The impact of traffic periodicities and spatial relationships on the validity of annual average daily traffic (AADT)

By

GIUSEPPE GRANDE

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Department of Civil Engineering

University of Manitoba

Winnipeg, Manitoba

ABSTRACT

This research presents a series of projects that contribute to the understanding of how traffic variability affects the measurement and application of annual average daily traffic (AADT). AADT is the most fundamental traffic statistic in transportation engineering. It is defined as the number of vehicles expected to use a facility on an average day. However, traffic is known to experience periodical fluctuations over time; these periodicities are location-specific. This underlying variability in time and space can be lost when calculating and reporting AADT.

This research comprises four research projects. The first evaluates the effectiveness of multiple AADT formulations using simulated data loss scenarios. It finds that a relatively new methodology, proposed by the Federal Highway Administration in the United States, removes a small, systematic bias (0.1%) from the existing calculation convention and reduces the width of the 95% confidence interval by 0.5%. The second project provides a method for measuring and reducing the error produced during the assignment step of the AADT estimation process. It applies this method to a case study, finding that the novel assignment method reduces errors by 2.5% on average. The third project explores the use of unconventional traffic data sources (passively-collected vehicle probe data) in tandem with conventional sources. The research finds that speed-based probe data are most closely correlated with truck-specific volume data, specifically around urban centres and along major trade routes. In the studied data, the Pearson correlation coefficient reached 0.9 at some sites. The final project tests the sensitivity of grade crossing design and regulation to predicted fluctuations in traffic. The results show that daily variations in traffic can cause sites to be apparently over- or under-designed for a day or group of days, when compared to regulatory standards. Moreover, they show that within-day variations

can be used to express more detailed grade crossing exposure estimates than the daily averages that are used in current regulations.

On aggregate, the research finds that, while AADT estimates are convenient to calculate and ubiquitously applied, there is a need to better disclose the source data and methodologies used to produce AADT estimates to avoid misuse and false assumptions about comparability. Further, AADT summarizes the traffic at a site into a single average volume, which fails to express the known periodical traffic variability at a site.

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1 INTRODUCTION

1.1 PURPOSE

This research investigates conventional and novel methods for estimating and applying annual average daily traffic (AADT) in light of known traffic volume periodicities and spatial variability. AADT is the most fundamental traffic volume statistic and is ubiquitously used within transportation engineering, planning, and policy applications. Its pervasiveness stems from: (1) a logical need to quantify the average daily traffic at a site in a given year, and (2) the relative ease with which it can be calculated or estimated using measurements of traffic volume readily-produced by traffic monitoring programs.

On the surface, AADT is seemingly simple to comprehend and offers a convenient way to compare traffic volumes between disparate sites or facilities. However, the perceived simplicity and convenience of AADT as a measure of traffic volume masks several underlying complexities. First, the source data used to estimate AADT may be produced by different types of equipment deployed at a fixed location for varying durations—from a partial day to a continuous deployment—or, more recently, from mobile probe devices within the traffic stream. Second, the methods used to estimate AADT vary depending on the source data used and local agency practice. This affects the validity of the AADT statistic and creates uncertainties in its application. Third, while some of the methods used to estimate AADT rely fundamentally on the inherent traffic volume periodicities at a site, paradoxically, the statistic itself—an average—disregards these periodicities. So, two sites with identical AADTs may experience different operational conditions but have the same average daily traffic volume over a full year.

In short, not all AADT estimates are created equal. Yet, transportation practitioners that routinely apply AADT statistics may do so without knowledge of this fact. The purpose of this research is to “unpack” AADT by evaluating methods used to estimate it, to propose novel alternatives to conventional estimation methods, and to demonstrate the need to better understand how the assumptions and uncertainties associated with estimating AADT impact its application.

This thesis comprises a series of independent projects, each of which is published or submitted for publication in a peer-reviewed journal. The themes explored in each project contribute to the purpose of this research.

1.2 BACKGROUND AND NEED

AADT is a fundamental statistic used to characterize traffic volume (Chowdhury et al., 2019; Gastaldi et al., 2013; Jessberger et al., 2016; Pulugurtha and Kusam, 2013). AADT is defined as the total volume of vehicle traffic of a highway or road for a year divided by 365 days (FHWA, 2016b). It is meant to represent traffic on a typical day of the year. Its transportation engineering, planning, and policy applications are varied, including safety analyses (Chen and Xie, 2016; Wang et al., 2014), infrastructure design and evaluation (Li et al., 2009; Muthadi and Kim, 2009), and environmental impact studies (Fu et al., 2017). This section discusses the estimation and application of AADT.

1.2.1 Methods for Estimating AADT

In North America, traffic monitoring practice for estimating AADT is prescribed by the *Traffic Monitoring Practices Guide for Canadian Provinces and Municipalities* (Regehr et al., 2017) in Canada and the *Traffic Monitoring Guide* (FHWA, 2016b) in the United States. Most agencies have minimum data reporting requirements, but in general have flexibility to monitor traffic for their own needs and purposes. Chief among these reporting requirements is to provide AADT estimates at representative sites across a network each calendar year. Specifically, In the United States, AADT is a required traffic data output for all states on an annual basis and will be required for all public roads by 2026 as part of the Highway Safety Improvement Program (FHWA, 2016a). No such federal mandate exists in Canada, though individual provinces and some municipalities effectively comply with this expectation.

Multiple methods exist to estimate AADT that depend on the source data and desired level of accuracy. The most accurate method uses daily traffic volumes obtained from a continuously monitored site for a full year and calculates the AADT as the arithmetic mean. In cases where data are lost or removed due to quality control practices, the American Association of State Highway and Transportation Officials (AASHTO) and Federal Highway Administration (FHWA) methods are recommended to minimize the resultant errors (FHWA, 2016b; Regehr et al., 2017). These errors can be significant, depending on the amount of data removed and the variability in daily traffic experienced at the site (Jessberger et al., 2016). Equation 1.1 shows the AASHTO method, considered the state-of-the-practice for calculating AADT using continuous count data.

$$AADT_c = \frac{1}{12}\sum_{m=1}^{12}\frac{1}{7}\sum_{j=1}^{7}\frac{1}{n_{jm}}\sum_{i=1}^{n_{jm}} VOL_{ijm,c} \tag{1.1}$$

Where:

VOL_{ijm} = total traffic on *i*th occurrence of *j*th day of week within *m*th month

i = occurrence of a particular day-of-week in a particular month

j = day-of-week (1 to 7)

m = month-of-year (1 to 12)

n_{jm} = number of times day j occurs in month m with available traffic data (1 to 5)

c = vehicle classification

Unfortunately, continuous count data are not readily available for large or dense networks, normally due to resource constraints. Instead, agencies collect short duration count data at a relatively large number of sites to maintain high spatial coverage on their networks without surpassing resource limitations. Meanwhile, continuous count data are collected at strategically selected sites to infer characteristic traffic patterns for different road classes and purposes. Generally, these traffic patterns are measured in terms of the average proportion of traffic at the continuous count sites by hour of day, day of week, and month of year (FHWA, 2016b; Regehr et al., 2017). Traffic patterns form the backbone of the entire monitoring program; continuous count data provide the strong temporal data needed to identify traffic patterns, which are used to extrapolate sampled short duration count data across a network. In this way, these complementary count types are used in tandem to produce reasonable AADT estimates given the needs and resources of the monitoring agency. This relationship is contingent on knowledge of which traffic patterns apply to which short duration count sites.

Ongoing research has aimed to develop improved AADT estimation methods (Liu et al.,2019; Monney et al., 2020; Syfridis and Agnolucci, 2020; Tsapakis et al., 2014; Fu et al., 2017; Zhang and Chen, 2020). In most cases, the improvements reduce the average bias of calculated AADT estimates and/or expand the spatial coverage of available estimates by utilizing data in unique ways. Moreover, there are numerous technologies that can be used to enhance the availability of traffic data either by reducing costs, providing multiple forms of traffic data, or by improving coverage in time or space.

Passive data sources have been identified as a potential revolutionary technology to estimate and understand traffic volume (Bachir et al., 2019; Cambridge Systematics Inc. and Massachusetts Institute of Technology, 2018; Fu et al., 2017; Wu et al., 2015). Passive data sources include those that are seemingly unrelated to traffic monitoring but can be used to infer traffic activity (e.g., using location data from cell phones). Passive data sources are desirable due to their relatively low cost and unique coverage capabilities. Cell phones have become increasingly plausible as a source for travel data (e.g., travel behaviour or speed), but have been sparingly utilized as a source for traffic volume to date (Chen et al., 2016). In response to promising research, the FHWA has created a pooled fund project specifically aimed at developing methods for inferring traffic volume from passively collected data (Transportation Pooled Fund Program, 2018).

Past projects have researched the use of call detail records (CDRs) from cell phones to model travel behaviour (Calabrese et al., 2013; Montero et al., 2019; Zhao et al., 2016). However, CDRs have been identified as being sparse in time (records are only generated when devices are in use) and coarse in space (the granularity of cell towers defines the resolution of the location data) (Becker et al., 2013; Cambridge Systematics Inc. and Massachusetts Institute of Technology, 2018), which limits their effectiveness when used in isolation. Thus, efforts have been made to combine CDR data with additional sources to estimate traffic volume (Toole et al., 2015; Wu et al., 2015).

Cell phone signals are not limited to cellular transmissions. Bluetooth and Wi-Fi are ubiquitous features in smartphones. Roadside sensors can be installed to detect active devices within a known radius. Every device has a unique identifier (MAC address) which can be re-identified by multiple sensors to provide trajectory information (Michau et al., 2017). Global positioning systems (GPS) provide highly accurate location information of cell phones. However, these require a constant connection to the GPS network through an active application (such as a mapping application) or for the user to opt-in to passively collect GPS traces (Cambridge Systematics Inc. and Massachusetts Institute of Technology, 2018).

Conventional and passive sensing technologies provide diverse options for measuring various characteristics of traffic with differing levels of accuracy. Table 1.1 summarizes the strengths and limitations of common conventional measurement devices and passive data sources.

Table 1.1: Strengths and limitations of traffic data sources

Data source	Strengths	Limitations
Inductive loops	Measure vehicles Well-known technology Provide all basic traffic measures High level of accuracy	Fixed installation Multiple loops required at most locations Invasive technology Affected by construction at site
Road-side and overhead units	Monitor multiple lanes with one device Provide all basic traffic measures High level of accuracy	Some signal types affected by weather Expensive
Pneumatic tubes	Inexpensive	Require factoring Susceptible to vandalism and wear Being replaced by inductive loops
Travel Surveys	Rich data Trip chaining evident	Low sample size Expensive Require respondent opt-in Infrequent
Cell Phones (CDRs)	High penetration rate Trip purpose evident Collected passively	Sparse temporally Coarse spatially Privacy concerns
GPS	High accuracy Can be collected passively	Require user opt-in
Bluetooth/Wi-Fi	High penetration rate Collected passively	Coarse spatially

The diverse methods and technologies used to estimate AADT are a testament to the importance of this research in further understanding their benefits, shortcomings, and underlying assumptions.

1.2.2 Application of AADT

Traffic volume data are critical inputs to a variety of transportation applications and functions (FHWA, 2016b; Regehr et al., 2017). However, given the widespread nature of transportation networks, there are often locations where traffic data may be limited to weak estimates of AADT. Moreover, transportation applications that use AADT as an input can be agnostic of context, since the means by which traffic volume data are collected and the methods used to estimate AADT may not be formally disclosed. Thus, it is possible that a particular application may rely on a relatively inaccurate or imprecise estimate of AADT without a robust consideration of the impacts of doing so (Sharma and Allipuram, 1993; Gadda et al., 2008).

Traffic volumes vary with time and often fall into patterns (FHWA, 2016; Regehr et al., 2017). Conventional AADT calculations apply knowledge of these cyclical variations (periodicities) to infer relationships between existing and missing or unmeasured data (i.e., they assume that missing or unmeasured data would exhibit patterns consistent with existing data from the same hour, weekday, and month) (Jessberger et al., 2016; Milligan et al., 2016; Monney et al., 2020). However, regardless of the method used to estimate AADT, the statistic itself remains an average that masks these underlying variations and their potential impacts within the application context. In other words, any application of AADT relies on an average value, which may never actually occur and which by its nature disregards real variations observed in the data.

To illustrate the foregoing point, consider an analogy in the field of pavement design and evaluation. For several decades, pavement design practice has utilized a summary statistic—equivalent single axle loads (ESALs)—as the principal traffic-related input for selecting pavement material thicknesses (AASHTO, 1993). An ESAL is an empirically-developed value that describes the load-response of an axle passage and expresses it in terms of the number of repetitions of a standard 80-kN (18-kip) single-axle load (AASHTO, 1993; Papagiannakis and Masad, 2008). In design, the cumulative number of ESALs is estimated based on the volume and loading characteristics of the traffic expected to use a facility. Thus, while the calculation of this cumulative value involves a disaggregated assessment of specific axle passages, the design value itself masks this underlying complexity. This situation is analogous to the estimation and application of AADT.

In recognition of this limitation, pavement design practice has evolved toward a mechanistic-empirical approach, which estimates the spectrum (or distribution) of loads that vehicles will impose on the road (Applied Research Associates, 2004; Li et al., 2009; Muthadi and Kim, 2009). This approach retains relevant details that may be lost by using summary statistics and, more broadly, aligns with probabilistic (or reliability-based) design approaches that are emerging within civil engineering practice (Ellingwood, 2000; Porter et al., 2019). Returning to the analogy, the spectrum of loads imposed on roads is analogous to the known temporal variations in traffic volume. Like in pavement design, there is merit in examining the impact of retaining the underlying distributions when reporting and applying traffic volume, rather than relying solely on summary statistics. To demonstrate the foregoing concept, this thesis analyzes how accounting for traffic volume periodicities rather than reliance on AADT impacts the design and regulation of grade crossings. A grade crossing is the intersection of a railway and a roadway at the same elevation. Regulations specify minimum grade crossings treatment requirements, which may range from passive treatments (e.g., static signs), to active treatments (e.g., crossing gates), to full grade separation. The product of AADT and annual average daily rail movements (AADRM) at a crossing is commonly used as a basis for treatment selection and design (FHWA, 2019; National ALCAM Group, 2016; Taggart et al., 1987). Transport Canada defines this product as the cross-product (Transport Canada, 2014). It is synonymous with crossing exposure (FHWA, 2019; National ALCAM Group, 2016) and traffic moment (Liang et al., 2018; Pyrgidis et al., 2016; RSSB, 2010). In some cases, non-annualized versions of average daily traffic (i.e., ADT) and rail movements are considered when calculating these statistics. Regardless of the term used, cross-product represents the exposure at a grade crossing and acts as a surrogate for both safety risk and user delay costs (Nichelson and Reed, 1999). Chapter 5 of this thesis examines cross-product regulations in Canada in the context of the uncertainties that exist when estimating AADT.

