodities ranged from two to 28,000 acres. A distribution of responses across quadrants shows about 22% to 28% of response farms in each of the farm size groups, defined as (1) less than 300 harvested acres, (2) 301 to 750 harvested acres, (3) 751 to 1,500 harvested acres, and (4) 1,501 or more harvested acres. The distribution across the farm group strata shows good representation of each group (Table 2).

Table 2: Farm Group Characteristics

Farm Group	Count	Percent	Average Harvested Acres
300 acres or fewer	706	26%	156
301 to 750 acres	594	22%	479
751 to 1,500 acres	772	28%	1,057
1,501 acres or more	672	24%	3,079
not reported=261			

Economies of size in the farm industry have been a key component in the continued evolution of this mature industry, especially for the commodity grains that are at the core of this study. Average farm size continues to increase (NASS 2014b). The ability of farms to spread costs, such as equipment and labor, over more acres is increasingly important with technology-enhanced farming and more expensive equipment needed to adopt it. The farm size has also been shown to relate positively to truck size, based on the economics of farm truck fleet decisions and with what has been observed in the market (Berwick et al. 2003).

MARKETING PATTERNS

Farm markets vary substantially across respondents because transportation for these major grains can simply be a short haul to on-farm storage or a longer haul to an elevator, feedlot, or processor facilities. The transportation resources consumed do reveal patterns for individual commodities.

In addition, responses to on-farm storage questions provide some insight into the timing of grain deliveries. Overall regional marketing patterns are useful. In addition, insight is provided in the market patterns among state and farm group strata. Statistical tests confirm that the marketing patterns do vary significantly for all commodities across farm group strata when considering the share of production transported directly to market when harvested for wheat [$F(1,566)=5.13$, $\rho=<.002$], corn [$F(1,912)=12.99$, $\rho=<.001$], and soybeans [$F(1,796)=6.77$, $\rho=<.002$] are significant at the 99th percentile based on generalized linear model results. Significant variance is also found among states for the wheat [$F(1,591)=22.28$, $\rho=<.001$] and soybeans [$F(1,827)=4.97$, $\rho=<.002$] marketing patterns, considering the share delivered directly from field to market.[1]

On-Farm Storage

On-farm storage for corn, soybeans, or wheat was confirmed by 83% of the respondent farms. The availability of on-farm storage was not answered in 10% of the surveys and was left blank in the remaining 7%. South Dakota had lowest share of farms with on-farm storage for corn, soybeans, or wheat at 84%. In North Dakota and Montana, 94% of the respondents confirmed on-farm storage availability. Minnesota had on-farm storage reported in 84% of responses. The role of on-farm storage is important in understanding farm-generated crop traffic. On-farm storage provides an easily accessible option to delay grain delivery beyond the harvest season. South Dakota reported the highest average storage capacity and Montana the lowest (Table 3).

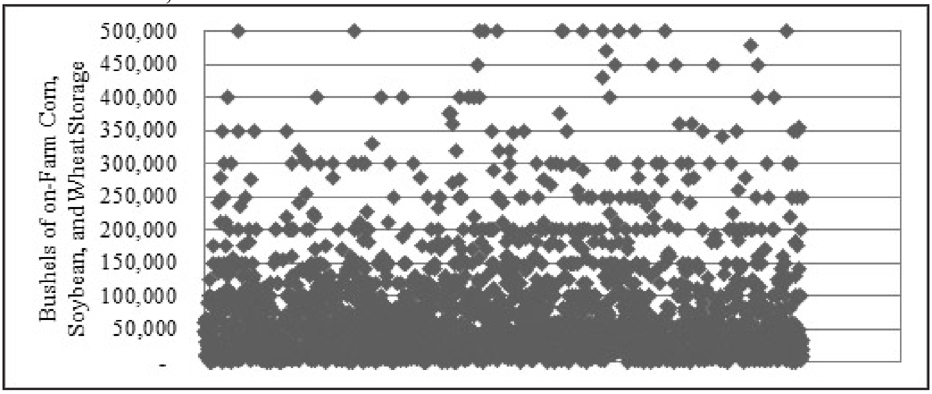
Table 3: Corn, Soybean and Wheat Storage Capacity, by State

Crop Reporting Districts	n	Storage Ratio, Bushels per Harvested Acre*	Average On-Farm Storage, Bushels*
Western Minnesota	769	77	156,276
Eastern Montana	360	70	103,904
All North Dakota	864	63	222,607
Northern South Dakota	751	69	374,173

*Weighted by Harvested Acres

On-farm storage is concentrated on the larger farms in terms of average capacity. In terms of flexibility, however, the smaller farms appear to be more able to adapt when increased on-farm storage is needed (Table 4). For the smallest farms, the ratio of storage capacity bushels per harvested acre was 151. The largest farms have an average of 62 bushels of on-farm storage for each harvested acre. The difference in the storage density may be related to expectations for yield among commodities. The median on-farm storage capacity was 50,000 bushels, with 25% reporting fewer than 20,000 bushels. A scatterplot illustrates the distribution for the responses with storage of 500,000 bushels or less (Figure 2). The survey had 28 responses from farms with more than a half-million bushels of storage. Among the facilities, 11 were in North Dakota, 10 in the northern South Dakota CRDs, six in the western Minnesota region, and a single location in eastern Montana. The higher storage volumes were attributed to the large farms of over 1,500 acres in 26 of the 28 cases.

Figure 2: Scatterplot of Reported On-Farm Storage Capacity, Farms with 500,000 Bushels or Less



The storage capacity density, measured by farms as bushels produced per harvested acre (including corn, soybean, and wheat), was inversely related to farm size (Table 4). The storage capacity volume, however, is substantially greater for the larger farms. Average on-farm storage was 329,097 bushels of corn, soybean, and wheat capacity for farms of 1,501 acres or more. The smallest farms averaged only 26,252 bushels of capacity for the three commodities.

Table 4: Corn, Soybean and Wheat Storage Capacity, by Farm Group

Farm Group	n	Share in Farm Groups	Average Storage Ratio, Bushels per Harvested Acre*	Average On-Farm Storage, Bushels*
300 acres or fewer	706	26%	151	26,252
301 to 750 acres	594	22%	82	40,003
751 to 1,500 acres	772	28%	73	80,718
1,501 acres or more	672	24%	62	329,097

*Weighted by Harvested Acres

On-farm storage is concentrated on the larger farms in terms of average capacity. In terms of flexibility, however, the smaller farms appear to be more able to adapt when increased on-farm storage is needed (Table 4). For the smallest farms, the ratio of storage capacity bushels per harvested acre was 151. The largest farms have an average of 62 bushels of on-farm storage for each harvested acre. The difference in the storage density may be related to expectations for yield among commodities. For instance, average corn yield in 2013 was 110 bushels per acre compared with 31 and 45 bushels per acre for soybean and wheat, respectively (NASS 2014a). Survey responses do support this premise for the larger farms reporting more harvested corn acres. Among farms larger than 1,501 acres reporting at least half of their harvested acres were corn, the ratio of storage bushels to harvested acres was 75 (n=198) 95% CI [50, 59] compared with 54 (n=436) 95% CI [69, 81] for farms attributing less than half their harvested acres to corn. Understanding farm-based storage capacity is important in discussing and predicting transportation scenarios for the industry.

The role of on-farm storage is important in understanding farm-generated crop traffic. On-farm storage provides an easily accessible option to delay grain delivery beyond the harvest season. In addition to the insight gained from the higher-yield corn stratification of the responses regarding the density of farm storage capacity, farmers were asked the share of the crop production delivered directly to market from the field at harvest time. Responses weighted by bushels produced, showed 36% of wheat (n=1,518) 95% CI [32%, 39%] and 32% of corn (n=1,835) 95% CI [30%, 36%]

was delivered directly to an elevator, feedlot, or processor market. The average share of soybeans delivered directly to market from field is substantially higher at 66% (n=1,748) 95% CI [63%, 69%]. Among the state strata, the adjacent South Dakota farmers reported delivering the largest share of wheat directly to market at harvest at 50%, compared with 31%, 33%, and 36% for Minnesota, Montana, and North Dakota, respectively. On average, corn share delivered to market at harvest ranged from 32% in South Dakota to 39% in Montana. Minnesota farmers reported an average 34% and North Dakota farmers reported 33%. All averages are weighted based on respondents' reported production of the commodity.