1.3 OBJECTIVES AND SCOPE

The purpose of this research is to investigate conventional and novel methods for estimating and applying annual average daily traffic (AADT) in light of known traffic volume periodicities and spatial variability. This purpose is accomplished through four research objectives, framed below as a set of questions:

Objective 1: What magnitude of errors are produced when estimating AADT from continuous count traffic data using state-of-the-practice methods? What are the implications of recent modifications to the methods?

Objective 2: What magnitude of errors are produced when estimating AADT from short duration traffic count data using the state-of-the-practice approach? Can a novel assignment method reduce the errors caused by poor assignment to traffic pattern groups?

Objective 3: What attributes of passively-collected probe data can be used to improve short duration count programs?

Objective 4: How sensitive are grade crossing design and regulation to the known variability in traffic relative to average statistics (i.e., AADT)?

The analyses conducted to pursue the foregoing objectives use traffic data sourced from the Manitoba Highway Traffic Information System (MHTIS), the traffic monitoring program in the province of Manitoba, Canada. The MHTIS provides traffic statistics for all provincially-owned roads.

The scope for Objective 1 is defined by the source data, the analysis methods, and the selected analysis period. Study locations are selected where vehicle classification data are available, in an hourly volume format, for an entire year from the MHTIS. Thus, the geographic scope of Objective 1 includes 31 automatic vehicle classification sites distributed on Manitoba's provincial highway network. The temporal scope of Objective 1 includes data from 2010 to 2015, inclusive. The research uses median percent error and mean absolute percent error as evaluation measures to align with previous research (Gastaldi et al., 2013; Jessberger et al., 2016; Milligan et al., 2016; Wang et al., 2014; Zheng and Liu, 2017). Objective 1 considers five methods for calculating AADT. Four of these methods are explicitly discussed in Jessberger et al. (2016), while the remaining method is an implicit improvement to the state-of-the-practice (AASHTO) method.

The scope for Objective 2 is defined by the source data and the analysis methods. Study locations are selected where hourly traffic data are available for an entire year from the MHTIS. Thus, the geographic scope of Objective 2 includes 86 continuous count sites distributed on Manitoba's provincial highway network. The temporal scope of Objective 2 includes traffic data from 2018. The research uses mean percent error and standard deviation to assess the accuracy and precision of AADT estimates, based on the findings from previous research Jessberger et al. (2016). Methodologically, Objective 2 samples continuous count data to produce simulated short duration traffic count data, as is done in Gadda et al. (2008) and Milligan et al. (2016), and uses these simulated traffic count data to estimate AADT following the conventional approach (FHWA, 2016b; Regehr et al., 2017).

The Scope for Objective 3 is defined by the source data and the analysis methods. Study locations on the Manitoba highway network are selected where hourly traffic data are available for an entire year from the MHTIS. Transport Canada provides passively-collected probe data from HERE Technologies™ , which are available on all highways in Canada. These data are combined with Manitoba highway traffic data. Thus, the geographic scope of Objective 3 includes 86 continuous count sites distributed on Manitoba's provincial highway network. The temporal scope of Objective 3 includes traffic data from 2018. Methodologically, the research analyzes the correlation between multiple attributes of passively-collected probe data and traditional traffic data.

The scope for Objective 4 is defined by multiple data sources and the analysis methods. Transport Canada provides geometric, control, and traffic condition data for all grade crossings in Canada in their Grade Crossings Inventory, available through their open access data portal (Transport Canada, 2018). The Grade Crossings Inventory provides data for both publicly and privately controlled grade crossings. The MHTIS provides detailed traffic data for rural grade crossings on provincially governed (i.e. publicly controlled) roads. Urban traffic data are estimated from the results of Regehr et al. (2012). These estimates are also limited to publicly controlled roads. Finally, detailed rail data are provided by TRAINFO® sensors at selected grade crossings in Winnipeg. Thus, the geographic scope of Objective 4 varies with the analysis being conducted. Specifically, the scope is limited to publicly controlled grade crossings in rural Manitoba for analyses only involving detailed traffic data. The scope is further refined to urban roads in Winnipeg for analyses that combine detailed traffic and rail data. The temporal scope of Objective 4 is 2015 to 2017, the years for which sensor data are available. Methodologically, the scope of Objective 4 is limited to procedures which yield metrics that are directly comparable to current grade crossing regulation in Canada (i.e., that are relatable to the cross-product).

1.4 APPROACH, THEME, AND CONNECTING CONCEPTS

The approach for this research achieves the objectives by conducting a series of four interrelated projects whose scopes and outcomes map directly to one objective. As a whole, the projects contribute to the over-arching research theme of improving the estimation and application of AADT in light of known traffic volume periodicities and spatial variability.

The first two projects evaluate uncertainties (accuracy and precision) associated with AADT estimates produced through conventional traffic monitoring methods. In these projects, accuracy is expressed as the mean percent error or absolute mean percent error between a group of estimates and the assumed true value. This represents the tendency for estimates to be close to the target value. For example, a group of estimates whose mean deviates from the target value by 1% is, on aggregate, more accurate than a second group whose mean deviates from the target value by 2%. Conversely, precision represents the tendency for estimates to be close to each other. Precision is expressed by the variance or standard deviation within a group of estimates.

More specifically, the first project evaluates the formulations used to calculate AADT at a continuous count site. It uses continuous count data to create simulated data-loss scenarios while maintaining knowledge of the ground truth AADT at each tested site. Then, it tests each of five different formulations in each scenario to measure the bias, or error relative to the ground truth, when estimating AADT. The results are used to reveal the effects of each step in the formulations on the resultant AADT estimates in terms of their accuracy and precision.

The second project focuses on AADT estimates obtained from short duration count data using conventional methods and proposes a new method that reduces estimation error related to the assignment of short-duration counts to traffic pattern groups. Continuous count data are sampled to produce simulated short duration count data (in this case, 48-hour counts). In this way, as in the first project, this process maintains knowledge of the ground truth AADT at each tested site. The simulated short duration count data are used to benchmark the errors produced when estimating AADT using the conventional method. The analysis specifically isolates the portion of this error that can be attributed to the assignment step of the AADT estimation procedure by applying temporal adjustment factors from various traffic pattern groups. Finally, it develops and applies a method for assignment that is data-driven and independent of the roadway or operational characteristics at the short-duration count site.

Like the second project, the third project also proposes a potential enhancement of short-duration count programs, in this case by exploring the potential to integrate passively-collected probe data. The analysis explores relationships between attributes of continuous count data and speed-based probe data, provided by a third party data analytics company. These relationships are evaluated to identify trends temporally, spatially, and with respect to vehicle classifications. The strength and form of the relationships reveal opportunities to use probe data to enhance short-duration truck traffic monitoring programs.

Finally, the fourth project demonstrates the sensitivity of a particular traffic volume data application—the design and regulation of grade crossings—to the use of detailed traffic volume distributions relative to average statistics. In this project, continuous count data and available rail traffic data are used to artificially create daily variations in grade crossing exposure. These variations are compared to regulatory limits to test the sensitivity of this application to natural fluctuations in traffic over time. The research extends this line of thinking by using detailed rail traffic data to test the average variability in grade crossing exposure within a single day. Again, this variability is compared to the regulatory limits to develop insights on the validity of using daily averages to assess grade crossing exposure.

1.5 THESIS ORGANIZATION

The thesis is organized as a grouped manuscript or sandwich style thesis. The following four chapters each reproduce self-contained research papers. The papers each accomplish one of the objectives of the thesis and provide further detail on the methods and findings from the conducted work. Chapter 2 presents a research paper on the effects of various calculation techniques on AADT estimates. This chapter addresses Objective 1 of the research. Chapter 3 presents a research paper on an approach to quantifying and reducing errors related to the assignment step of AADT estimation using short duration count data. It addresses Objective 2 of the research. Chapter 4 presents a research paper on the relationships between speed-based probe data and conventional traffic data. It addresses Objective 3 of the research. Chapter 5 presents a research paper on grade crossing warning system design and the use of AADT when more detailed traffic data are available. It addresses Objective 4 of the research.

Finally, Chapter 6 concludes the thesis. It summarizes the contributions to knowledge made by each of the individual research papers, draws conclusions from the connecting themes between the works, and presents future research opportunities that stem from the findings of this research.

1.6 THESIS TERMINOLOGY

- Annual average daily traffic (AADT) – the expected number of vehicles using a facility or passing a point on a facility on a typical day for a given year.
- Bias – the difference between an estimated or calculated value and its true value.
- Exposure – the number of users that are in a situation involving some risk (e.g., of a collision).
- Grade Crossing – an intersection of at least one roadway and one railway facility that are at the same elevation.
- Passively-collected data – data that are collected for non-traffic applications that have use in traffic monitoring.
- Traffic volume – the number of vehicles using a facility or passing a point on a facility over a period of time.

2 EVALUATING AADT CALCULATION METHODS WITH CONTINUOUS TRUCK TRAFFIC DATA

This chapter begins the investigation of AADT estimation and application by testing the validity of AADT formulations using continuous count data. It seeks to answer the first set of objective questions: *What magnitude of errors are produced when estimating AADT from continuous count traffic data using state-of-the-practice methods? What are the implications of recent modifications to the methods?*

The analysis in this paper simulates data-loss scenarios at continuous count sites and tests five difference formulations to measure the resultant biases. It contributes to the thesis theme of improving AADT estimation and application by distilling a novel estimation method into two steps and isolating the effect of each step on the validity of the resultant AADT estimates.

The material in this chapter is published in (Grande et al., 2017), and reprinted with permission of the publisher and co-authors Steven Wood, Auja Ominski, and Jonathan Regehr. The chapter is self-contained with its own abstract, introduction, and conclusion; references are provided at the end of the thesis. The thesis author conducted the analysis, interpreted results, and prepared the manuscript.

2.1 ABSTRACT

Traffic volume, often measured in terms of annual average daily traffic (AADT), is a fundamental output of traffic monitoring programs. At continuous count sites, unusual events or counter malfunctions periodically cause data loss, which influence AADT accuracy and precision. This paper evaluates five methods used to calculate AADT, including the use of a simple average, the commonly-adopted method developed by the American Association of State Highway and Transportation Officials (the AASHTO method), and methods that incorporate adjustments to the AASHTO method. The evaluation imposes data removal scenarios designed to simulate real-life causes of data loss to quantify the accuracy and precision improvements provided by these adjustments. Truck traffic data are used to reveal issues arising when volumes are low or when they exhibit unusual temporal patterns.

The evaluation showed that the FHWA method, which unlike the AASHTO method incorporates a weighted average and an hourly base time period, provided the most accurate and precise results in all data removal scenarios. Specifically, when up to 15 days of data are randomly removed, application of the FHWA method can be expected to produce errors within approximately ±1.4 percent of the true AADT, 95 percent of the time. The results also demonstrated that including a weighted average primarily improves AADT accuracy, while precision is influenced by the use of hourly rather than daily count data. As possible, practitioners contemplating the adoption of the FHWA method should assess its relative advantages within their local context.

2.2 INTRODUCTION

Traffic monitoring programs are implemented by jurisdictions to characterize traffic usage of a road network, often as part of broader transportation information or performance measurement systems. Traffic volume is a fundamental output of these programs. Volume is commonly expressed in terms of the annual average daily traffic (AADT), which is the mean daily traffic volume in a given year at a site. At continuous count sites, AADT can be calculated directly from available data. At sites where only a sample of data are available, AADT can be estimated by applying adjustment factors derived from continuous datasets which account for expected temporal variations in traffic volume at the site. AADT is a fundamental input to a range of transportation-related applications including, inter alia, road network planning, infrastructure design, and safety analyses (FHWA, 2016b; AASHTO, 2009).

Because of the numerous applications of AADT, it is worthwhile to consider opportunities to improve AADT accuracy and precision. To this end, Jessberger et al. (2016) evaluated currently-adopted methods of calculating AADT at continuous count sites under various data removal scenarios. This analysis utilized data from nearly 500 continuous count sites across the United States, representing 43 states plus the District of Columbia, 12 of the 14 highway functional classes, and various daily total traffic volume ranges. The analysis resulted in a proposed new method to calculate AADT at a continuous count site (referred to hereafter as the FHWA method). This method improved both AADT accuracy and precision relative to current methods.

The motivation for the research presented in this paper stems from the need to evaluate the new FHWA method using locally-collected traffic data to assess its suitability for adoption in Manitoba, Canada. The primary objective of the evaluation is to quantify the potential improvement provided by the FHWA method at continuous count sites with low volumes and which exhibit unusual or highly variable traffic patterns. To accomplish this, the evaluation utilizes truck traffic data extracted from a network of 45 continuous classification sites in Manitoba. Truck traffic is normally a relatively small component of total traffic at a continuous count site and is known to generate unique temporal traffic patterns in response to a host of industry-specific influences (FHWA, 2016b; AASHTO, 2009; Weinblatt, 1996; Cambridge Systematics Inc., Washington State Transportation Center, and Chapparral Systems Corporation, 2005; Regehr and Reimer, 2013). A secondary objective of the paper is to quantify separately the effects of the two changes proposed in the FHWA method—namely, the introduction of a weighted average and the use of an hourly rather than daily base time period. While the evaluation presented in this paper utilizes data from Manitoba, the findings are transferrable to any jurisdiction interested in assessing the local suitability of the new FHWA method. Moreover, the paper presents an independent corroboration of the results reported by Jessberger et al (2016).

To achieve the foregoing objectives, the evaluation includes five methods used to calculate AADT from continuous count data. The first of these utilizes a simple average, while the other four are variants of the commonly-adopted American Association of State Highway and Transportation Officials (AASHTO) method. The modifications made to the AASHTO method are expected to improve AADT accuracy and precision (Jessberger et al., 2016). Each method is evaluated under data removal scenarios devised to simulate real-world causes of data loss. The following sections of this paper provide a detailed description of the evaluation methodology, summarize and discuss the results of the evaluation, and outline conclusions and implementation considerations.

2.3 METHODOLOGY

This section describes (*a*) AADT calculation methods, (*b*) source data, (*c*) data removal scenarios, and (*d*) bias and statistical measures.

2.3.1 AADT Calculation Methods

Continuous counters ideally provide 24 hours of data for every day of the year. Counters with vehicle classification capabilities provide these data by vehicle class, for example, by applying the FHWA 13-vehicle classification scheme. The methods available to determine the AADT at a continuous count site can be applied to the total traffic dataset, or to class-based subsets of the dataset. The evaluation in this paper uses only truck traffic data (i.e., data for FHWA classes 5 to 13). Thus, annual average daily truck traffic (AADTT) is used as a metric instead of AADT.

When a complete dataset is available for a year (i.e., data exist for each of the 24 hours in each day of the year), a simple average of daily traffic can be used to calculate the true AADT at a continuous count site (*1*)(*3*). Thus, for the Simple Average method, the formula for calculating AADT for a vehicle class, *c*, is given by Equation 2.1:

$$AADT_c = \frac{1}{n}\sum_{i=1}^{n} VOL_{i,c} \tag{2.1}$$

where

VOL_i = total traffic on ith day of year;

n = number of days in a particular year; and

c = FHWA vehicle class.

When data are missing because of counter malfunctions, roadway construction, or other causes, the Simple Average method misrepresents the true AADT.