A differentiation in the timing for crop delivery can also be recognized when considering the farm group strata. Table 2 shows that among the farm groups, the larger farms tend to deliver a smaller share of their production directly to market at harvest. Table 5 shows a larger proportion of soybeans are delivered directly to market by farms of all sizes, but the smallest share is for the largest farms. With a continued trend toward larger farms, note the storage propensity for larger farms is a factor in the farm-generated crop traffic. Operational factors, such as seasonal load regulations, may require additional consideration as the industry's production and marketing practices continue to evolve.

Table 5: Crop Delivery from Field to Market, by Farm Group

Commodity	Farm Group	n	Average	Standard Error[2]	95% Confidence Limit	
Wheat	300 acres or fewer	303	45%	3%	39%	52%
	301 to 750 acres	316	43%	3%	37%	48%
	751 to 1,500 acres	455	39%	2%	35%	42%
	1,501 acres or more	441	33%	3%	28%	38%
Corn	300 acres or fewer	391	47%	3%	42%	52%
	301 to 750 acres	372	49%	2%	45%	54%
	751 to 1,500 acres	553	37%	2%	33%	40%
	1,501 acres or more	514	29%	2%	24%	33%
Soybeans	300 acres or fewer	313	71%	3%	65%	78%
	301 to 750 acres	375	74%	2%	69%	78%
	751 to 1,500 acres	548	70%	2%	66%	74%
	1,501 acres or more	508	62%	2%	58%	67%

Note: Averages Weighted by Bushels Produced

Regional Markets

Farmers were asked to describe their corn, soybean, and wheat marketing patterns in 2013. For wheat harvested, farmers reported that as of May 1, 2014, about 16% of bushels produced remained in on-farm storage with the largest share, 79%, transported to elevators (Table 6). A small 2% share was hauled to processors. Soybean marketing patterns were similar for the share moved to elevators, but processors were a larger receiver at 9%. Farmers were less likely to use on-farm storage for soybeans than for wheat or corn. About half of the corn grown during 2013 was sold to an elevator. Similar to wheat, 17% of the 2013 corn crop was held in on-farm storage. Feed use accounted for about 14%, with the largest share being used for feed on farm.

Table 6: Regional Markets, 2013

	Wheat		Corn		Soybean	
n=	*1521*		*1821*		*1115*	
Market	Average	95% CI	Average	95% CI	Average	95% CI
Elevator	79%	77%, 81%	54%	51%, 58%	79%	77%, 82%
Processor	2%	1%, 4%	11%	8%, 13%	9%	6%, 13%
Feed Lot	0%	0%, 0%	4%	2%, 5%	0%	0%, 1%
Feed Own	0%	0%, 1%	10%	8%, 13%	0%	0%, 1%
Storage	16%	14%, 18%	17%	14%, 20%	7%	5%, 10%
Other	2%	1%, 3%	4%	0%, 8%	4%	0%, 8%

Markets, State Strata. Minnesota farmers in the western CRDs report a smaller share of wheat and soybeans delivered to elevators compared with the regional market average (Table 7). For wheat, a larger share of the 2013 crop was held on-farm at the time of the survey. A larger share of corn had been sold to elevators versus the regional average, with less used for feed on their own farms.

Table 7: Regional Markets for Wheat Produced in 2013, Minnesota

	Wheat		Corn		Soybean	
n=	*319*		*595*		*678*	
Market	Average	95% CI	Average	95% CI	Average	95% CI
Elevator	70%	63%, 76%	61%	56%, 65%	76%	73%, 80%
Processor	4%	0%, 8%	10%	5%, 14%	9%	6%, 13%
Feed Lot	1%	0%, 2%	5%	2%, 8%	1%	0%, 2%
Feed Own	0%	0%, 0%	6%	4%, 9%	0%	0%, 0%
Storage	23%	16%, 30%	17%	14%, 21%	8%	5%, 10%
Other	2%	0%, 3%	1%	0%, 1%	6%	1%, 10%

Montana farmers in the eastern CRDs had sold a larger share of their 2013 crop to elevators by May 1, 2014, compared with the regional average (Table 8). They held a smaller share in storage than other farmers in North Dakota and adjacent state CRDs. The limited response for corn production shows a much larger proportion of the corn grown in Montana is marketed to feedlots than in the remainder of the region. Montana farmers sold only about one in five bushels of corn to elevators compared with about one in two for the region on average.

Table 8: Regional Markets for Wheat Produced in 2013, Montana

	Wheat		Corn	
n=	*327*		*54*	
Market	Average	95% CI	Average	95% CI
Elevator	83%	79%, 87%	21%	51%, 58%
Processor	3%	0%, 7%	4%	8%, 13%
Feed Lot	0%	0%, 0%	54%	2%, 5%
Feed Own	1%	0%, 1%	16%	8%, 13%
Storage	12%	8%, 16%	4%	14%, 20%
Other	1%	0%, 2%	2%	0%, 8%

North Dakota mirrors the regional averages with regard to wheat, marketing 79% to elevators and storing 16% on-farm (Table 9). North Dakota farmers were more likely to sell corn to elevators and processors compared with the regional average, with a larger share remaining on-farm at the time of the survey. With regard to soybeans, North Dakota sold a larger share to elevators compared with the regional average. This soybean market pattern is expected given the longer distances for North Dakota farmers from soybean growing regions to processing plants in Minnesota and South Dakota. North Dakota elevators are strong suppliers to the Pacific Northwest soybean export market.

Table 9: Wheat, Corn, and Soybean Markets for 2013 Production, North Dakota

	Wheat		Corn		Soybean	
n=	*655*		*522*		*527*	
Market	Average	95% CI	Average	95% CI	Average	95% CI
Elevator	79%	77%, 82%	59%	55%, 64%	89%	87%, 91%
Processor	2%	0%, 3%	9%	5%, 13%	2%	0%, 3%
Feed Lot	0%	0%, 0%	2%	0%, 3%	1%	0%, 3%
Feed Own	0%	0%, 1%	3%	2%, 5%	0%	0%, 0%
Storage	16%	13%, 19%	23%	18%, 29%	6%	3%, 9%
Other	3%	1%, 4%	4%	0%, 7%	3%	1%, 5%

South Dakota's northern CRDs marketed a larger share of wheat and soybeans to elevators compared with the region on average with both crops at 82% (Table 10). South Dakota farmers had the smallest share of each crop held on-farm compared with the region. The figures are, however, close to the regional averages. South Dakota farmers sold a relatively smaller share of their corn, 49%, to elevators, and used a substantially larger share, 16%, for feed on their own farms.

Table 10: Wheat, Corn, and Soybean Markets for 2013 Production, South Dakota

	Wheat		Corn		Soybean	
n=	*220*		*669*		*541*	
Market	Average	95% CI	Average	95% CI	Average	95% CI
Elevator	82%	78%, 86%	49%	43%, 55%	82%	78%, 85%
Processor	1%	0%, 2%	12%	8%, 16%	10%	6%, 15%
Feed Lot	0%	0%, 0%	3%	1%, 5%	0%	0%, 0%
Feed Own	0%	0%, 0%	16%	12%, 21%	0%	0%, 1%
Storage	15%	10%, 20%	13%	10%, 17%	6%	4%, 9%
Other	2%	0%, 4%	6%	0%, 14%	2%	0%, 3%

Markets, Farm Group Strata. Farm Group 1, including farms with fewer than 300 acres, held a larger share of wheat, at 23%, in storage than the region average. These farm storage practices may be related to specialty or small scale milling operations that tend to have limited on-site inventory or to individual farmer decisions to hold inventory multiple years. Wheat that graded with higher milling quality characteristics has historically garnered a premium during years where weather or other factors lead to below average crop quality. The corn market is also somewhat different from the region for these farms using corn for feed, 19%, nearly double the share for the regional average. These smaller farms also report storing less of their corn and an equal share of their soybean crop, relative to the regional averages (Table 11).