The AASHTO method (Equation 2.2) mitigates the potential for error in AADT calculations when data are missing by leveraging the predictable weekly and monthly periodicities of traffic volume (*1*)(*2*)(*3*). The AASHTO method requires a complete day of data for at least one of each day-of-week in each month. The underlying assumption is that the traffic volumes on a particular day-of-week in a month are constant. The multiple averages included in the formula—sometimes referred to as an 'average-of-averages'—correspond to the day-of-week and monthly factors required for adjusting short-duration counts.

$$AADT_c = \frac{1}{12}\sum_{m=1}^{12}\frac{1}{7}\sum_{j=1}^{7}\frac{1}{n_{jm}}\sum_{i=1}^{n_{jm}} VOL_{ijm,c} \qquad (2.2)$$

where

$\mathrm{VOL_{ijm}}$ = total traffic on ith occurrence of jth day of week within mth month;

i = occurrence of a particular day-of-week in a particular month;

j = day-of-week (1 to 7);

m = month-of-year (1 to 12);

$\mathrm{n_{jm}}$ = amount of times day j occurs in month m for which traffic data is available; and

c = FHWA vehicle class.

The AASHTO method is inherently biased, as it assigns equal weights to each of the 84 averages (7 days-of-week for 12 months) used to calculate AADT (Jessberger et al., 2016). The AADT produced by this method may differ from the true AADT due to the imbalanced occurrence of weekdays in a given month (e.g., some months may have five Tuesdays but only four Wednesdays) and the imbalanced number of calendar days in each month (i.e., 28, 29, 30, or 31). Jessberger et al. (2016) quantified the median AADT bias of the AASHTO method at -0.05 percent, even when no data were missing.

In the FHWA method, Jessberger et al. (2016) proposed two modifications to the AASHTO method. First, the FHWA method makes use of weighted averages to eliminate the bias in the AASHTO method. Second, the FHWA method uses an hourly rather than daily base time period. This means that the first step in the calculation is the summation of hourly counts rather than an averaging of daily counts for a particular day-of-week in a month. This allows for the use of data from days without a full 24 hours of data. Including partial days of data is beneficial because fewer valid data are discarded and the hourly factors needed to adjust partial-day counts are directly available from the calculation process. Equation 2.3 combines these two modifications:

$$AADT_c = \frac{\sum_{m=1}^{12} d_m * \dfrac{\sum_{j=1}^{7} w_{jm} * \sum_{h=1}^{24}\left[\frac{1}{n_{hjm}}\sum_{i=1}^{n_{hjm}} VOL_{ihjm,c}\right]}{\sum_{j=1}^{7} w_{jm}}}{\sum_{m=1}^{12} d_m} \tag{2.3}$$

where

VOL_{ihjm} = total traffic on ith occurrence of the hth hour within jth day-of-week within mth month;

i = occurrence of a particular day-of-week in a particular month;

h = hour-of-day (1 to 24);

j = day-of-week (1 to 7);

m = month-of-year (1 to 12);

n_{hjm} = number of times hour h within day j of week occurs during month m for which traffic data are available;

w_{jm} = number of times day j occurs during month m;

d_m = number of days in month m; and

c = FHWA vehicle class.

This paper evaluates the two modifications in the FHWA method independently. Thus, five AADT calculation methods are evaluated: (*a*) the Simple Average method, (*b*) the AASHTO method, (*c*) the AASHTO method modified to use a weighted average (AASHTO Weighted), (*d*) the AASHTO method modified to use hourly counts rather than daily counts (AASHTO Hourly), and (*e*) the FHWA method. Table 2.1 summarizes the attributes of these methods.

Table 2.1: Attributes of AADT Calculation Methods

Method	Systematic adjustment for missing data?	Proper weighting of days?	Hourly base time period?
Simple Average		✓	
AASHTO	✓		
AASHTO Weighted	✓	✓	
AASHTO Hourly	✓		✓
FHWA	✓	✓	✓

2.3.2 Source Data

Source data used for the evaluation of the methods were extracted from Manitoba's database of continuous classification data for 2010 to 2015, inclusive. Manitoba currently maintains a network for 45 continuous classification sites. For a site to be included in the evaluation, a complete set of hourly truck traffic data was required for at least one calendar year. In Manitoba, normal data retrieval protocols occasionally result in the loss of a small number of hours in a particular day. Thus, to increase the number of eligible sites for this evaluation, sites with at least 22 hours of data for every day of the year were considered. In these cases, every hour of missing data was imputed, prior to the evaluation, by taking the average of every other occurrence of that hour in that day-of-week within the month. In total, 31 sites were used in the evaluation. As shown in Table 2.2, these sites capture different truck trip-making purposes and represent a range of truck traffic volumes and years.

Table 2.2: Summary of Continuous Classification Sites Used in the Evaluation

Classification by Prevalent Truck Trip Types at Site		Classification by AADTT Range		Classification by Year	
Trip Type	**Number of Sites**	**AADTT**	**Number of Sites**	**Year**	**Number of Sites**
Roads that serve inter- and intra-provincial trips	11	0 - 240	14	2010	4
		241 - 480	9	2011	4
		481 - 960	3	2012	8
Roads that serve primarily intra-provincial trips	20	961 - 1920	3	2013	2
		1920 - 3840	2	2014	10
				2015	3

2.3.3 Data Removal Scenarios

The evaluation examines the accuracy and precision of the AADTT calculated using the five methods under three data removal scenarios, as described in the subsequent paragraphs. The three scenarios simulate real-life situations known to cause data loss such as road closures, road construction, and counter malfunctions. Moreover, the scenarios were designed to test the expected advantages and disadvantages of the five calculation methods. Holidays were treated as normal weekdays in all data removal scenarios.

Scenario 1 simulates a short-term data loss corresponding to a day-long non-recurrent event (e.g., an extreme weather event) at or near the count site which generates invalid truck traffic volumes. As shown schematically in Figure 2.1a, data were removed for the full 24-hour period (12:00 AM to 11:59 PM) for each day of the year. This data removal scenario was repeated 365 or 366 times for every site, depending on the year. The scenario was designed to reveal the impact of removing a relatively small amount of data and to isolate the effect of using a weighted average. Since a full 24 hours of data were removed, the use of an hourly base time period is expected to have no effect on the AADTT calculation.

Scenario 2 simulates a longer-term data loss corresponding to a non-recurrent event at or near the count site which generates invalid truck traffic volumes during normal working hours for a two-week period (e.g., a construction project involving a lane closure). As shown in Figure 2.1b, data from 7:00 AM to 4:59 PM were removed for every weekday (Monday to Friday, inclusive) for two consecutive weeks. Thus, for each iteration of the scenario, a total of 100 hours (10 hours for 10 days) of data were removed when applying the methods with an hourly base time period, whereas 240 hours (24 hours for 10 days) of data were effectively removed when applying the methods with a daily base time period. This data removal scenario was repeated 50 times for each site, once per week in the year while avoiding partial weeks at the beginning and end of the year. The scenario was designed to reveal the effects of two conditions: (*a*) the loss of data for specific days of the week (i.e., by only removing data for weekdays, which tend to have different truck traffic patterns than weekends), and (*b*) removal of data in well-defined hourly cycles (i.e., by removing the same 10 hours from every day for a pre-determined interval). It is expected that these changes will reveal the impacts of using an hourly base time period instead of a daily base time period.

Scenario 3 simulates the loss of data for a random duration, ranging from one hour to fifteen days, starting at a random time in the analysis year. This type of data loss corresponds to a counter malfunction. The data removal in this scenario was conducted in two steps. First, a random duration was established within the aforementioned range. Second, a random starting hour of the year was chosen, subject to a constraint to ensure that the entire duration remain within the analysis year. Figure 2.1c shows one example of data removal in this scenario. In this case, data removal starts at 2 PM on January 5^{th} and extends for 75 hours to January 8^{th} at 4 PM (data up until 4:59 PM are removed). The next iteration would select another random duration and starting hour. The fifteen-day maximum duration ensures that sufficient data existed in every month to apply each of the calculation methods. Unlike Scenarios 1 and 2, Scenario 3 does not iterate sequentially through the year; rather, this data removal scenario was repeated 3000 times for each site. This scenario was designed to produce comprehensive results to compare the five methods and to evaluate how the duration of data removal influences AADTT accuracy and precision.

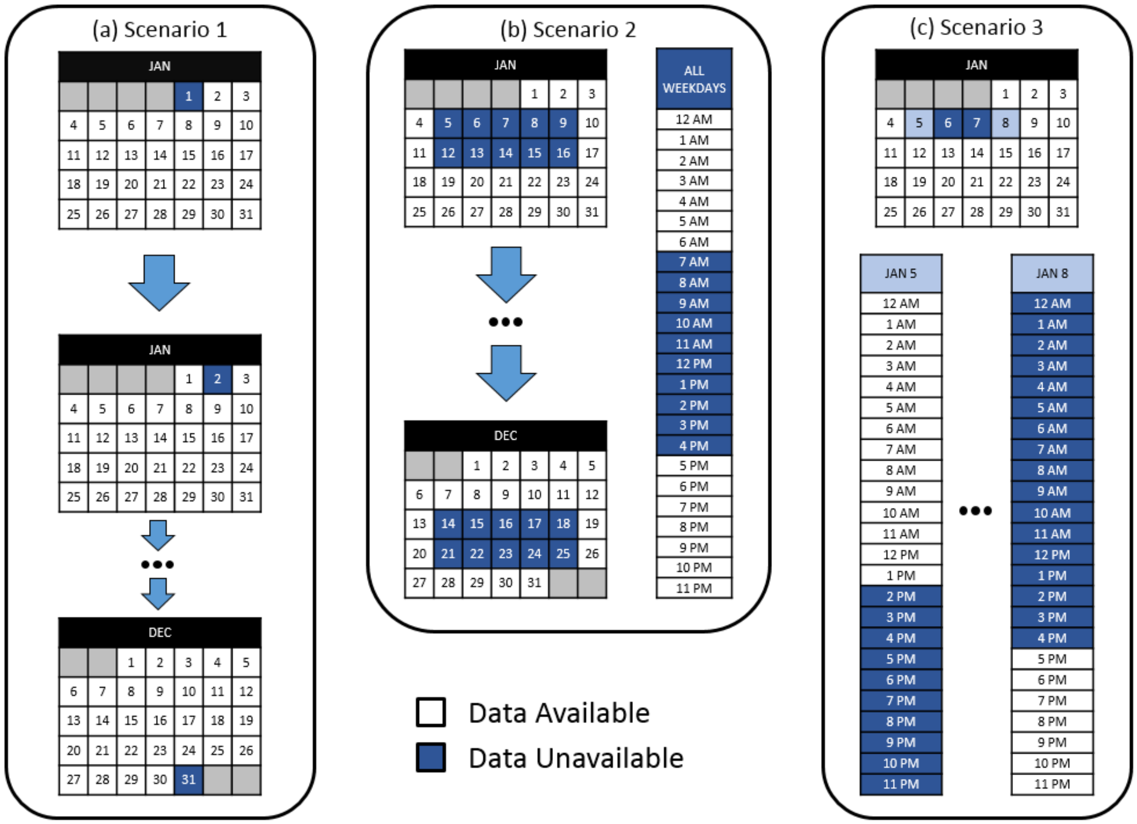


Figure 2.1: Illustration of data removal for (a) scenario 1, (b) scenario 2, and (c) scenario 3

2.3.4 Bias and Statistical Measures

The five methods were evaluated by determining the bias or error of the AADTT calculated by each method, similar to the work documented by Jessberger et al (2016). In the evaluation, bias is defined as the percent difference between the calculated AADTT and the true AADTT at a site, as given by Equation 2.4:

$$bias = \frac{Estimated\ AADTT - True\ AADTT}{True\ AADTT} \times 100 \tag{2.4}$$

Since the source data are complete, the true AADTT is given by the Simple Average method (Equation 2.1). The evaluation references three common statistical measures:

- The median bias is an indication of the accuracy of the AADTT, accounting for both positive and negative biases.
- The mean absolute bias is an indication of the accuracy of the AADTT which describes how far the calculated AADTT is from the true AADTT, without regard for the direction of the bias.
- The 95 percent confidence interval (95% CI) of the biases is a measure of the precision of the calculated AADTT. Narrower 95% CIs indicate less deviation from the median bias.

2.4 RESULTS

This section summarizes the evaluation results for each of the three data removal scenarios. It presents the aggregated scenario results for all sites and also discusses site-specific results to illustrate salient points. For context, key attributes of the two sites discussed for illustrative purposes in the evaluation follow:

- Site 1 is located on an inter-provincial trucking route. The AADTT at the site in 2012 was 1140 trucks per day. This site experiences larger truck volumes on weekdays than weekends and increased truck traffic during spring and fall.
- Site 2 is located on an intra-provincial trucking route. The AADTT at the site in 2014 was 90 trucks per day. This site experiences larger truck volumes on weekdays than weekends. In 2014, the truck traffic was relatively constant throughout winter and spring, but exhibited substantial increases in July, August, and October due to a construction project in the vicinity of the site.

2.4.1 Scenario 1

Scenario 1 involves the removal of a whole day (i.e., 24 hours) of data for each iteration. Thus, as expected, the results for the AASHTO and AASHTO Hourly methods are identical, as are the results from the AASHTO Weighted and FHWA methods. For simplicity, only results for the Simple Average, AASHTO, and FHWA methods are discussed.

Figure 2.2 shows the bias associated with the removal of data for each day of the year when the AADTT is calculated using the Simple Average, AASHTO, and FHWA methods at Site 1 and Site 2. The figure reveals three pertinent findings. First, application of the AASHTO method yields a consistently larger bias compared to the FHWA method. This bias is positive at Site 1 and negative at Site 2. Generally, the biases for the FHWA method are within ±0.25 percent for both sites, with smaller biases evident at Site 1 which exhibits more stable daily truck volumes. Second, the biases generated from the FHWA method appear to be less variable than those generated from the AASHTO and Simple Average methods. This is particularly evident at Site 2. Third, the relatively high daily truck traffic volumes during the summer and fall at Site 2 coincide with erratic results for all three methods. In other words, none of the three methods fully compensates for the bias introduced when removing data for a day with atypical (but valid) volumes.