Table 11: Wheat, Corn, and Soybean Markets for 2013 Production, Farm Group 1

	Wheat		Corn		Soybean	
n=	*303*		*392*		*314*	
Market	Average	95% CI	Average	95% CI	Average	95% CI
Elevator	72%	68%, 77%	56%	52%, 60%	85%	81%, 90%
Processor	1%	0%, 2%	3%	1%, 6%	5%	1%, 9%
Feed Lot	0%	0%, 1%	9%	6%, 13%	0%	0%, 0%
Feed Own	0%	0%, 1%	19%	15%, 23%	0%	0%, 1%
Storage	23%	16%, 29%	11%	8%, 14%	7%	1%, 12%
Other	3%	0%, 6%	2%	0%, 3%	3%	0%, 5%

Farm Group 2, which includes farms sized 301 to 750 harvested acres, was close to the regional averages in its wheat marketing. This group did report selling a larger share of each commodity to elevators compared with the regional average. With 80% of wheat, 62% of corn and 88% of soybeans marketed at the elevator, the shares are one percentage point higher for wheat and nine and eight percentage points higher than the region average for corn, and soybeans, respectively (Table 12).

Table 12: Wheat, Corn, and Soybean Markets for 2013 Production, Farm Group 2

	Wheat		Corn		Soybean	
n=	*313*		*372*		*375*	
Market	Average	95% CI	Average	95% CI	Average	95% CI
Elevator	80%	76%, 83%	62%	57%, 66%	88%	85%, 90%
Processor	1%	0%, 3%	6%	2%, 9%	5%	1%, 8%
Feed Lot	0%	0%, 0%	4%	0%, 8%	0%	0%, 0%
Feed Own	0%	0%, 1%	15%	10%, 19%	0%	0%, 1%
Storage	16%	12%, 20%	13%	10%, 17%	7%	4%, 10%
Other	2%	1%, 4%	1%	0%, 1%	0%	0%, 1%

Farms Between 751 and 1,500 acres comprise the operations in Farm Group 3. This group is similar to the regional market average in the distribution of corn, soybeans, and wheat. Elevators are the primary market for each commodity. Corn has the greatest diversification with regard to markets (Table 13).

Table 13: Wheat, Corn, and Soybean Markets for 2013 Production, Farm Group 3

	Wheat		Corn		Soybean	
n=	*457*		*555*		*550*	
Market	Average	95% CI	Average	95% CI	Average	95% CI
Elevator	76%	73%, 79%	57%	53%, 60%	81%	78%, 83%
Processor	3%	1%, 5%	9%	6%, 11%	8%	5%, 12%
Feed Lot	0%	0%, 1%	3%	2%, 4%	1%	0%, 2%
Feed Own	0%	0%, 1%	10%	7%, 13%	0%	0%, 0%
Storage	18%	15%, 21%	19%	16%, 23%	7%	5%, 8%
Other	2%	1%, 4%	3%	1%, 4%	3%	2%, 5%

Farm Group 4 includes the largest operations among the respondent farms, at least 1,501 acres. These operations are also similar to the regional market distributions. Farm Group 4 sells slightly more than the regional average share of its wheat and soybeans to elevators (Table 14). The average corn shares sold to elevators and for own feed use are slightly lower while the corn share sold to processors is above the regional average. Corn does show a greater variability with regard to market distribution, considering the standard errors. Figures for each commodity market sales share fall within the regional 95% confidence intervals.

Table 14: Wheat, Corn, and Soybean Markets for 2013 Production, Farm Group 4

	Wheat		Corn		Soybean	
n=	*441*		*516*		*508*	
Market	Average	95% CI	Average	95% CI	Average	95% CI
Elevator	80%	77%, 83%	53%	48%, 58%	82%	79%, 84%
Processor	2%	1%, 4%	12%	8%, 15%	7%	4%, 10%
Feed Lot	0%	0%, 1%	4%	2%, 6%	1%	0%, 2%
Feed Own	0%	0%, 1%	9%	6%, 13%	0%	0%, 1%
Storage	15%	12%, 18%	17%	14%, 21%	7%	4%, 9%
Other	2%	1%, 3%	5%	0%, 11%	4%	1%, 6%

SUMMARY

Agriculture is a large part of the economy in the Northern Plains region. Approximately 800 million bushels, or 30 million tons, of grain was moved to subterminal elevator facilities and local agricultural processors in 2010. These grain movements generate an estimated 900 million farm truck ton-miles. The objective of this study was to provide information about grain marketing patterns in the region since there is no other source for the information.

A survey of 6,000 farm operators in this Northern Plains region was conducted to gather information about transportation of crops and on-farm storage capacity. The survey was mailed to a sample of farmers and followed up with a phone survey of non-respondents. The survey responses represent corn, wheat, and soybean farms in North Dakota and the adjacent crop reporting districts.

The storage capacity density, measured by farm as bushels produced per harvested acre (including corn, soybeans, and wheat), was inversely related to the farm size. Storage capacity volume was substantially greater for the larger farms. Average on-farm storage was 26,525 bushels for the smallest farms and 329,097 bushels among the largest farms. Storage density for the smallest farms, considering a ratio of storage capacity bushels per harvested acre, was 151 and an average 62 bushels for the largest farms. On-farm storage provides an easily accessible option for delaying grain delivery beyond the harvest season. Responses, weighted by bushels produced, showed 36% of wheat, 32% of corn and 66% of soybeans were delivered directly to market from the field at harvest time.

Regarding shipment beyond the farm, about 79% of wheat and soybean production was delivered elevators. The share for corn to elevators was only 54%. Corn had the most diversity in terms of market patterns among the states and farm size strata with on-farm storage and feed use varying substantially among groups. Survey results reveal differences in marketing patterns among commodities. In addition, marketing differs significantly among states and by farm size. Farm grain truck transportation demand is expected to continue to evolve with agronomic advancements and continued industry consolidation. Findings will be useful in updating farm-to-market truck flows that are used to assess economic competitiveness, calibrate local traffic demand, and plan future investments.

Endnotes

1. Note that in this paper 'state' always refers to the group of CRDs surveyed from each respective state in the cases of Minnesota, Montana, and South Dakota so caution should be used in extrapolating any statewide figures based on the survey results for these states.
2. Standard Error figures are standard error of the mean for all reported survey statistics.

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Disclaimer

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Canada's Grain Handling and Transportation System: A GIS-based Evaluation of Potential Policy Changes

by Savannah Gleim and James Nolan

This research re-examines both transportation allocation and infrastructure capacity problems associated with moving grain from the Western Canada to export position. The analysis is conducted with geographic information system software using grain industry data. In contrast with historical grain industry logistics methods, the analysis and simulation framework allows us to re-examine logistic solutions in this vast supply chain in the interest of improving overall delivery efficiency. In addition, we find that rail network capacity should not constrain any major expansion of grain movement in the system over the foreseeable future.

INTRODUCTION

While rooted in Canada's history, the transportation of Prairie wheat from grain elevators across Western Canada continues to be an issue of contention for Canadian agriculture. Recent changes in the sector have only deepened this concern. In August 2012, the Canadian Wheat Board (CWB), an organization that was the sole international marketer of Canadian wheat, barley, and durum since 1935 was stripped of this function. This event also transferred grain logistics oversight over to grain handling firms operating in Canada. Since Western Canada is a major exporter of grain, the handling system will continue to rely on efficient logistics to move these commodities for export. Now that the CWB no longer controls the allocation and marketing of these grains, significant changes have and will continue to occur within the future logistics and allocation system for Western Canadian grain.

Up until the federal government's decision to stop the marketing function of the CWB, it was the largest marketer of wheat and barley in the world (Canadian Wheat Board 2011). Marketing grain to over 70 countries meant that the CWB played a major role in the Canadian grain sector. For example, in the 2011/12 crop year, the CWB exported approximately 21.3 million metric tonnes (MMT) of grain (Canadian Grain Commission 2012). Of those exports, wheat was the largest export grain, with 15.4 MMT moved through Western Canada. With the CWB policy change, the export of Canadian grain will necessitate an updated and possibly quite different grain logistics system. The vastness of the grain sector means that transition is unlikely to be smooth.

As Western Canada's grain handlers absorb more grains into their new supply chains, their individual and collective transportation problems will shift and become more complex. We expect that novel logistics solutions will need to be identified in order to efficiently move primary export grains across the three Prairie provinces, using the two Class 1 Canadian railways to connect to the four major Western Canadian export points (Vancouver, Prince Rupert, Thunder Bay, and Churchill). Considering the collectivist goals of the CWB, future grain transportation solutions will necessarily shift emphasis away from a farmer profitability focus over to the profitability of grain handling firms themselves.

Currently, it is not well understood how any such changes in Canadian grain logistics will affect overall grain movement and system efficiency. To this end, a spatially oriented optimization analysis is developed in an attempt to literally map out potential evolution of the new grain handling and transportation system in Western Canada. Thus, the primary contribution of this research is to simulate a likely future grain handling logistics system whereby multiple grain companies are responsible for transporting Canadian grain.

GRAIN LOGISTICS IN CANADA

To begin this research, it is useful to understand how grain logistics were conducted under the former CWB. One major point worth highlighting is that CWB grain logistics were based solely on minimizing system transportation costs, in the form of rail freight rates paid by each individual farmer. As a collectivist solution imposed by a monopoly grain marketer, CWB optimization objectives will likely contrast with the new competitive marketing environment for grain in Canada. Due to this, our model is designed at the outset to better align with the objectives of individual grain handling firms as they seek to maximize profit in the new system. On this point, our model assumes that time (as an opportunity cost) is the critical factor governing the movement of grain within the transportation system.

The CWB was created by the federal government in Canada as a means to maximize returns to grain producers through single-desk marketing of grain purchases, sales, and exports (Schmitz and Furtan 2000). In 1995, the CWB changed its grain logistics system to more formally reflect the value of grain at each grain delivery location across the region. The CWB did this by computing a hypothetical shadow price known for delivered grain. This algorithm was called the freight adjustment factor, or FAF.

Mostly based on forecasted demand data, the FAF was a rate adjustment that signalled to every farmer in the region the lowest cost direction to move their grain. Each year, a system-wide FAF was computed to capture not only the flow of grain trade for that year, but also to reflect any other export capacity constraints (Gray 1996). As a single optimization problem that was applied to the entire region altogether, the CWB's logistics system under FAF effectively minimized the collective costs of grain freight for all producers simultaneously.

FAF priced away any inherent locational advantages among farmers, particularly those located along the hypothetical boundary of the major Prairie grain catchment area. In fact, the CWB effectively divided Prairie farmers in West and East catchments, so defined by the lesser cost of FAF plus freight to Thunder Bay, or the freight rate to Vancouver. As the CWB possessed complete logistical control over almost all Western Canadian grains, the FAF shadow price signal allocated yearly grain movement either to the East (Thunder Bay) or West (Vancouver/Price Rupert) as needed, subject to the constraints inherent in the supporting rail system. In summary, CWB logistics at the time of their elimination from this function was designed to minimize collective (not individual) freight rate payouts across all farmers in the region.

In some contrast to the collectively driven logistics methods used by the CWB, in this research the transportation problem for grain movement in a new era of multiple competing grain marketers will be studied using explicit spatial analysis. The scale of the Canadian grain transportation problem is enormous, spanning four provinces with numerous delivery points (elevators) and a few distant port locations. Fortunately, geographic information systems (GIS) software can be programmed to solve as well as map out complex spatial transportation solutions. Here, ArcGIS software is programmed to use a standard vehicle routing problem (VRP) toolkit. In our model, the solution identifies the least costly (based on time transported) set of grain transportation routes that allocate (monthly) wheat supplies from across the Prairie elevator system to meet particular (monthly) export demands at each port.

In a competitive grain transportation market, grain handlers incur both the benefits and costs associated with delivering grain to port within a particular time frame. For instance, if a grain handling firm can deliver grain to port before a set date, it receives what is known as a dispatch payment. However, if grain is not delivered within the time frame of the contract, in Canada a demurrage fee (on FOB contracts) is charged to the grain handling firm and is often passed onto farmers (Wilson et al. 2004). In order to get a better sense of the importance of delivery reliability, for the 2009/10 crop year, grain handling firms were paid C$6.0 million in dispatch, whereas for 2010/11, they incurred a net of C$40.6 million in demurrage fees (Quorum Corp 2012). It is for these reasons that the movement of grain across the Prairies in the post CWB era will very likely focus on reducing the risks of incurring additional delivery costs and maintaining reliability, rather than simply focusing on reducing the collective farmer costs of grain transportation.

METHODOLOGY

The scale of the problem to be solved here is large and is accomplished using appropriate software, which reduces the time and complexity of finding optimal solutions. Since this particular logistics problem occurs over a large region, our spatial data interface uses GIS software. Essentially, GIS develops an interactive transportation network map that allows the researcher to create both a visual and numerical solution for the programmed transportation problem. What follows is a basic description of the analysis and data used here, but the interested reader is referred to Gleim (2014) for additional details.

Spatial analysis begins with GIS software interpreting the relationships between spatial data layers. Layers of points, lines, or polygons, which all share the same physical coordinates are virtually stacked on top of one another and then linked together through their geographic coordinates. As information is overlaid, the map begins to take shape and various relationships can form between the different elements or properties of the layers (Scurry 1998).

One of the most widely used GIS software packages in North America is ArcGIS. The analytic portion of this research is conducted using ArcGIS optimization tools. The Network Analyst (NA) toolkit in ArcGIS solves network data problems comprising either of the fastest, shortest, closest, best routes or locations within a specified geographic region. Examples include routing vehicles to a nearest facility, identifying a particular service area for a region, or routing a set of vehicles for the delivery of goods. The transportation problem developed in this research requires a tool to optimize grain routings and minimize time costs of transport, both of which are within the capabilities of the vehicle routing problem (VRP) tool in NA.

DATA STRUCTURES

To perform a VRP within ArcGIS, data describing the transportation network and its associated constraints are needed. These data should possess three key attributes: cost, descriptors, and restrictions (ESRI 2012a). Cost attribute data are values associated with the edges and lines of the network dataset. The VRP requires a minimum of one cost attribute to solve the problem. Descriptors are information attributes that do not contain actual measurements, but other classes and properties use this information to select data for calculations. Descriptor examples are the number of lanes within a segment of highway, direction of traffic, or whether a transportation path permits a certain mode. Finally, restriction data are used to prohibit movements along a network. For example, there could be restrictions for movements around a construction site, restrictions on left turns, and limits for one-way streets. (ESRI 2012b).