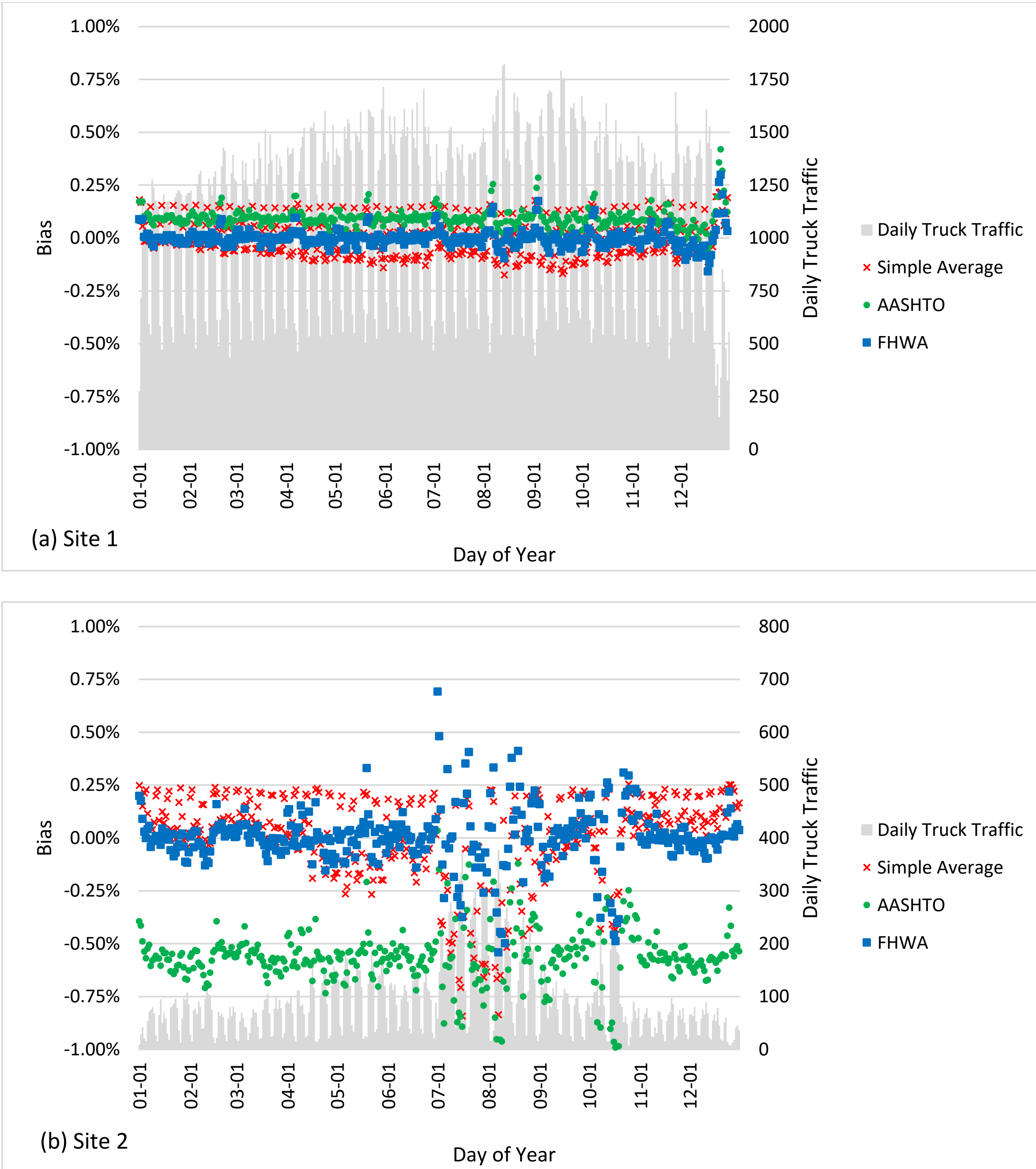


Figure 2.2: Results from scenario 1 for (a) site 1 and (b) site 2

Table 2.3 provides the Scenario 1 results for all sites combined; these results reinforce the foregoing site-specific findings. Application of the FHWA method yields smaller median and mean absolute biases relative to the Simple Average and AASHTO methods. Specifically, for the FHWA method, effectively no median bias is observed and the mean absolute bias is 0.05 percent. While larger, the median and mean absolute biases for the Simple Average and AASHTO methods are all very small (the median biases are nearly zero and the mean absolute biases are within 0.15 percent). Additionally, application of the FHWA method produces biases with a narrower 95% CI width than the other methods (0.33 percent compared to 0.45 percent for the Simple Average method and 0.86 percent for the AASHTO method). Overall, Scenario 1 results show that the introduction of the weighted average within the AASHTO Weighted and FHWA methods improves AADTT accuracy and may also contribute to better precision.

Table 2.3: Summary of Results from Scenarios 1, 2, and 3

	Scenario 1			Scenario 2			Scenario 3		
Method	**Median Bias**	**95% CI Width**	**Mean Abs. Bias**	**Median Bias**	**95% CI Width**	**Mean Abs. Bias**	**Median Bias**	**95% CI Width**	**Mean Abs. Bias**
Simple Average	-0.02%	0.45%	0.11%	-0.58%	2.56%	0.74%	-0.01%	2.23%	0.38%
AASHTO	0.03%	0.86%	0.13%	-0.01%	2.09%	0.37%	0.01%	1.87%	0.30%
AASHTO Weighted	- [a]	- [a]	- [a]	-0.03%	2.01%	0.35%	-0.02%	1.78%	0.27%
AASHTO Hourly	- [b]	- [b]	- [b]	0.00%	1.61%	0.29%	0.01%	1.73%	0.27%
FHWA	0.00%	0.33%	0.05%	-0.02%	1.51%	0.26%	-0.01%	1.64%	0.24%

CI denotes confidence interval
[a] identical to results for FHWA method
[b] identical to results for AASHTO method

2.4.2 Scenario 2

Scenario 2 involves the removal of data for the weekday working hours (i.e., 7:00 AM to 4:59 PM, Mondays through Fridays) for two consecutive weeks. Table 2.3 provides the

Scenario 2 results for all sites combined. When comparing these results to those obtained for Scenario 1, it is evident that, regardless of method, the mean absolute biases and 95% CI widths for these biases are larger for Scenario 2. Notably, despite the extent of data loss, all the mean absolute biases remain within one percent. The median biases do not exhibit a consistent trend. Moreover, because a larger quantity of data is removed, the relative weakness of the Simple Average in terms of median bias, 95% CI width, and mean absolute bias is more apparent in Scenario 2 than in Scenario 1.

When comparing the performance of the methods within Scenario 2 specifically, the results indicate that the FHWA method has the smallest mean absolute bias (0.26 percent) and the AASHTO Hourly method has the smallest median bias (0.00 percent). The 95% CI widths for the biases produced by the AASHTO and AASHTO Weighted methods are nearly identical. Likewise, the 95% CI widths for the biases produced by the two hourly methods (AASHTO Hourly and FHWA) are similar to each other, but narrower than those produced by the AASHTO and AASHTO Weighted methods. This appears to imply that the ability to limit data loss by using an hourly rather than daily base time period (as is evident when comparing the AASHTO Hourly and AASHTO methods) is the primary contributor to the improved precision of the results, since a precision improvement is not evident when comparing the AASHTO Weighted and AASHTO methods.

2.4.3 Scenario 3

Scenario 3 involves the removal of data for 3000 random durations and starting times at each site. Thus, the results enable comprehensive comparisons of the methods and reveal the influence of the duration of data loss on accuracy and precision. Comparisons between the Scenario 3 results and those from Scenarios 1 and 2 are not as instructive.

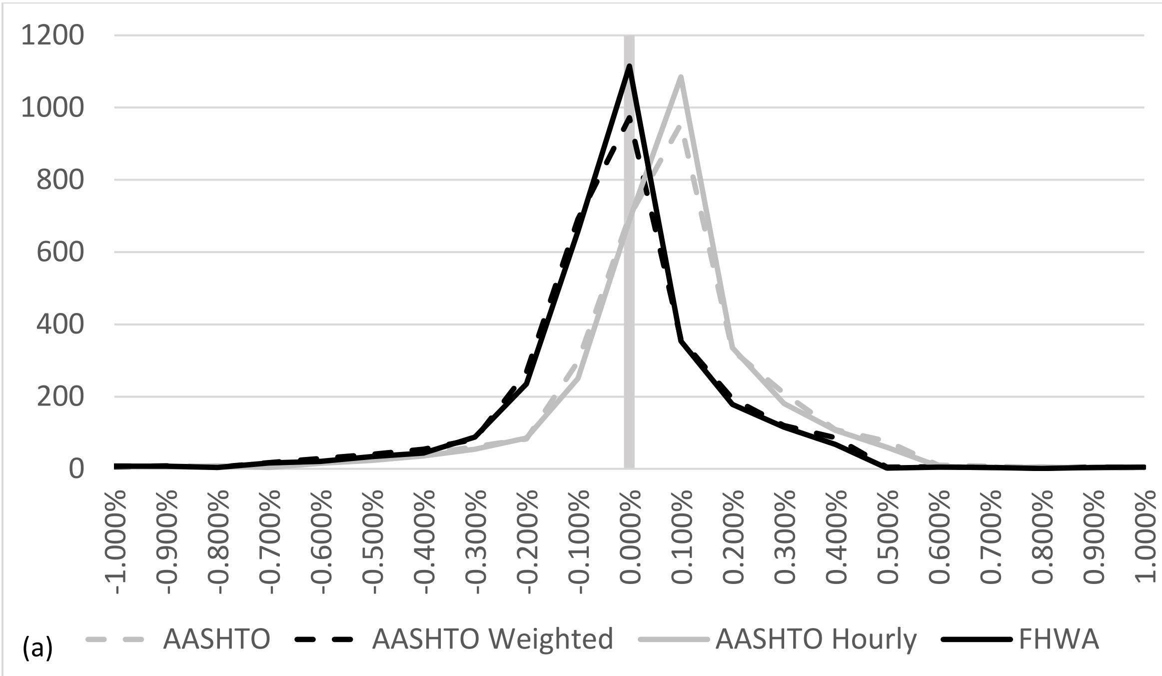
Referring again to Table 3, which considers all sites combined, the application of the FHWA method produces biases with the narrowest 95% CI width and the smallest mean absolute bias (1.64 percent and 0.24 percent, respectively). For all methods, the mean absolute bias is within 0.4 percent. As in Scenario 2, the two hourly methods have the two smallest 95% CI widths.

The median biases produced by the five methods in this scenario are all very small (within 0.02 percent). However, unlike the mean absolute biases and the 95% CI widths, the median biases do not exhibit a clear trend. (This was also evident in the results for Scenario 2). To investigate this further, the 31 sites were disaggregated into two groups: one group containing 18 sites for which the AASHTO method produced positive median biases (Group A), and the other group containing the remaining 13 sites for which the AASHTO method produced negative median biases (Group B). To illustrate the results, consider the probability distribution functions for the biases calculated at Site 1 (from Group A) and Site 2 (from Group B), as shown in Figure 2.3. At both sites, the application of the two weighted methods (i.e., the AASHTO Weighted and FHWA methods) shifts the distributions produced by their un-weighted counterparts (i.e., the AASHTO and AASHTO Hourly methods) towards a median bias near zero. Table 4 shows the results for all sites combined, Group A, and Group B. When applying the AASHTO method, the median biases for Groups A and B are 0.09 percent and -0.12 percent, respectively. The AASHTO Weighted and FHWA methods correct these median biases for both groups by moving them closer to zero. This effect is not evident when all sites are combined, presumably because the positive and negative biases offset one another. Comparatively, the AASHTO Hourly method appears to have little influence on the median biases. Moreover, regardless of whether the median bias is positive or negative, the improvements in the mean absolute bias and 95% CI widths remain when applying the FHWA method.

Table 2.4: Scenario 3 Results for All Sites and Groups with Positive (Group A) and Negative (Group B) Median Biases for the AASHTO Method

	All Sites (31 Sites)			Group A (18 Sites)			Group B (13 Sites)		
Method	**Median Bias**	**95% CI Width**	**Mean Abs. Bias**	**Median Bias**	**95% CI Width**	**Mean Abs. Bias**	**Median Bias**	**95% CI Width**	**Mean Abs. Bias**
AASHTO	0.01%	1.87%	0.30%	0.09%	1.78%	0.29%	-0.12%	1.90%	0.32%
AASHTO Weighted	-0.02%	1.78%	0.27%	-0.01%	1.74%	0.26%	-0.02%	1.83%	0.27%
AASHTO Hourly	0.01%	1.73%	0.27%	0.09%	1.63%	0.26%	-0.11%	1.77%	0.29%
FHWA	-0.01%	1.64%	0.24%	-0.01%	1.61%	0.23%	-0.01%	1.68%	0.24%

CI denotes confidence interval



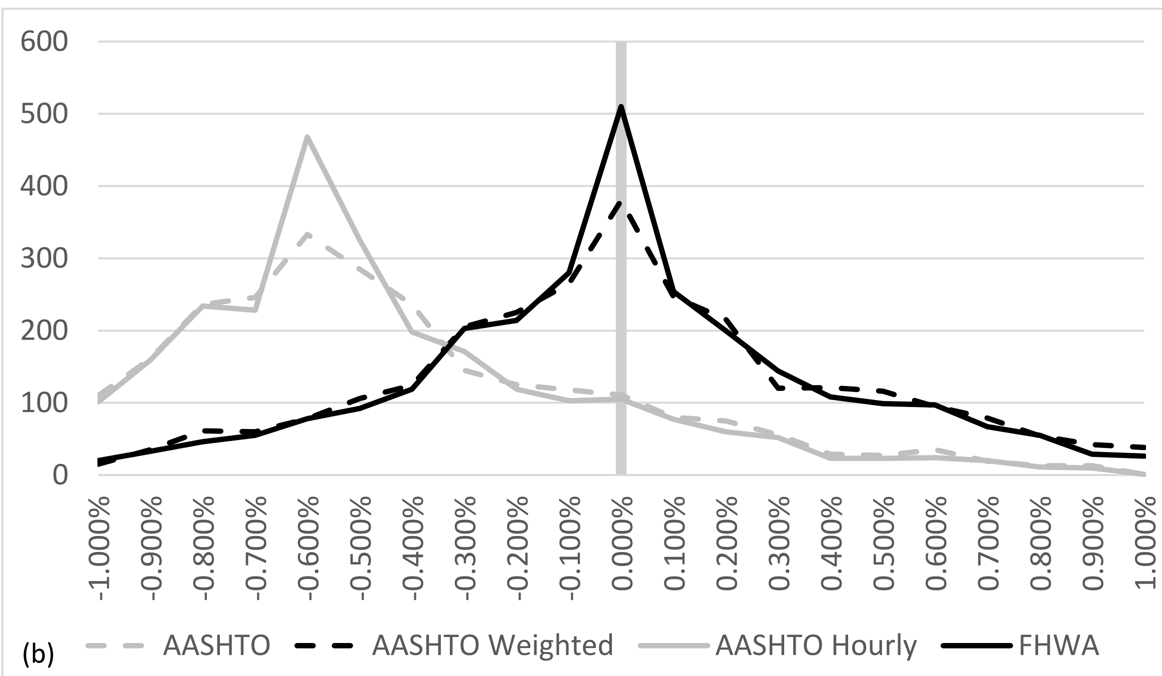


Figure 2.3: Probability distribution functions of biases for scenario 3 by method from (a) site 1 and (b) site 2

Both accuracy and precision are influenced by the duration of data removal. As shown in

Figure 2.4, there is a strong, positive, linear relationship between the duration of data removal and the mean absolute bias for each of the methods (R-squared > 0.96). The FHWA method has the smallest mean absolute bias regardless of the duration of data removal, whereas the Simple Average method yields the largest mean absolute bias for data removal durations exceeding the equivalent of one day. As shown in Figure 2.5, the FHWA method produces the most precise results (narrowest 95% CI widths) regardless of the duration of data removal. For example, when less than seven days of data were removed, the 95% CI of biases using the AASHTO method was -0.56 percent to 0.64 percent. The same CI when using the FHWA method was -0.44 percent to 0.43 percent, or 28 percent narrower. For all methods, precision decreases as the duration of data removal increases. The median bias is consistently near zero for all methods and durations of data removal.