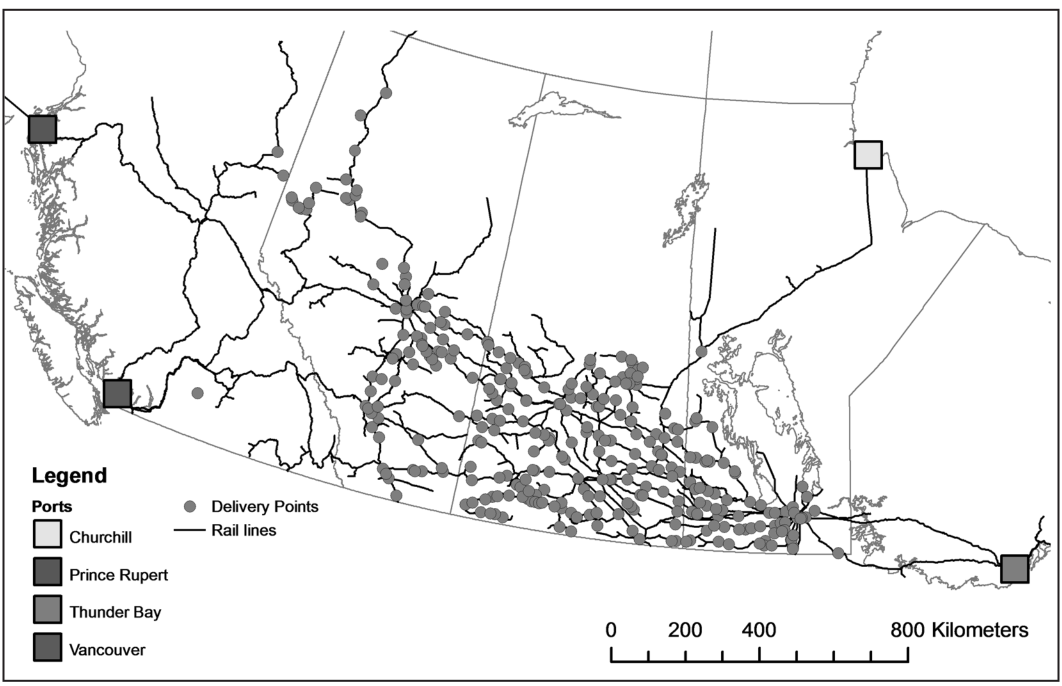
Within all GIS programs, input data layers are required and output data layers are created. In ArcGIS, the VRP can use up to 13 classes of data layers. In this research, just four layers are necessary. These are 1) orders, 2) depots, 3) routes, and 4) route zones. And from each VRP emerge a number of key outputs. These are added to the order, depot, and route layers. These solutions are descriptive results, including items like the route name to which an order point is assigned along with the sequence in which orders were picked up. Cost data are also recorded, such as the time and distance travelled between order points and the total costs of routings. By virtue of the software, these VRP results are readily converted into new visual or mapping representations to display the set of optimized solutions (ESRI 2012c).

Once the network dataset, classes, and parameters have been input, the objective function associated with the VRP can be solved. While the ArcGIS VRP algorithm is proprietary, the VRP used here observes time windows and relies on a modified travelling salesman problem (TSP) to fit the constraints of the set VRP. This means the VRP solver works in two parts. First the origin-destination (OD) matrix shortest path for cost is solved. Within ArcGIS, these paths are identified using Dijkstra's algorithm (ESRI 2013). Next, a Tabu Search (TS) is used to find an improved sequence of routes. Thus, the VRP algorithm within ArcGIS uses a combination of Dijsktra's algorithm to generate an initial low-cost feasible solution, which is subsequently checked and improved upon through iterations of Tabu search to further minimize transportation costs in order to optimize the solution of the VRP.

To construct a spatial VRP of western grain transportation, data representing demands, supplies, and networks serving grain movement are needed. The data used to build our base model were collected from a time prior to the August 2012 removal of the CWB's primary marketing function. We used monthly data from the crop years 2009/10 through 2010/11. By choosing two consecutive crop years near the end of CWB influence on logistics, our base VRP model should closely match actual patterns of supply and demand in the grain handling system. For these years, approximately 12-13 MMT tonnes of wheat alone were exported from Western Canada, which is a level close to average for the last decade (Canadian Grain Commission 2012).

Since the scale of this research problem is large and the relevant base model data and analysis covers 24 consecutive months, only essential data classes and their properties are used in order to reduce the degree of difficulty in VRP estimation. Thus, our model is built over four data classes: order points (elevator delivery points), depots (port facilities), the network dataset (railway network), and routes. We assume there are multiple order points for each month representing primary producer deliveries across Western Canada, while the four port locations receive goods over the two Class 1 railway networks. The base grain handling configuration is shown in Figure 1.

Figure 1: Model Classes and Scale



Maps were created using data from the following sources (Canadian Grain Commission, 2012b; Oak Ridge National Laboratory, 2012; DMTI Spatial, 2012; Canadian Wheat Board, 2011).

The locations reported by the CWB data become the order locations for the VRP. The data are further aggregated into a total available supply of deliveries per location. The total monthly supplies of wheat (in tonnes) for each order location account for all the wheat reported as transported by rail to the ports. Together, the CWB data and total grain tonnes reported by the CGC are combined to form the order supply location list for the VRP. Then to incorporate the deliveries of grain producers from order points, map coordinates are used to represent physical proximity to the railway network and distance from port. As constructed, the final order point data are then used by the ArcGIS VRP to solve for new routings for the 12.6 (2009/2010) and 10.9 (2010/2011) MMTs of wheat actually delivered each year in the Western Canadian handling system.

Port facilities demand wheat to fill their monthly export orders, so the ports are represented in the VRP as depots, and are the aggregated volume demanded by each port over each railway network. To account for port export demands in the VRP in ArcGIS, the same monthly CGC data on the volume of wheat moved from Prairie origins to port for export are used. As an example, in August of 2009, the CGC reported 283,384 tonnes of wheat moved by railway from Prairies to Vancouver. Thus, the export demand for Vancouver over the month of August 2009 is set at 283,384 tonnes.

The railway data used here combines the Oak Ridge National Laboratory North American railway network and CanMap railway data. The ORNL railway network has multiple link attributes for each segment of railway, including distance, track ownership, access, main line class, access control (Peterson 2003), and track type (ORNL 2012). The data from CanMAP are added to fill any gaps within the ORNL railway network (DMTI Spatial 2012). Together, the two railway data sources generate over 27,291 km of track operated in the region by Class 1 railways and 3,440 km by short line rail. The network dataset also constrains access to each track by its owner. Since the VRP utilizes time as the optimization criterion, the code was set to allow only one train to travel over a segment of rail network at a time (ESRI 2013).

In this manner, we develop a formal transportation problem that maps out modern logistics solutions in the Canadian grain handling system. Using appropriate data about the rail network and grain elevator system, we formulate a VRP and use ArcGIS and its software capability. The objective function of our new VRP for grain is to minimize the total travel time of rail routings subject to the constraints of supplies, demands, routes, network access, speeds, and space in the network. In essence, the VRP solved here minimizes the sum of commodity travel times while maximizing demand throughput.

BASE RESULTS

Considering post CWB grain logistics, we focus on developing a more reasonable, modern, and market driven grain transportation solution. With recent problems in the Canadian grain handling system, we plan to generate grain routings that no longer minimize collective freight rates (as was the case under the CWB), but instead optimize route times. Foremost, this objective seems reasonable since it will necessarily reduce risk of unreliable wheat deliveries in the system and associated charges for port demurrage. Given the existing institutions and relationships among the players in the Canadian grain supply chain, this switch of objective focus for the grain system optimization problem is more compatible with the objectives of independent profit-seeking grain companies, and also represents a move away from the collectivist farmer perspective of the CWB logistics function. In addition, since wheat is generally a comparatively low value commodity, greater benefits will likely be generated by improving system capacity utilization rather than reducing inventory costs for grain handlers and railways (Quorum Corporation 2012). The most important metric for a supply chain in this sense is whether it can provide consistent and timely delivery.

Our base model is solved using historical industry data in order to re-optimize routings and travel times for monthly grain movement. We then examine our base model results in order to determine what factors have most affected grain logistics, including identifying any constraints leading to bottlenecks and delays. This in turn will lead us to the subsequent analysis where some of these constraints are relaxed in order to re-optimize logistics in the grain transportation system.

Simulation Results and Mapping

Over the time-frame re-analyzed and simulated here, each month's grain allocations resulted in a spatial overlapping of routes to ports. The occurrence of overlapping routes results from the limited number of railway lines available and the clustering of delivery points along the Prairies. In addition, there appears to be no visible spatial allocation trend that stays consistent from one month to the next, suggesting that each monthly VRP is unique. As one final point, we find that CWB's East-West grain catchments in these months do not emerge from the optimization criterion used here. While not entirely surprising, it does show that a new grain handling system will likely generate vastly different grain logistics allocations as compared with the old CWB monopoly marketing regime.