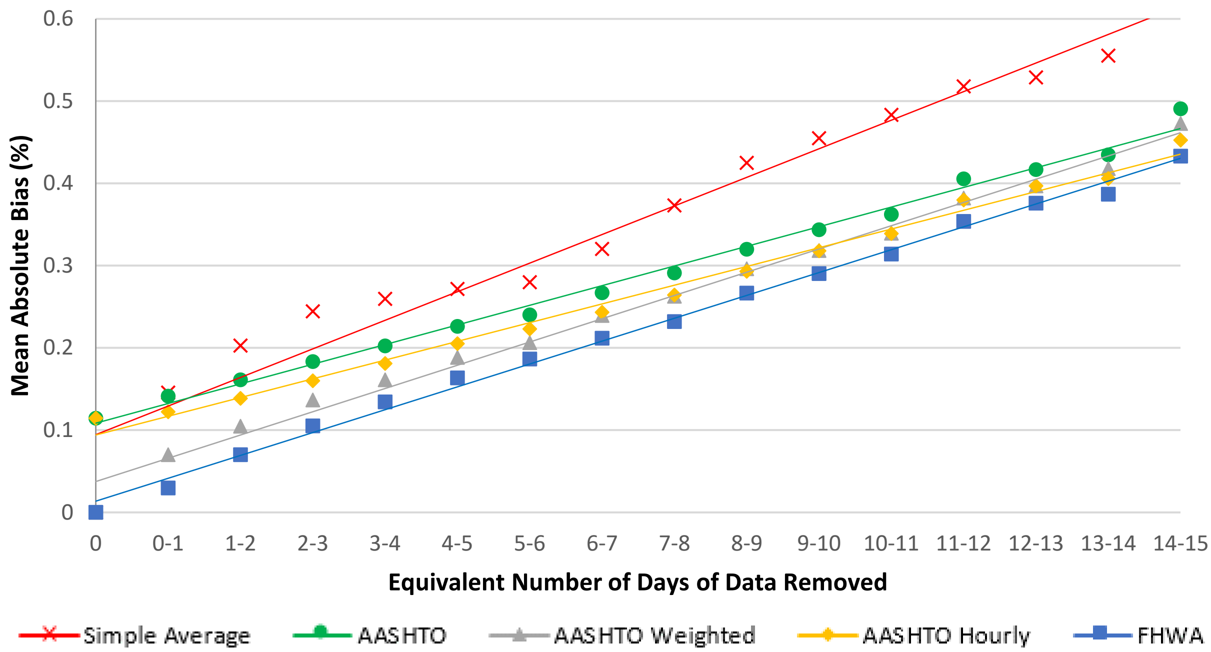


Figure 2.4: Relationships between duration of data removal and mean absolute bias by method

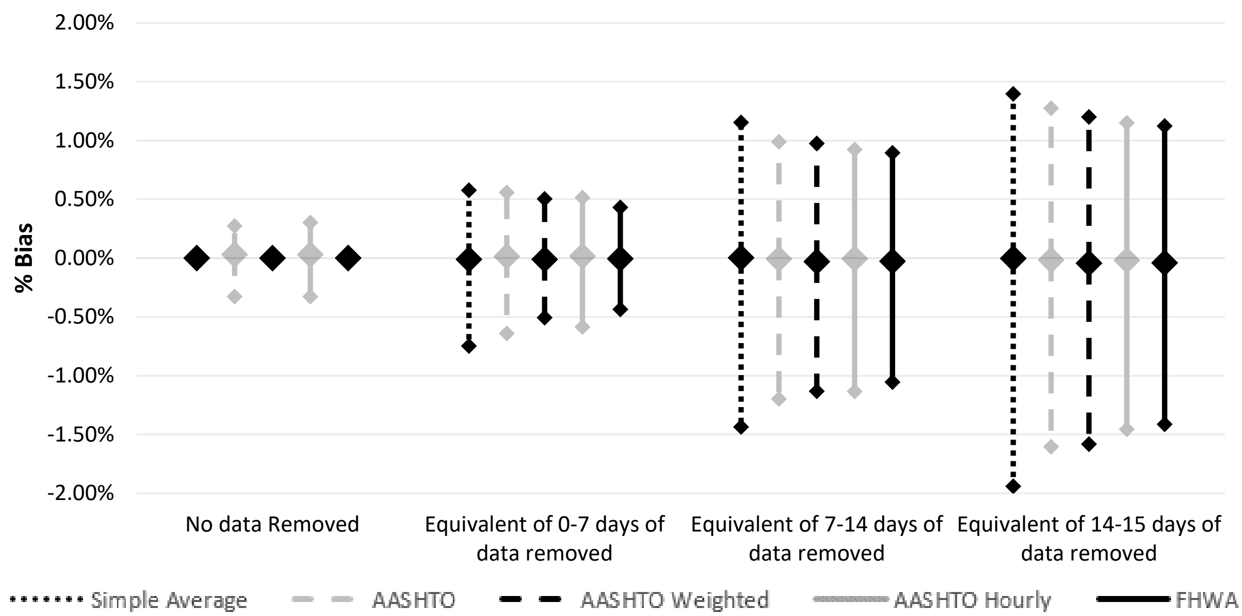


Figure 2.5: Median bias and 95% confidence intervals for biases by duration of data removal and method

2.5 DISCUSSION

The results of the evaluation demonstrate the relative strengths and weaknesses of the five AADTT calculation methods when subject to data removal scenarios. In general, the findings align with those obtained by Jessberger et al. (2016) although specific results reveal opportunities for further research and relevant considerations for practitioners considering adoption of the FHWA method.

Key findings for each of the methods follow:

- The Simple Average method produced the least precise results for all three scenarios. When data loss exceeded one day, this method also produced the least accurate results, as measured by the mean absolute bias.
- Application of the AASHTO method improved the accuracy and precision of the results

relative to the Simple Average method when more than a single day of data were removed. However, this method was less accurate and precise than the three methods that introduced adjustments to the AASHTO method.

- Application of the AASHTO Weighted method improved the accuracy of the results relative to the AASHTO method. This was evident in Scenario 1 under conditions specifically designed to isolate the effect of using a weighted average. Scenario 3 revealed the accuracy improvements provided by applying the weighted average even when only small amounts of data were missing (or when no data were missing). It was also evident from Scenario 3 that the introduction of the weighted average corrected the median bias produced by the AASHTO method regardless of whether this bias was positive or negative.
- Application of the AASHTO Hourly method improved the precision of the results relative to the AASHTO method when partial days of data were removed (as in Scenarios 2 and 3). Improvements in accuracy were also evident when applying the AASHTO Hourly method.
- Application of the FHWA method resulted in the most accurate and precise results under all scenarios. Essentially, this method combines the benefits provided by introducing the weighted average and those provided by using an hourly base time period.
- The specific analyses included in this evaluation revealed three issues which warrant further consideration by researchers and practitioners. First, while the FHWA method provided the most accurate and precise results overall, the method was not clearly superior when subject to substantial daily traffic volume fluctuations (see results for Site 2 in Figure 2.2b). Such conditions are not unusual at sites with low volumes, particularly when considering truck traffic which is known to exhibit industry-influenced

temporal patterns.

Second, the site-specific results produced by the AASHTO method in Scenario 3 revealed both positive and negative median biases. This finding appears to depart from the consistently negative overall median biases produced by the AASHTO method in the work by Jessberger et al. (2016) although this work does not provide site-specific results. Further investigation suggested that the calendar year being analyzed may partially influence the median bias, because each calendar year has a particular day-of-week arrangement. This evaluation used data from calendar years 2010 through 2015, inclusive. Each of these years starts on a different day-of-week and thus the number of days-of-week in a particular month varies from year to year. Sites using data from certain years showed a tendency to over- or underrepresent AADTT. For example, when data were disaggregated into Groups A and B in Scenario 3, the sites using data from 2011 and 2012 predominantly fell into Group A (the first day-of-week in these years is Saturday and Sunday, respectively). The mean absolute bias ignores the signs of the biases and does not appear to be affected by this issue. Thus, while additional research is needed to fully quantify this effect, it is instructive to consider both median bias and mean absolute bias when assessing AADT accuracy.

Third, the relative accuracy improvement (as measured by the mean absolute bias) of the weighted methods tends to decrease as the duration of data removal increases. This is evident in Figure 2.4, where the AASHTO and AASHTO Weighted methods and the AASHTO Hourly and FHWA methods appear to converge. It is possible that as more data are removed, the inaccuracies associated with missing data outweigh the inaccuracies associated with the non-weighted methods. Further research is needed to examine the impacts of data removal durations longer than 15 days.

2.6 CONCLUSION

This paper evaluated five methods for calculating AADT at continuous count sites by imposing data removal scenarios designed to simulate real-life causes of data loss. The five methods were: (*a*) the Simple Average method, (*b*) the AASHTO method, (*c*) the AASHTO Weighted method, (*d*) the AASHTO Hourly method, and (*e*) the FHWA method. The evaluation focused on quantifying the accuracy and precision improvements provided by the FHWA method, particularly at low volume sites with potentially erratic temporal patterns. Truck traffic volume data collected in Manitoba exhibit these characteristics. While the findings stem from the analysis of these particular data, it is expected that they are transferrable to other similar contexts.

Overall, the FHWA method, which leverages two modifications to the AASHTO method, provided the most accurate and precise results in all three data removal scenarios. Specifically, when up to 15 days of data are randomly removed, application of the FHWA method can be expected to produce errors within approximately ±1.4 percent of the true AADT, 95 percent of the time. These results, which were obtained for sites with generally low truck traffic volumes, corroborate those reported by Jessberger et al. (2016). In addition, the evaluation contributed to a more detailed understanding of the various AADT calculation methods. In particular, the results demonstrated that including a weighted average primarily improves AADT accuracy, while precision is more influenced by the base time period being used. Moreover, the particular arrangement of days-of-week in a calendar year appears to systematically influence the median bias observed at a site.

While the evaluation demonstrated the relative benefits of the FHWA method, practitioners should consider several points when contemplating its adoption into a traffic monitoring program. In its favour, the FHWA method reduces a known, yet small, systematic bias in AADT calculations at continuous count sites by introducing a weighted average. It also improves the reliability of AADT calculations at these sites and enhances the value of traffic data obtained from partial-day counts that require hourly adjustment factors. These advantages should be assessed against the level of effort required to implement the FHWA method. Additionally, the rounding policies adopted by a jurisdiction and the insensitivity of certain applications to AADT inputs may mitigate the accuracy and precision improvements provided by the FHWA method.

2.7 ACKNOWLEDGEMENTS

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3 DATA-DRIVEN APPROACH TO QUANTIFY AND REDUCE ERROR ASSOCIATED WITH ASSIGNING SHORT DURATION COUNTS TO TRAFFIC PATTERN GROUPS

This chapter continues the investigation of AADT estimation techniques by moving to short duration count data, the counterpart to continuous count data that was analyzed in Chapter 2. It seeks to answer the second set of objective questions: *What magnitude of errors are produced when estimating AADT from short duration traffic count data using the state-of-the-practice approach? Can a novel assignment method reduce the errors caused by poor assignment to traffic pattern groups?*

This analysis develops a procedure to measure and mitigate errors produced when assigning traffic count sites to the wrong traffic pattern group. It contributes to the thesis theme by applying the traffic patterns developed from continuous count data, which are predicated on periodicities in traffic with time, and by considering the possibility of grouping traffic count sites using a purely data-driven approach.

The material in this chapter is submitted for publication to the Transportation Research Record and has been accepted for presentation at the 100th Annual Meeting of the Transportation Research Board in 2021. It is reprinted with permission of co-authors Puteri Paramita and Jonathan Regehr. The chapter is self-contained with its own abstract, introduction, and conclusion; references are provided at the end of the thesis. The thesis author conducted the analysis, interpreted results, and prepared the manuscript.

3.1 ABSTRACT

Traffic monitoring agencies collect traffic data samples to estimate annual average daily traffic (AADT) at short duration count sites. The steps to estimate AADT from sample data introduce error that manifests as uncertainty in the AADT statistic and its applications. Past research suggests that the assignment of a short duration count site to a traffic pattern group (TPG), characterized by known traffic periodicities, represents a significant but poorly quantified source of error.

This paper presents an approach to quantify the range of errors arising from such assignments and to mitigate these errors using a novel data-driven assignment method. The approach uses simulated 48-hour short duration counts sampled from continuous count sites with known AADT to develop a benchmark of the total error expected when AADT is estimated from such samples. Likewise, the analysis produces a set of AADT estimates using temporal factors from pre-defined TPGs to quantify the range of assignment errors. The data-driven assignment method aims to mitigate these errors by minimizing the absolute mean deviation in AADT estimates produced from multiple short duration counts in a single year.

The approach is applied to traffic data collected in Manitoba, Canada, as a case study. The results indicate that the mean absolute error from 48-hour short duration counts is 6.40% of the true AADT and that improper assignment can lead to a range in mean absolute errors of 9%. When applied to previously unassigned sites, the data-driven assignment method reduced mean absolute errors from 10.32%, using a conventional assignment method, to 7.86%.

3.2 INTRODUCTION

A principal objective of traffic monitoring programs is to produce accurate and precise estimates of traffic volume—ideally expressed as annual average daily traffic (AADT)—across the system-wide extent of an agency's highway network. Conventionally, traffic monitoring programs estimate AADT on extensive networks by deploying a series of short duration counts. These counts use portable equipment to obtain traffic data samples that provide broad spatial coverage. While economical, such counts monitor traffic for relatively short periods of time (often one to three days); this limits their effectiveness in producing annual averages. Practitioners compensate for this limitation by adjusting the measured traffic volumes using average temporal factors obtained from continuous traffic counts. However, assigning short duration counts to the appropriate continuous count sites is a potential source of error in the AADT estimation process. This paper develops a data-driven approach to quantify and reduce this error.

3.2.1 Background

AADT is a ubiquitous traffic statistic, essential for applications such as infrastructure design and management, road safety assessments, resource allocation, economic appraisals, roadway and transport system planning, operational and environmental analyses, and transportation research (Albright, 1991; Tsapakis, 2019; Jessberger et al, 2016; Grande et al., 2017; Sharma and Allipuram, 1993; Olfert et al., 2019; Eom et al., 1968; Li et al., 2006). In the United States, state and municipal transportation agencies submit system-wide estimates of AADT (and vehicle-miles travelled) on their highway networks as required by the Highway Performance Monitoring System (HPMS) (FHWA, 2016). Having access to AADT for all paved public roads in the United States by 2026 is also a requirement of the 2016 Highway Safety Improvement Program (HSIP) Final Rule.

In Canada, despite a lack of formal data reporting requirements, there is widespread acknowledgement of the value of standardizing and continuously improving highway traffic monitoring practices at all levels of government. This is evident through the recent national-level publication of the *Traffic Monitoring Practices Guide for Canadian Provinces and Municipalities* (Regehr et al., 2017).