Figure 2 is a set of maps comparing two of our new VRP solutions using minimized time travelled. While the maps are mostly similar between the two sample months in spite of the time separating the data used, we note any differences between the respective VRP allocations stem from how they treat grain located near the center of the region, a region very near to the East-West catchment demarcation enforced by the CWB. The maps generated by the VRP simulation are all very similar to these and, not surprisingly, most often vary within the central portion of the Prairies.

More formally, we need to check how well the simulation allocated actual grain demands. See Figure 3. We found that over all the months simulated, the total volume of cars allocated to port by the model met 92.7% of all wheat export demands at port. But this level of service was somewhat inconsistent. For example, during the 2009/10 crop year, the simulation generated monthly variations for fulfilling port demands ranging from 61.9% to 99.0%, while the 2010/11 crop year narrowed this variation somewhat to between 81.3% and 99.0%. Over the period studied, 18 out of 24 months possessed 90% fulfilled port demand or higher. In 2009/10 and 2010/11, port demands were met on average by between 92.3% and 94.0%. So while this is a complex and large optimization problem, the simulation model is generally able to allocate grain to port demands with a high success rate, in comparison to the actual delivery data.

One reason the model cannot route 100% of port demand in each month is caused by the distribution of supplies along CN and CP VRP solutions and routings. Wheat supplies and associated VRPs within each month are split between CN and CP, as are route demands. In the optimization problem, this process limits a CP delivery point from being picked up by a CN routing. While there are always sufficient supplies to meet the total port demands, individual port demands are distributed between the Class 1 railways (based on regulatory data). As a result of splitting port demands between CN and CP, the model often identifies greater supplies available on the CP network than demanded, while CN's port demands for several of the months are greater than the available CN supplies. In fact, CP routes were able to deliver 98.8% and 97.9% of total demands each crop year while, for example, CN in 2009/10 made only 88.2% of demanded deliveries and 91.6% the next year. We believe that the improvement of CN deliveries during 2010/11 was likely the result of better balance between elevator supply and port demands. This also indicates that improvements can be gained by a better balance of railway provider distribution and supply. The imbalance of supplies along each of the railway networks effectively creates a bottleneck, which reduces the efficiency of the simulated solutions.

Figure 2: Simulated Grain Deliveries to Port, Minimum Time Criterion, May 2010 (top) vs. June 2011 (bottom)

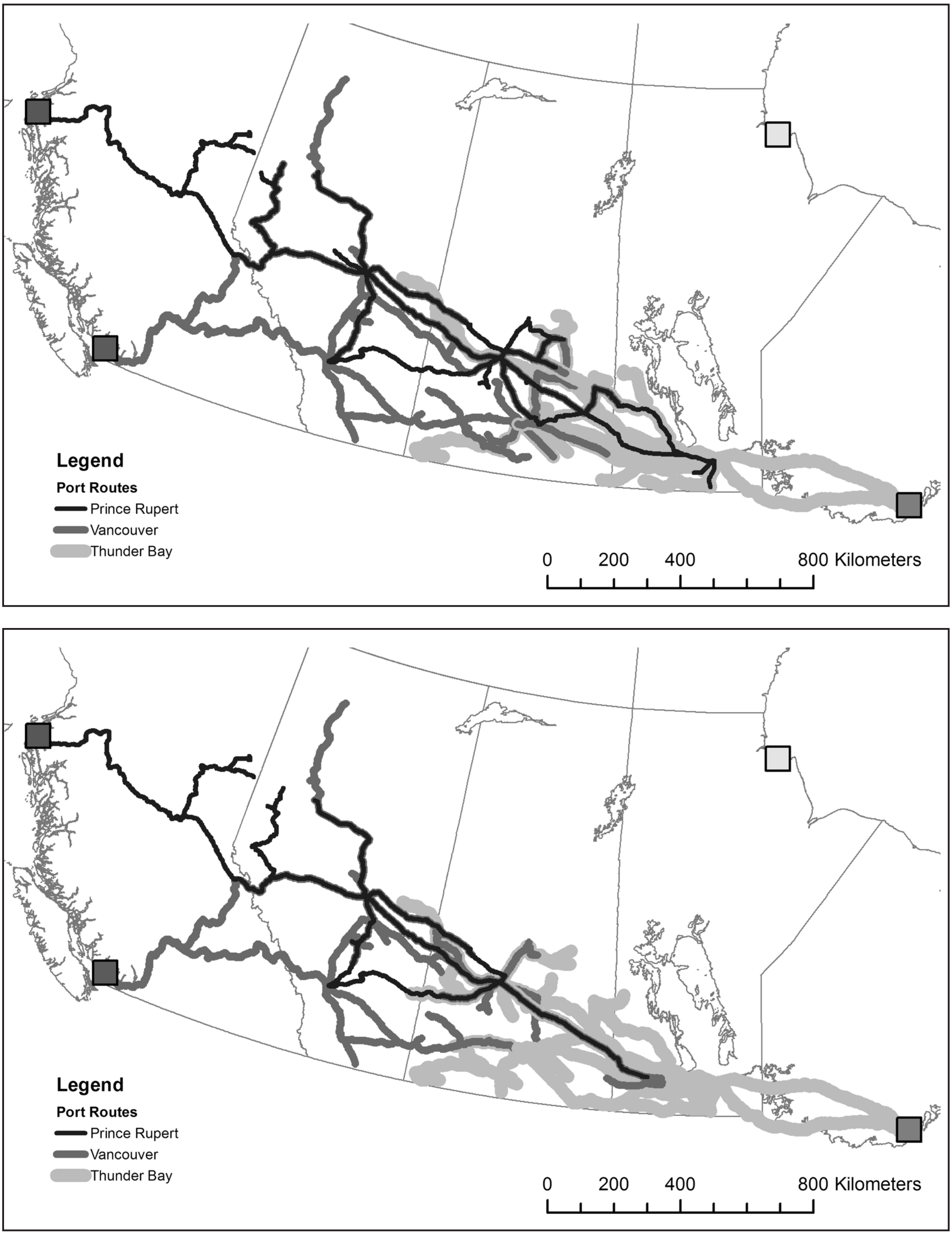
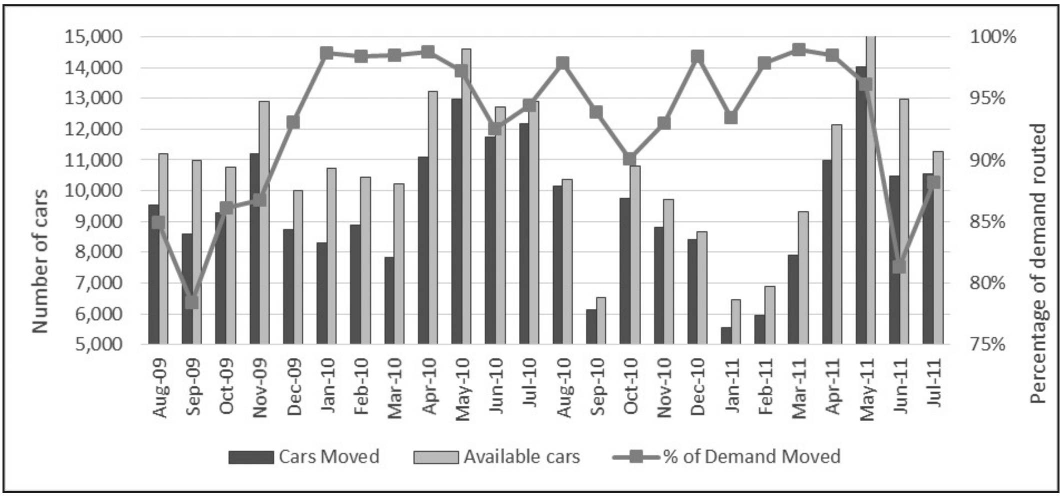


Figure 3: Tracking Simulated Rail Car Deliveries to Ports



There are other aspects of the base VRP that require further discussion. To start, the base model VRP also often showed a tendency to route grain to the ports of Vancouver and Thunder Bay over Prince Rupert and Churchill. If there was a high demand for northern (CN served) ports, the tendency of the VRP to route grain trains to Thunder Bay and Vancouver created a bottleneck in the optimization problem. Given these broad findings, there would appear to be improvements available, particularly for grain distribution on the more northern CN rail network. In addition, we allowed each solution to be created using several discrete sizes of trains, approximately corresponding to train sizes used in reality. Not surprisingly, we always found that the system VRP optimization favored larger capacity grain trains over smaller ones. In addition, the southern CP network was often optimized using all available routes, both small and large. This situation was likely due to its more favorable location within the region, meaning that large grain supplies on elevators on the CP network (coupled with smaller trains) could lead to serious inefficiencies with respect to route timing in the supply chain.