The conventional approach for estimating AADT at short duration count sites, first introduced by Drusch (1993), leverages data collected at continuous and short duration count sites (Tsapakis, 2019; FHWA, 2016; Regehr et al., 2017). Table 3.1 describes the six main steps of this approach. The first three steps involve data obtained from continuous count sites. These data are used to calculate temporal factors at each site (Step 1), to develop traffic pattern groups (TPGs)—sometimes referred to as factor groups—comprising sites that exhibit similar periodicities (Step 2), and to produce average adjustment factors for each group (Step 3). Due to their high cost of installation, operation, and maintenance, an agency typically deploys a limited number of continuous count sites. Thus, agencies use portable equipment to collect short duration (sample) counts for broader spatial coverage (Step 4) (Sharma and Allipuram, 1993). The assignment of each short duration count site to a TPG (Step 5) facilitates the application of the TPG's temporal adjustment factors and the estimation of AADT at the short duration count site (Step 6). In other words, the assignment step presumes that the average traffic periodicities (monthly, day-of-week, hourly) observed at the sites comprising the appropriate TPG apply to the short duration count site, even though such periodicities are never directly observed at that short duration count site.

Each step of this approach has the potential to introduce error that ultimately manifests as uncertainty in the estimated AADT (Tsapakis, 2019). For the first three steps, error arises because average temporal adjustment factors derived from TPGs do not perfectly represent traffic variations at any particular continuous count site. In the latter three steps, these errors propagate through to the estimation of AADT when assumptions are made about the traffic periodicities at short duration count sites. Overall, the table reveals a major limitation of the conventional approach, namely that the accuracy and precision of the AADT estimated from short duration counts are conditional on multiple sources of error, which may not be quantified in practice even when they are duly recognized.

Table 3.1: Main steps and potential error sources associated with the estimation of AADT at short duration count sites

Step	Potential error source	Relevant research
1. Calculate temporal factors at each continuous count site.	Temporal factors summarize data by arbitrarily pre-defined periods (e.g., months, days-of-week) and thus do not fully-represent non-periodic traffic variations.	Jessberger et al. (2016); Grande et al. (2017)
2. Group continuous count sites into traffic pattern groups (TPGs) with similar temporal factors.	Continuous count sites may be incorrectly or sub-optimally grouped, producing TPGs with dissimilar temporal factors.	Reimer and Regehr (2013); Regehr et al (2015)
3. Calculate average temporal adjustment factors for each TPG.	Grouped sites have similar, but not identical, traffic periodicities; thus, the average factors do not represent the traffic at any individual continuous count site in a group.	FHWA (2016); Regehr et al. (2017); Regehr et al (2015)
4. Collect sample traffic data at short duration count sites.	Sampled traffic data may not sufficiently represent the predominant traffic periodicities at the count site.	Sharma and Allipuram (1993); Sharma et al (1996); Gadda et al (2007); Nordback et al.(2013); Jackson et al (2015); Minge et al.(2017)

Step	Potential error source	Relevant research
5. Assign short duration count sites to TPGs based on roadway and land use characteristics.	Short duration counts may be assigned to the wrong TPG, particularly if observed roadway and land use characteristics poorly correlate with expected traffic characteristics at the site.	Sharma and Allipuram (1993); Sharma et al (1996); Gadda et al (2007)
6. Estimate AADT using temporal adjustment factors and short duration count data.	The average temporal adjustment factors from the assigned TPG may not represent the traffic periodicities at the short duration count site.	Sharma and Allipuram (1993); Sharma et al (1996); Gadda et al (2007); Milligan et al. (2016); Jessberger and Schroeder (2016)

As cited in Table 3.1, the literature includes several evaluations of uncertainties arising when estimating AADT from short duration counts. Three earlier works specifically focus on error arising from the assignment of short duration counts to TPGs (Step 5):

- Gadda et al (2007) quantified multiple types of error arising from using short duration count data to estimate AADT, including what they refer to as misclassification error (equivalent to the assignment error discussed in Step 5 above). Using data from continuous count sites in Florida, they found that misclassification raised errors from 6.69% (with ideal factors applied) to 19.35%. They suggested that classifying the count sites into different categories based on the functional classification, lane count, and area types would help to reduce the estimation error of AADT.
- Sharma et al (1996) investigated the statistical precision of AADT estimates resulting from short duration counts in Minnesota and verified their results using data from two

Canadian provinces. They identified that emphasizing proper assignment has a more positive impact on estimation errors than extending the length of short duration counts. For example, a 72-hour count with improper assignment was expected to produce an estimate with higher error than a 24-hour or even 6-hour count using proper assignments.

- Sharma and Allipuram (1993) developed a systematic method to assign short duration count sites to pre-existing TPGs in the context of seasonal traffic counts. In this case, seasonal traffic counts referred to a series of week-long counts conducted at short duration sites for the purpose of assignment. Their method was designed to select the most appropriate seasonal traffic count schedule to accurately assign sites to TPGs. However, the method used week-long counts and ignored the effects of daily traffic variability. They quantified assignment error in terms of 'assignment effectiveness', which measured the difference between adjusted traffic volumes and ground truth AADT, and the percent difference in daily traffic, which compared unadjusted measured volumes with ground truth AADT.

The literature review reveals a limited number of studies that have concentrated on the assignment of short duration counts to TPGs and the error associated with this step. Further, while some studies have attempted to quantify and reduce the overall error in AADT estimates, only Sharma and Allipuram (1993) have gone on to propose a method for reducing assignment errors, specifically. Their approach required significantly more data than a typical short duration count program would collect. Thus, there is a gap in research regarding the quantification and reduction of assignment errors that is addressed by the generic approach presented in this paper.

3.2.2 Research Objectives and Scope

This paper seeks to improve upon the state-of-the-practice in short duration count programs by addressing three research questions:

- **What are the expected errors in current AADT estimates produced from short duration counts?** By answering this question, the paper benchmarks errors to provide context for subsequent steps.
- **What portion of AADT estimation errors can be attributed to the assignment of short duration counts to TPGs?** Answering this question identifies the component of the error that can be reduced or eliminated by proposing a novel assignment method.
- **What reduction of AADT estimation errors is possible by employing a novel assignment method?** The paper proposes and evaluates a data-driven method to reduce the error in AADT estimates that arises when assigning short duration counts to TPGs.

This paper addresses these research questions through a generic approach for quantifying and reducing the errors produced during the assignment step of AADT estimation. The next section describes this approach. The paper then applies the approach using traffic data obtained from Manitoba, Canada as a case study. While the results presented are specific to this case study, the insights generated are considered transferable to other jurisdictions. The final section of the paper discusses these insights and their implications for traffic monitoring programs.

3.3 APPROACH

The proposed approach comprises three steps, which map directly to the three foregoing objectives:

1. Benchmark the total error produced when using the conventional AADT estimation approach for short duration count data.
2. Evaluate the range of errors attributed to the assignment of short duration counts to TPGs by applying factors from multiple TPGs.
3. Develop and apply a data-driven method to assign short duration counts to TPGs and compare the errors produced using this method to those evident from the conventional assignment approach.

The following subsections provide detailed descriptions of each step.

3.3.1 Step 1: Benchmarking total error using the conventional AADT estimation approach

This step begins by calculating the (true) AADT at all continuous count sites, by direction, using the AASHTO formulation shown in Equation 3.1 (FHWA, 2016). AADT can only be calculated in this fashion if there exists at least one daily volume for each day-of-week within each month (i.e., $n_{jm} \geq 1$ for all days-of-week, j, and months, m) at a site. In this case, vehicle classification data are not considered (so *c* represents all vehicle classes).

$$AADT_c = \frac{1}{7}\sum_{i=1}^{7}\left[\frac{1}{12}\sum_{j=1}^{12}\frac{1}{n_{jm}}\left(\sum_{k=1}^{n_{jm}} VOL_{ijk,c}\right)\right] \tag{3.1}$$

Where:

VOL_{ijm} = total traffic on i^{th} occurrence of j^{th} day-of-week within m^{th} month

i = day-of-week (1 to 7)

j = month-of-year (1 to 12)

k = occurrence of a particular day-of-week in a particular month

n_{jm} = number of times day-of-week *i* occurs in month *j* with available traffic data

c = vehicle class (optional)

Next, simulated short duration count data are produced by sampling data from continuous count sites. Forty-eight-hour samples are taken at each site, by direction, at which AADT can be calculated. To ensure the assumption of normally distributed errors is valid, 100 independent samples are taken per site-direction. The sampling periods are the same for all studied sites and must meet the following criteria, established based on guidance in the literature:

- All short duration counts are conducted between May and September, inclusive.
- All short duration counts begin on Mondays or Tuesdays and cannot include holidays.
- All short duration counts begin between 6:00 a.m. and 6:00 p.m. and last exactly 48 hours.

In some cases, sites with the requisite data to produce AADT estimates may have relatively short periods of missing data (i.e., a few hours, but not enough to preclude the use of Equation 3.1). The sampling criteria require each sample to comprise data from a full 48 hours. To address the missing hourly data, the average volume for each hour on each day-of-week within each month are calculated at each site. These averages are used to impute the missing data at all sites at which AADT can be estimated. Existing data are not altered by this method, as only missing data are imputed.

The simulated short duration data are used to estimate AADT using the method recommended in the FHWA *Traffic Monitoring Guide* (FHWA, 2016). Continuous count sites in each TPG are used to develop average temporal adjustment factors for each day-of-week and month. Equation 3.2 shows how these factors are used to estimate AADT using a single short duration count. Note that the conventional subscripts are presented, whose definitions do not align with those shown in Equation 3.1.

$$AADT_{hi} = VOL_{hi} \times M_h \times D_h \times A_i \times G_h \tag{3.2}$$

Where:

$AADT_{hi}$	= the estimated annual average daily traffic at site *i* of traffic pattern group *h*
VOL_{hi}	= the 48-hour volume measured at site *i* of traffic pattern group *h*
M_h	= the applicable seasonal (monthly) factor for traffic pattern group *h*
D_h	= the applicable day-of-week factor for traffic pattern group *h* (if needed)
A_i	= the applicable axle-correction factor for site *i* (if needed)
G_h	= the applicable growth factor for traffic pattern group *h* (if needed)

The analysis applies Equation 3.1 to the continuous count data at each site to calculate the true AADT and Equation 3.2 to each sampled short duration count at each site to calculate the estimated AADT. Each estimated AADT is compared to the true AADT for that site. The analysis measures the deviation between the 100 sampled AADT estimates and the true AADT at each site. The range of errors is quantified to establish a benchmark of the errors expected when using the conventional AADT estimation approach. Results are discussed in terms of percent error and absolute percent error relative to the true AADT. Equation 3.3 shows how the mean percent error (MPE) is calculated for any combination of site and TPG using the 100 sampled short duration counts from the site. Mean absolute percent error (MAPE) is similarly calculated, considering the absolute values of the summands. The analysis identifies the spectrum of errors that are produced using this AADT estimation method for current TPG assignments, thus addressing the first research question: *What are the expected errors in current AADT estimates produced from short duration counts?*

$$MPE_{i,h} = \frac{1}{100} \times \sum_{k=1}^{100} \frac{AADT_i - AADT^*_{i,h,k}}{AADT_i} \tag{3.3}$$

Where:

$AADT_i$	= the ground truth AADT at site *i*
$AADT^*_{i,h,k}$	= the estimated AADT at site *i*, based on traffic pattern group *h*, for the k^{th} data sample
$MPE_{i,h}$	= the mean percent error of AADT estimates at site *i*, based on traffic pattern group *h*

3.3.2 Step 2: Evaluating assignment-specific errors

In *Step 2*, sampled data are again used to estimate AADTs by applying Equation 3.2. However, in this step, the analysis considers temporal adjustment factors from all TPGs, not only those to which sites had been previously assigned. This simulates the case in which short duration counts are assigned to different TPGs, including those which would be expected to result in sub-optimal AADT estimates.

The sampled data from each continuous count site are used to estimate AADT as if they were assigned to each TPG. Equation 3.3 finds the MPE for each combination of site and TPG. The results for *Step 2* indicate the range of errors that exist when short duration count data are used to estimate AADT. The least of these errors is assumed to be the best case, where the TPG is optimally selected based on the available data. In this case, the remaining error is also assumed to be the aggregated error produced during each other step of the AADT estimation process. Conversely, the highest of these errors is taken to be the worst case. Thus, the resulting difference of errors in the AADT estimates represents the potential range of assignment errors. This range provides an answer to the second research question: *What portion of AADT estimation errors can be attributed to the assignment of short duration counts to TPGs?*

3.3.3 Step 3: Developing a novel assignment method

The third step develops a novel method (hereafter referred to as the data-driven assignment method or DDA method) to assign short duration counts to TPGs using short duration count data and available continuous count data. The DDA method is contingent on multiple short duration counts being conducted at each short duration count site during a study year. This is not typical practice for every monitoring agency, but is recommended in traffic monitoring guidance and the literature (Sharma and Allipuram, 1993; Sharma et al, 1996; FHWA, 2016b; Milligan et al, 2016; Regehr et al., 2017). Normally, the AADT at a site is estimated by taking the average of all AADT estimates in a year. Theoretically, if traffic patterns at a given site follow the periodicities of a TPG to which it is assigned, these AADT estimates should be close to each other. If instead these AADT estimates are disparate, it suggests that the TPG assignment is inappropriate.

The DDA method applies this theory by measuring and minimizing the absolute mean deviation in AADT estimates when using short duration count data and temporal adjustment factors from multiple TPGs. The method is an optimization problem that selects a TPG by minimizing the absolute mean deviation between all AADT estimates at a site by changing the applied TPG, as expressed in Equation 3.4.

$$TPG_{i,assigned} = \underset{h \in H}{\arg\min} \left| \frac{1}{n} \sum_{k=1}^{n} \left(AADT_{i,k,h}^{*} - \overline{AADT}_{i,h} \right) \right| \tag{3.4}$$

Where:

$TPG_{i,assigned}$	= traffic pattern group assigned to site *i*
h	= selected traffic pattern group
H	= set of all traffic pattern groups
$AADT_{i,k,h}^{*}$	= AADT estimate for site *i* using short duration count *k* and traffic pattern group *h*
$\overline{AADT}_{g}$	= average AADT estimate for site *i* using all short duration counts and traffic pattern group *h*
n	= number of short duration counts conducted at a site

The DDA method hypothesizes that minimizing the absolute mean deviation between AADT estimates produced from two or more counts at the same site within a year selects a TPG which also reduces the error produced during the assignment step (i.e., the TPG producing the most precise AADT estimates is also expected to produce the most accurate estimate). The following case study tests this hypothesis using data from

Manitoba, Canada, thus offering a response to the final research question: *What reduction of AADT estimate errors is possible by employing a novel assignment method?*

3.4 CASE STUDY: EVALUATION OF SHORT DURATION COUNT ASSIGNMENTS IN MANITOBA, CANADA

3.4.1 Overview of Manitoba's Traffic Monitoring Program

The Manitoba Highway Traffic Information System (MHTIS) processes and analyzes traffic data collected on Manitoba's provincial highway network. Principal traffic volume data sources include 85 continuous count sites and approximately 2000 short duration count sites. The continuous count sites provide the source data for this case study. Each site records hourly traffic volumes by direction, yielding a possible 170 total site-direction pairs. However, if data are missing from a site for a significant portion of the year, Equation 3.1 cannot be used to calculate AADT (FHWA, 2016; Regehr et al., 2017); thus, some site-directions were unavailable for use in this study. Figure 3.1 shows the continuous count sites used in the case study, including those where one or both directions of traffic data did not meet the criteria for estimating AADT in the study year (2018). Missing data are normally the result of temporary equipment malfunctions.

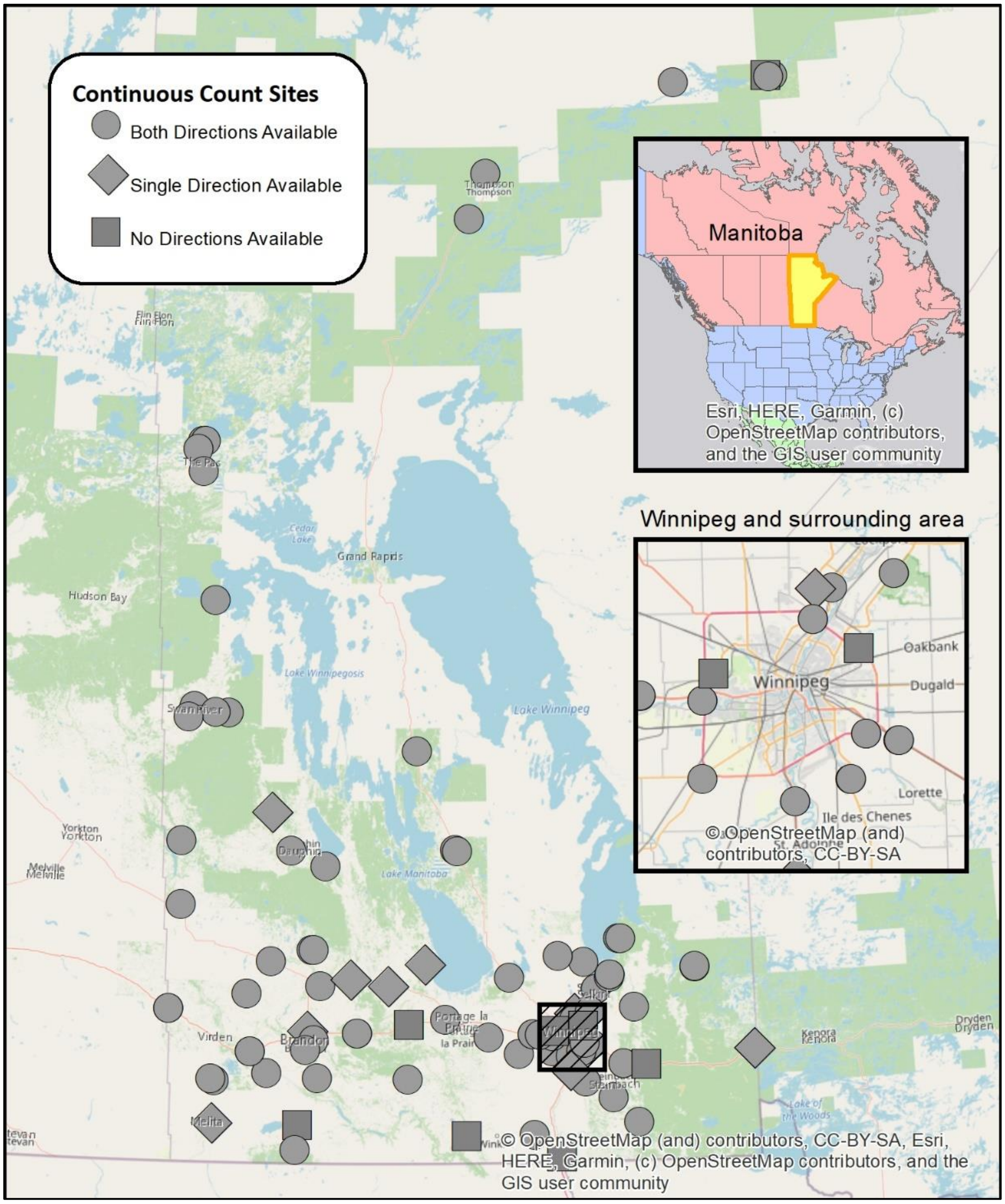

Figure 3.1: Continuous count sites in Manitoba, Canada, 2018

The MHTIS has seven established TPGs. Each TPG comprises a set of sites that exhibit similar temporal traffic patterns and share common roadway and land use characteristics. An unpublished cluster analysis formed the basis for defining these TPGs. The cluster analysis considered the average monthly variation of traffic volume at the continuous count sites to develop initial groupings. A secondary cluster analysis further sorted these sites into groups based on their hourly and day-of-week traffic variations. Finally, the grouping process identified common roadway and land use characteristics shared by the continuous count sites within the clusters formed through the statistical analyses. These characteristics are used to assign short duration count sites to TPGs. An assignment algorithm, based on a sequence of binary-response questions, assists in the assignment process (see Figure 3.2). Inherent in this process is the assumption that the unmeasured traffic patterns at short duration count sites resemble the measured traffic patterns at the continuous count sites that comprise the TPG to which the short duration count is assigned.

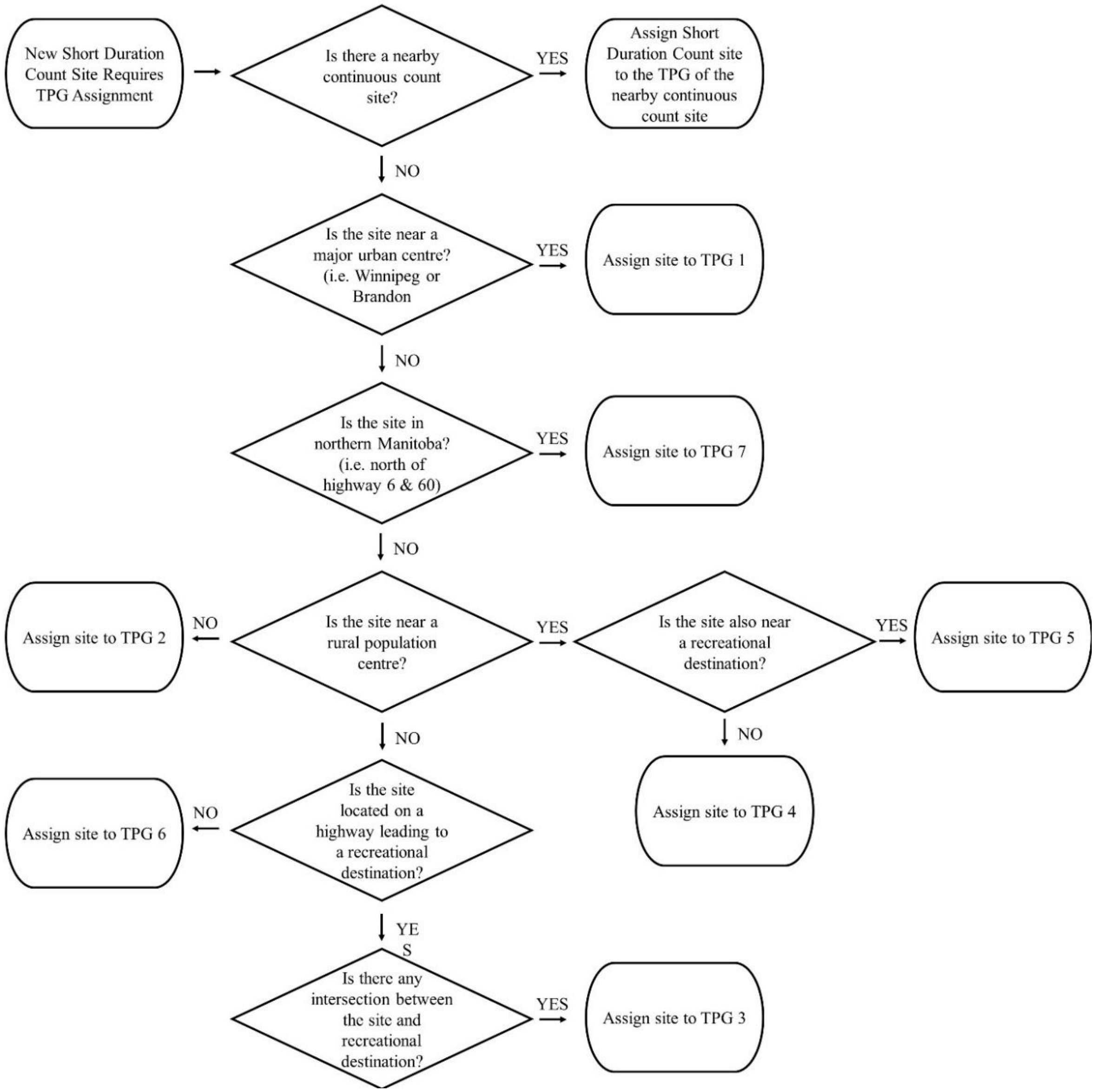

Figure 3.2 Algorithm for assigning short duration count sites to TPGs in Manitoba, Canada

Table 3.2 shows the defining characteristics for each of the seven TPGs in Manitoba (Olfert et al., 2019). In general, distinctions between the TPGs depend on their proximity to population centres and recreational destinations, and related predominant trip-making characteristics. For example, sites close to major urban centres generate strong morning and afternoon peaks, higher weekday than weekend traffic, and relatively low seasonal variations (e.g., as in TPG 1). In contrast, sites close to recreational destinations generate relatively high weekend traffic and more pronounced seasonal variations (e.g., as in TPG 6). TPG 7 comprises sites located in northern Manitoba. There are 17 continuous count sites that are not assigned to any TPG, either because they were installed after the initial cluster analysis took place or because they did not align with the characteristics of any TPG.

Table 3.2: Characteristics of Manitoba's traffic pattern groups

Traffic Pattern Group (TPG)	Temporal Characteristics	Roadway, Land Use, and Related Trip-Making Characteristics	Number of Site-directions Used/Total
TPG1	• High a.m./p.m. peaks on weekdays • Steady weekday traffic with lower weekends • Low seasonal variation	• Highways near major urban centres	21/28
TPG2	• Gradual increase and decrease in hourly traffic • Steady weekday traffic with lower weekends • Moderate seasonal variation	• Long-distance trips away from major urban centres	44/48
TPG3	• Gradual increase and decrease in hourly traffic • Low weekend traffic and high Friday/Sunday • Very high summer peak	• Long-distance trips that connect to recreational destinations	3/6
TPG4	• p.m. peak on weekdays • Steady weekday traffic with lower weekends • Low seasonal variation	• Highways near rural population centres	23/28
TPG5	• p.m. peak on weekdays and weekends • Low weekend traffic and high Friday/Sunday • High summer peak	• Highways near population centres that connect to recreational destinations	6/6
TPG6	• Steady, high, daytime traffic on weekends • Low weekend traffic and high Friday/Sunday • Very high summer peak	• Highways near recreational destinations	10/10
TPG7	• p.m. peak on weekdays • Steady weekday traffic with lower weekends • High summer peak	• Highways in northern Manitoba	10/10
No TPG	• Excluded from other groups	• N/A	29/34
Total			146/170

For this case study, of the 170 total continuous count site-directions, 146 met the requirements for calculating AADT using Equation 3.1 (i.e., they measured traffic volumes for at least one day-of-week in every month). Of these, 117 site-directions had pre-assigned TPGs (note that normally TPGs are assigned to sites and not site-directions). Data from these sites were used to develop the temporal adjustment factors for each TPG.

3.4.2 Results

3.4.2.1 Step 1

Simulated short duration count data were produced by extracting 48-hour samples from the continuous count data at all 146 site-directions for which AADT could be estimated. At first, only data from the 117 pre-assigned site-directions were used to estimate AADT, using Equation 3.2 and inputting the calculated temporal adjustment factors for the assigned TPGs. Figure 3.3 shows the resulting percent errors in a histogram, aggregated for all studied sites that have an assigned TPG. Table 3.3 provides a detailed summary of results in tabular form. The distribution of errors is approximately normal, with a mean of 0.2% and standard deviation of 8.6%. In absolute terms, the MAPE was 6.4% with a standard deviation of 5.7%.

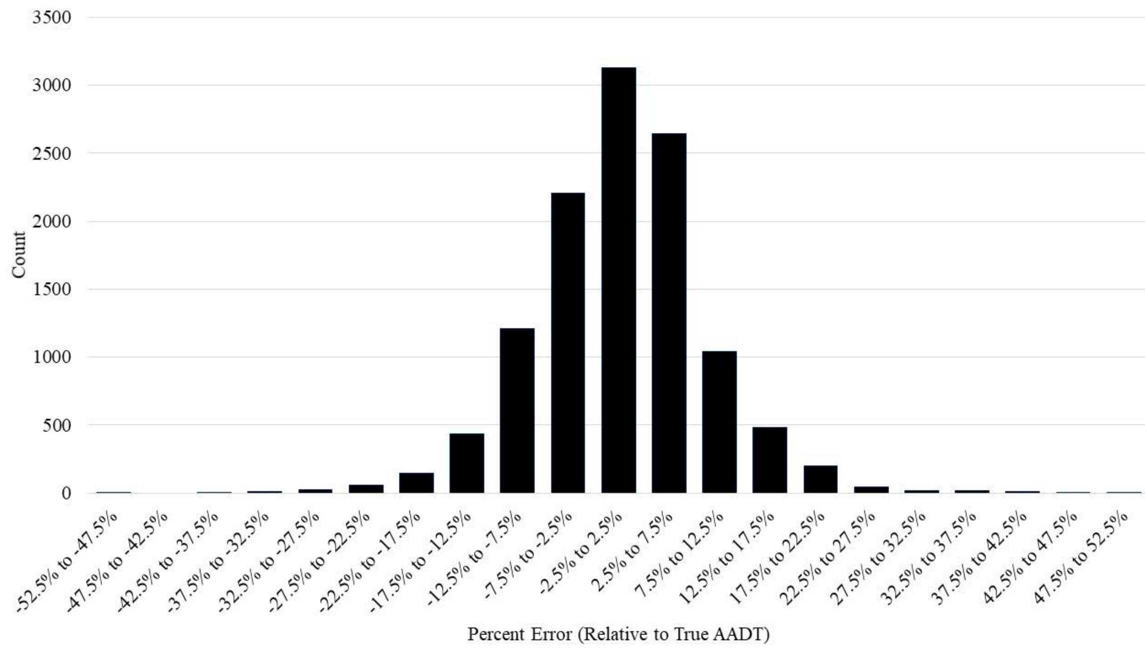

Figure 3.3: Histogram of total errors for AADT estimates from short duration counts

Table 3.3: Summary statistics of total errors for AADT estimates from short duration counts

Statistic	Percent Error	Absolute Percent Error
Minimum	-85.23%	0.00%
2.5th percentile	-16.46%	0.23%
First quartile	-4.76%	2.34%
Median	0.38%	4.95%
Third quartile	5.07%	8.84%
97.5th percentile	17.49%	20.63%
Maximum	50.64%	85.23%
Mean	0.19%	6.40%
Standard Deviation	8.58%	5.72%

3.4.2.2 Step 2

The analysis was repeated using input temporal adjustment factors from each of the seven TPGs to isolate assignment errors. In this case, unassigned sites are included in the analysis. Table 3.4 shows the MAPE of AADT estimates using the sampled short duration count data from all sites. For comprehensibility, the sites are grouped by their existing TPG assignments and averages are reported across these groupings. The 'best' and 'worst' columns represent the average errors that are generated by using the TPGs that produce the lowest and highest MAPE, respectively. The 'actual' column shows the MAPE when using the site's assigned TPG (there is no result for this category for the unassigned sites). The average error, aggregated for all assigned sites, ranges from 5.57% using optimal assignments to 14.28% using the worst assignments. As expected, given that some of the unassigned sites have unique temporal characteristics, the average error at these sites is higher, ranging from 10.21% to 19.56%.