ALTERNATIVE GRAIN TRANSPORTATION SCENARIOS

In this section, we examine a couple of interesting alternative simulation scenarios using insights drawn from our base model results. They offer insight as to the future of the grain handling system in the new era in Canada of private grain marketing and logistics. For ease of exposition, each of these additional comparative simulations was only conducted for a few specific but representative months of the complete data set. See also Gleim (2014).

Scenario 1 – Larger Trains

The first counterfactual policy simulated off of the base model is referred to as the *larger trains (LT)* scenario. This is simulated to address bottleneck inefficiencies potentially created by smaller modular train capacities. This scenario alters the base model routes so as to use fewer sizes of small modular trains, and allows us to examine whether policies to increase average modular train capacities could also improve efficiencies in the grain transportation problem.

To test this, whereas the base model assumed six modular train capacities, here these are reduced to three. The three modular train capacities imposed are for 50, 100, and 150 car trains. Routes larger than 150 cars are not permitted, noting that regional siding data did not uncover any extant elevators that possessed the capacity to handle a greater train spot (Informa Economics 2012).

In fact, Canadian Pacific Railway stated in 2008 that its average grain train was 114 cars long, a level hoped to increase to 168 cars in the future (Vantuono 2011).

Given this, the scenario simulates a policy to increase average capacity of the routes. Further, we assume that 90% of routings have greater than 50-car modular trains, or that 50% of modular train capacities carry 100 cars, 40% carry 150 cars, and 10% carry 50 cars. Here, the average modular train capacity is 115 cars, compared with the base model, which carried 93 cars on average in 2009/10 and 102 cars on average during the 2010/11 simulation.

Two simple criteria allow us to compare the base and alternative LT scenarios. First, comparative route durations are shown in Table 1. Note that the LT scenario dominates the base case, especially in the total hours travelled and total distance covered categories. Overall, we see that the LT scenario delivers grain more efficiently than the base by, on average, moving loaded grain for longer durations and distances per routing.

Table 1: Overall Route Durations

	Base	Larger Trains
Total distance travelled (km)	777,848	644,712
Average distance per route	1,583	1,789
Total hours travelled	14,118	11,356
Average hours per route	28.5	31.4
Average car pick-up (minutes)	22.5	18.1

The next criterion measures the ability of the scenario to meet port demands. Table 2 shows how each scenario performed using this metric. The base scenario was only improved upon by about 0.5% as compared with the LT scenario. But it is worth pointing out that other simulated scenarios performed much worse than LT at meeting demands, compared with the base (Gleim 2014).

Table 2: Model Demand Deliveries Routed

	Base	Larger Trains
Cars Moved	38,001	38,059
Cars Demanded	43,270	43,270
Demands routed (%)	87.8%	88.0%

Scenario 2 – Greater Grain Volumes

This section addresses concerns about future increased grain movements in the system. A very basic grain transportation scenario is developed and optimized consisting of higher supplies and demands than exist in the data. As motivation, recent statements by the government of Saskatchewan concerning the growing issue of food security imply that agronomists expect average grain yields in the province to at least double over current levels by the year 2020.

For the hypothetical scenario, wheat demands and supplies are doubled. In fact, this level approximates the actual volumes moved over the past few months in Canada (2013-2014) with a bumper grain crop. The effects of such higher grain volumes are evaluated using both the base model (HVB – see Figure 4) as well as the large trains policy (HVLR). For tractability, the results of the hypothetical higher volume simulation do not account for any changes that increased supplies or demands of other agricultural commodities may have on the grain transportation problem. The exercise will demonstrate whether there is enough capacity in the rail system in the face of potential increased grain transportation demand.

Figure 4: High Grain Volumes, Base Model (HVB), May 2010

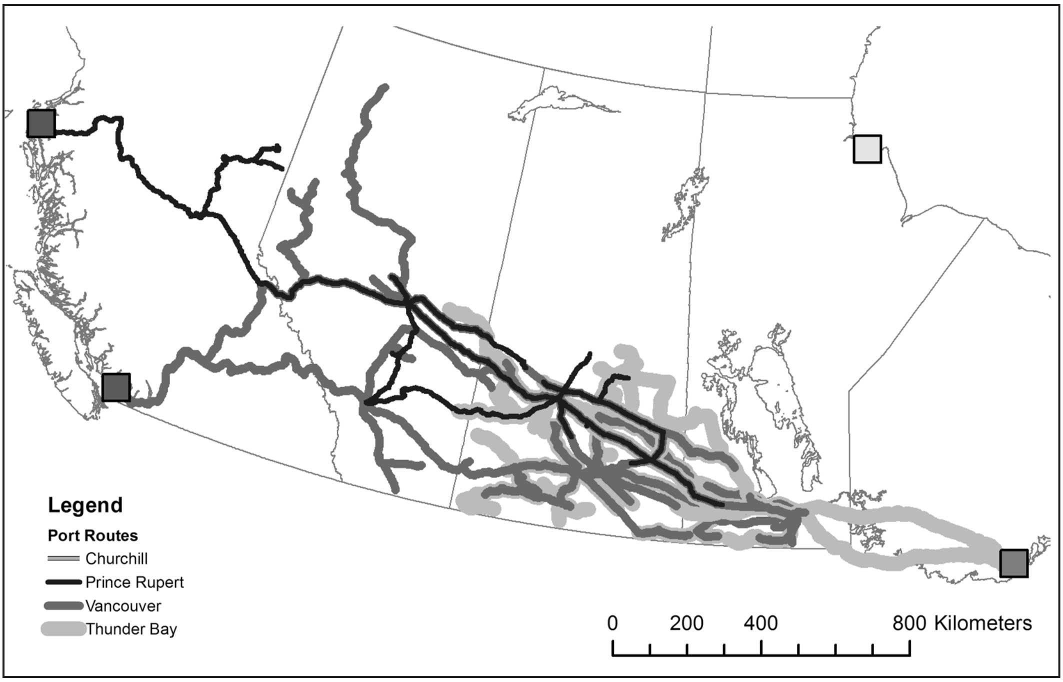


Figure 4 shows grain train routings under the high volume base scenario, and the reader should also compare this to the upper map in Figure 1. Results of specific performance metrics in this scenario are shown in Table 3. Again, note that these simulations were only conducted for a single representative month (May 2010), so the actual metrics listed in the table are somewhat different than those listed in previous tables. We tracked performance metrics under both base and LT scenarios, each simulated with doubled grain volumes over the entire system.

Examining the base scenario in this case, we find that transportation efficiencies are actually improved with greater grain volumes. For example, route capacities are improved to close to 100% efficiency. More importantly, to future agricultural policy considerations, we find that the LT policy under larger volumes (HVLT) does not seem to restrict the efficiencies generated by our logistics solution. Table 3 shows that these scenarios generated shorter, quicker routes under the high volume LT policy. Staying mindful that we did not model other commodity movements in this analysis, we offer that contrary to current public statements by the railways, it appears that the current Canadian grain transportation system is not at capacity and that the system could realistically accommodate additional wheat movement. Finally, we note that the HVLT policy in particular led to greater use of the port of Prince Rupert, extending routes serving Prince Rupert much farther East than under the base scenario. This finding supports a general feeling in the system that Rupert is currently underused relative to its grain handling capacity compared with the other ports.

Table 3: System Efficiency Metrics, Double Grain Volumes Transported

	Base	High Volume Base (HVB)	Larger Trains (LT)	High Volume Larger Trains (HVLT)
Cars routed	12,971	26,116	13,002	26,106
Cars demanded	13,337	26,674	13,337	26,674
Demands routed (%)	97.3%	97.9%	97.5%	97.9%
Efficiency of routed capacity	98.6%	99.5%	99.3%	99.4%
Total KM	228,673	594,633	224,900	447,460
Change (%) [a]	-	106%	-	99.0%
Total hours	5,231	10,228	3,939	7,688
Change (%) [b]	-	95.5%	-	95.2%
Average car pick up (min)	24.2	23.5	18.2	17.7

[a, b] Measures the increased totals as a percentage from the original simulation (base or larger trains).

CONCLUSIONS

The grain handling system in Canada is undergoing significant change. It was the goal of this research to examine the nature of changes that might occur under new organizational structure in grain handling and transportation. Using historical monthly data on wheat supplies and demands through the 2009/10 and 2010/11 crop years, we simulated both base and alternative optimized transportation allocations of wheat across Western Canada. Compared to reality and a very different logistics criterion, the base simulation outcomes were found to be efficient.

The base transportation model simulated novel grain transportation re-allocations using actual grain system data. The nature of the analysis meant that alternative scenarios could be created and simulated as variations on the simulated base solutions. Effectively, these were done to better understand system bottlenecks while potentially improving those solutions generated by the base transportation scenario.

These latter simulations showed that while the base model did a good job finding a good feasible solution for grain logistics, in particular, the larger trains (LT) policy improved system logistics allocations over the base results and also reduced effects of system bottlenecks. In effect, this latter policy resulted in greater hopper car turnover, marginal increases in deliveries, as well as enhanced route capacity efficiencies. Within the current and evolving grain transportation system in Canada, we were able to confirm that larger capacity unit grain trains will certainly improve overall grain logistics efficiency.

The second set of hypothetical simulation results were done to address concerns about future grain transportation volumes to be exported with respect to rail network capacity. In contrast to continued public comments made by the Canadian railways about capacity concerns in their networks, we find that even if double current typical volumes needed to be moved, rail capacity issues should be not a concern with respect to the future movement of grain.

Overall, relying on the assumption that grain handling companies will want to minimize transport time rather than the cost to transport grains, we showed that efficient grain routes over rail will become larger in capacity and move greater distances. Longer routes will occur between locations, which will need to perform quicker loading or handling services for a grain train. Ultimately, our findings confirm that the preference of Canadian Class 1 railroads will be to move grain almost exclusively along their main corridors, forming a so-called "pipeline" model for commodity movement. Not surprisingly, something akin to this situation was observed during the recent (and controversial) 2013 harvest, where limited routes available for grain moved almost exclusively along mainline track of either CN or CP (Cross et al. 2014 and Franz-Warkentin 2014).

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Book Review

Roth, Ralph, and Divall, Colin, eds. From Rail to Road and Back Again? A Century of Transport Competition and Interdependency. *Modern Economic and Social History Series. Burlington, VT: Ashgate/Lund Humphries Publishing Co., 2015. ISN 978-1-4094-4046-8.*

From Rail to Road and Back Again?

by Gabriel Roth

The main thesis of this fact-filled book is that rail and road networks both compete and interact with one another. Ralf Roth sets out this thesis in its first chapter. His conclusion (page 72) is that "the contemporary dominance of road and air transport is not necessarily the end of the story. Factors such as energy, emissions, limited resources of space, and gaps in capacity might suddenly shift the whole system of global networks into another direction." This conclusion is not supported by the numerous facts in the 14 chapters that follow.

The book contains a wealth of information on transport in the 19th and 20th centuries. The countries covered include not only the United Kingdom and United States, but also France, Germany, Italy, and other European countries, all of which are usually excluded from books written in English. The main text, which is supported by numerous footnotes, is not confined to road and rail transport. For example, three chapters deal with the design and introduction of containers developed for use by the marine, road, and rail modes, and which still play a key role in their collaboration.

While it is natural that the periods covered by this book are those in which both roads and rails were actively used, the omission of Roman roads, and of the United Kingdom and United States turnpike roads, weakens the book as readers are not reminded that road transport existed for many centuries and in many countries without interacting with rails. An example of this neglect is the statement (page 235) that in the United States, "the pressure for road improvements started with the bicyclists in the 1880s." Could the authors not have known of the importance of the massive investment in turnpikes in the 19th century United States? In the 10 eastern states alone, in the period 1800-1830, private investment in turnpike roads exceeded, as a proportion of GDP, government expenditure on the construction of the U.S. Interstate Highway System in the period 1956-1995.

The book lacks in-depth discussions of road and rail finances, and the critical fact that today's passengers are generally willing to pay for roads but not for rails, even though rail transport was developed commercially, and the idea of paying for passenger or freight carriage by rail is generally recognized as acceptable in market economies. Not so with roads. Collecting money for road use depended on toll collection and, until the twentieth century, was practicable only for selected toll roads. However, the 20th century saw the possibility of charging for road use without requiring vehicles to stop to pay tolls. This can be done either by means of surcharges on fuel or tires or, more selectively, by electronic means such as the E-ZPass. The implication of such payments for road use, and for commercial investment in roads, are not explored in the book, though they are likely to influence the conclusion suggested in its title that roads might replace rails.

Another area neglected in the book is the role of government in promoting and/or impeding different transport modes. Thus, in Chapter 1, Roth presents an interesting review of the pros and cons of the mobile steam engines, independent of rails, which were introduced in England in the 1820s and supported by such well-known experts as Thomas Telford, founder of the Institution of Civil Engineers. But Roth does not mention the tolls imposed by Parliament on such vehicles in the 1830s, which were at least six times the levels of the tolls on horse-drawn carriages, although the latter caused much more damage to the roads. Nor does he mention the law, revoked in 1894, which required each motor vehicle moving on a British road to be preceded by a man carrying a red flag.

Those tolls and restrictions, introduced at the behest of rail and horse-carriage interests, delayed the introduction of self-driven mechanical road vehicles by some 60 years. To this day, rails enjoy massive subsidies in Europe and road development is restricted, despite the substantial fuel taxes paid for road use.

Rails provide important services, especially for moving freight over long distances, but the book has little to say about this, even about the splendid freight services developed in the United States. Rails are also strong in providing underground passenger services in large urban areas. But roads (which do not seem to have been defined in this book) have been with us for millennia, while rails for less than two centuries. Unlike rails, roads are used in all countries. Rails cannot function without roads, but roads can function without rails. Rails for passengers are generally provided at a financial loss, roads often at a profit. It therefore seems that rail systems can never replace road systems, and that a better title for this interesting book would have been “From Road to Rail and Back Again?”

Gabriel Roth *is a transport and privatization consultant. His publications include* Paying for Roads: The Economics of Traffic Congestion *(Penguin Special, 1967);* The Private Provision of Public Services in Developing Countries *(World Bank, 1987*); and Roads in a Market Economy *(Ashgate, 1996). And he edited the 2006 Independent Institute book* Street Smart — Competition, Entrepreneurship, and the Future of Roads.

Transportation Research Forum

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A small group of transportation researchers in New York started the Transportation Research Forum in March 1958. Monthly luncheon meetings were established at that time and still continue. The first organizing meeting of the American Transportation Research Forum was held in St. Louis, Missouri, in December 1960. The New York Transportation Research Forum sponsored the meeting and became the founding chapter of the ATRF. The Lake Erie, Washington D.C., and Chicago chapters were organized soon after and were later joined by chapters in other cities around the United States. TRF currently has about 300 members.

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Government Document:

U.S. Senate. Committee on Foreign Relations, *Investigations of Mexican Affairs*. 2 vols. 66th Cong., 2nd session, 1919-20.

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