Table 3.4: Mean absolute percent error (MAPE) by traffic pattern group

Traffic Pattern Group	Actual Assignment	Best Assignment	Worst Assignment
TPG1	5.34%	4.87%	15.45%
TPG2	5.79%	5.23%	13.69%
TPG3	7.71%	6.54%	13.53%
TPG4	4.86%	4.75%	14.91%
TPG5	7.34%	4.34%	11.81%
TPG6	9.93%	7.51%	12.81%
TPG7	10.31%	8.92%	16.10%
All assigned sites	6.40%	5.57%	14.28%
No assigned TPG	-	10.21%	19.56%

3.4.2.3 Step 3

Finally, the DDA method was applied to the unassigned count sites. To align with MHTIS operations, the sampled short duration counts from these unassigned sites were split into two groups: those that start during summer holidays in July or August (53 out of 100 counts), and those that start when school is in session in May, June, or September (47 counts). These counts were used to assign TPGs by applying Equation 3.3, using one count from each group of counts (i.e., n = 2 in Equation 3.3). In total, 2491 cases were tested for each site (the product of 53 July or August counts and 47 May, June, or September counts). As a comparison case, the assignment algorithm shown in Figure 3.2 was used to assign each of the unassigned sites to TPGs, based on their roadway and land use characteristics. Table 3.5 shows a sample calculation using the DDA method at site 5 NB with one pair of counts. In this case, the DDA method would select TPG 1 for this site because it has the smallest absolute difference between AADT estimates. This process is repeated for all 2491 combinations of counts at site 5 NB.

Table 3.5: Sample calculation of the DDA method

			AADT Estimated Using Factors from Each TPG						
Count	Date-time	48-hr Volume	TPG 1	TPG 2	TPG 3	TPG 4	TPG 5	TPG 6	TPG 7
Count 1	June 4, 1 pm	302	132.7	139.1	128.8	131.1	127.3	125.4	127.2
Count 2	Aug 14, 3 pm	317	132.7	129.1	113.0	133.0	118.7	116.4	121.8
Absolute Mean Dev.	-	-	0.0	5.0	7.9	1.0	4.3	4.5	2.7

Table 3.6 summarizes the results. The DDA method out-performs the algorithmic method (i.e., it produces an AADT that is closer to the true AADT) in 68.3% of tested cases. Both methods produce average errors of -3.46%. However, the overall average MAPE was 7.86% using the DDA method and 10.32% using the assignment algorithm. Using a paired

t-test, considering each site as an independent sample, the results were statistically significant at the 0.01 level (df = 28, t-statistic = 5.3).

Table 3.6: Comparison of the data-driven and algorithmic assignment methods

	Percent Error		Abs. Percent Error	
	DDA	**Algorithm**	**DDA**	**Algorithm**
Min	-42.25%	-44.30%	0.00%	0.00%
Max	68.42%	71.58%	68.42%	71.58%
2.5%	-26.60%	-29.57%	0.05%	0.24%
25.0%	-9.96%	-11.96%	0.77%	2.81%
50.0%	-0.80%	-2.82%	4.97%	8.16%
75.0%	0.74%	2.79%	12.05%	15.31%
97.5%	19.17%	23.35%	30.42%	32.84%
Mean	-3.46%	-3.46%	7.86%	10.32%
SD	11.33%	13.44%	8.86%	9.27%

When considering individual sites, the assignment algorithm will always assign the same TPG. This static assignment is based on the roadway and land use characteristics at the count site, regardless of the data collected. Conversely, the DDA method produces a dynamic TPG assignment for each site based on the combination of counts used. Table 3.7 shows the frequency of TPG assignment for each site-direction using both methods and the resulting MAPE. For example, the northbound traffic at site 5 was assigned to TPG 7 using the algorithmic method. When applying the DDA method, it was assigned to TPG 1 in 516 of the tested cases, to TPG 2 in 401 of the tested cases, and so on. As indicated in the final two columns, the MAPE for all test cases using the DDA method for this site was 10.97%, compared to 13.49% for the algorithmic method. Considering all sites examined, the DDA method out-performed the algorithmic assignment method in 23 of the 29 unassigned site-directions (79.3%).

Table 3.7: Frequency and accuracy of assignments to each TPG by assignment method at previously unassigned sites

			Assignment frequency to each TPG by DDA method								
Site-Dir	**True AADT**	**Alg.**	**TPG 1**	**TPG 2**	**TPG 3**	**TPG 4**	**TPG 5**	**TPG 6**	**TPG 7**	**DDA MAPE**	**Alg. MAPE**
5 NB	186.2	PG7	516	401	250	808	164	150	202	10.97%	13.49%
5 SB	175.9	PG7	449	524	321	556	238	182	221	8.20%	10.57%
6 NB	112.3	PG7	588	412	200	948	79	70	194	12.30%	15.09%
6 SB	100.9	PG7	1158	160	16	939	59	35	124	28.54%	30.42%
7 EB	96.4	PG7	911	267	70	1070	15	74	84	15.76%	18.42%
7 WB	93.9	PG7	1215	149	157	912	16	9	33	19.45%	22.20%
17 EB	569.9	PG6	55	181	1358	128	257	414	98	17.78%	20.02%
17 WB	576.6	PG6	57	202	1143	157	320	409	203	10.39%	12.63%
18 EB	560.6	PG6	202	249	930	238	232	485	155	6.51%	8.60%
18 WB	554.0	PG6	198	291	861	190	336	380	235	7.11%	9.48%
19 EB	8669.2	PG1	424	571	257	357	243	219	420	2.37%	2.50%
19 WB	8785.4	PG1	420	596	133	491	144	147	560	2.27%	2.00%
22 EB	1650.9	PG4	222	983	177	303	308	279	219	4.02%	2.73%
22 WB	1649.9	PG4	276	954	61	603	211	102	284	2.76%	2.56%
23 NB	295.8	PG2	92	186	815	138	380	621	259	3.85%	10.70%
23 SB	308.1	PG2	111	177	635	86	480	730	272	5.43%	13.02%
26 NB	6524.3	PG1	473	738	42	817	80	101	240	1.36%	2.40%
26 SB	6507.8	PG1	777	570	79	559	94	185	227	0.85%	1.47%
29 NB	225.1	PG3	461	645	86	750	116	85	348	7.03%	11.74%
29 SB	224.5	PG3	228	412	376	335	357	386	397	8.37%	11.31%
30 NB	438.1	PG2	374	899	62	633	170	43	310	7.29%	5.95%
30 SB	435.3	PG2	327	604	307	400	229	175	449	7.22%	6.10%
34 EB	125.8	PG7	1098	407	118	814	5	3	46	8.66%	12.33%

			Assignment frequency to each TPG by DDA method								
Site-Dir	**True AADT**	**Alg.**	**TPG 1**	**TPG 2**	**TPG 3**	**TPG 4**	**TPG 5**	**TPG 6**	**TPG 7**	**DDA MAPE**	**Alg. MAPE**
34 WB	126.8	PG7	849	526	2	959	35	17	103	8.79%	12.03%
44 EB	1560.0	PG4	387	568	229	227	356	241	483	2.75%	2.30%
52 EB	610.7	PG3	473	507	411	455	184	191	270	3.53%	7.41%
52 WB	615.2	PG3	481	463	356	425	334	190	242	3.50%	6.92%
93 EB	101.1	PG2	88	223	520	162	562	522	414	5.06%	11.34%
93 WB	89.0	PG2	32	63	786	33	415	890	272	5.86%	13.65%

3.5 DISCUSSION

The case study began by establishing a benchmark for typical (total) error ranges using the conventional methods for assigning and factoring short duration count data to estimate AADT. The results from *Step 1* showed that these values vary, depending on the characteristics of the site and its assigned TPG. On average, the simulated 48-hour short duration count data produced AADT estimates with an absolute error of 6.40%. These errors were roughly normally distributed with a standard deviation of 8.5%. Thus, to answer the first research question, an agency could expect a total average absolute error of 6.4% when estimating AADT from a single 48-hour count. Moreover, based on the distribution of errors, 95% of these estimates would be within 17% of the true AADT at the corresponding site. These results corroborate earlier findings by Milligan et al. (2016), which estimated the MAPE to be 6.7% using a similar dataset, but show a higher precision than the 95% confidence limits presented by Jessberger and Schroeder (2016), which were -22.47% to 25.09%. The errors identified here encapsulate each of the sources described in Figure 3.1 and represent the total expected error associated with using short duration count data to estimate AADT.

The analysis in *Step 2* disaggregated the results by TPG to isolate the assignment error (i.e., the portion of error that is associated with the assignment step). Considering the pre-assigned sites, the average MAPEs using the best and worst potential assignments were 5.57% and 14.28%, respectively. This suggests that the range of potential errors in the assignment step is up to 8.71%. However, from *Step 1*, the MAPE for all assigned sites was 6.40% using the existing assignments. Thus, the existing assignment error, given the study data, was found to be less than 1% on average (i.e., 6.40% minus 5.57%). Notably, these sites were already assigned to TPGs based on their roadway, land use, and traffic characteristics; this depth of knowledge about the site's characteristics would not exist at typical short duration count sites.

To address this issue, the currently unassigned sites were included in the analysis in *Step 2*. The unassigned sites showed a similar range in assignment errors as the pre-assigned sites. The best and worst potential assignments produced average MAPEs of 10.21% and 19.56%, respectively, or a range of 9.35%. Based on this result and the similar range reported for the pre-assigned sites, practitioners may conclude that the worst-case assignment would increase AADT errors by up to 9% of the true AADT. This addresses the second research question posed in this paper.

Step 3 considered only the previously unassigned sites. This removed the potential impact of autocorrelation between the sampled short duration count data and the temporal adjustment factors, both of which were created using continuous count data from the pre-assigned sites. The DDA method was used to assign each of these sites using the sampled short duration count data. This process was repeated for each combination of counts, producing a spectrum of assignments for each site. For comparison, the MHTIS assignment algorithm was also used to assign the same sites statically, based only on their roadway and land use characteristics. Only TPG 5 was unrepresented in the study set using this method. The MPE using both methods was -3.46% when aggregating results for all of the unassigned sites. This negative bias indicates that the group of unassigned sites have, on average, higher summer traffic volumes than the assigned TPGs. It is suspected that using samples from the full year would alleviate these biases, although this would deviate from the existing practice and guidance from the literature.

When considering absolute errors, the results using the DDA method were demonstrably more accurate than the assignment algorithm. The MAPE, aggregated for all sites, was reduced by nearly 2.5% (10.32% minus 7.86%) when using the DDA method. The results provide an answer to the third research question: the DDA method produces modest improvements in the overall accuracy of AADT estimates and could be used as a reasonable replacement to the existing algorithmic assignment method. However, the frequency with which the method assigned samples from the same site to the various pre-defined TPGs raises questions about the practicality of dynamically assigning short duration counts to TPGs in this way. Each site was assigned to each TPG at least once. In most cases, one or two TPGs emerge as the predominant assignment selections. While the results showed that, on average, dynamic assignments reduced the assignment error, in a real life application, the repeated simulated counts from these sites would be unavailable and a pair of counts would yield a single TPG assignment using the DDA method for a particular year.

Overall, the results show that given the available data from Manitoba, Canada, the DDA method can improve the accuracy of AADT estimates using sampled short duration count data. This finding is subject to at least two limitations. First, the study was limited in scope to a single year. It is unclear whether the accuracy improvements found using the DDA method would be consistent in a multi-year study. Second, the study assumed that sampled short duration count data, taken from a continuous count site, emulates the real-life short duration count data collected as part of a conventional traffic monitoring program. Past studies have also employed this technique (Sharma and Allipuram, 1993; Jessberger and Schroeder, 2016; Sharma et al., 1996; Milligan et al., 2016), lending to its credibility. Moreover, the results from Step 3 of the study focus solely on the unassigned sites to minimize the impacts of this limitation on the overall analysis findings.

This paper identifies three avenues for future work. First, the DDA method may be applied to other jurisdictions and for study periods spanning more than one year. The method is meant to be generally applicable, so the results from multiple regions would strengthen this assertion. Second, there is a need to further consider the appropriateness of a dynamic assignment approach, as embodied by the DDA method in this study. The assignment step is predicated on the assumption that a short duration count site experiences traffic periodicities that resemble those at a group of continuous count sites (for which traffic characteristics are well understood). The results from the case study suggest that, perhaps, this assumption does not hold at sites with relatively unknown traffic characteristics, as is the case at short duration count sites. Further study is needed to corroborate this finding. Finally, should practitioners opt to incorporate the principle of dynamic assignment into their traffic monitoring programs, there is a need to evaluate potential trade-offs between the error reduction offered by such a change and any necessary modifications to the existing short duration count program. Specifically, questions remain about the frequency (i.e., number of counts conducted in a calendar year), duration, and count cycle (i.e., the number of years between counts at the same site) that would generate optimal assignments and ultimately minimize the error in AADT estimates from short duration counts.

3.6 CONCLUSION

In general, the assignment step is used to infer some connection between the temporal traffic characteristics at a group of continuous counts and those expected at a site for which only short duration count data are available. The results in this paper show that this step can produce errors of over 9% in worst case scenarios, while the best case scenario produced assignment errors less than 1%.

The standard practice for assignment statically assigns short duration count sites to TPGs, inherently assuming that observed similarities in roadway and land use characteristics correlate with unobserved similarities in traffic periodicities. The results in this paper suggest that any pair of 48-hour counts provides sufficient data about a site's temporal traffic characteristics to yield more accurate AADT estimates than could be produced using the conventional approach based on this assumed correlation. In theory, an agency could apply these findings to improve their expected average accuracy in AADT estimates produced using short duration count data. However, the improved accuracy comes at the expense of consistency and context in TPG assignments. The question, then, is whether consistency and context are valuable or if these are ingrained in the current state-of-the-practice unnecessarily.

3.7 ACKNOWLEDGEMENTS

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4 EXPLORING PROBE DATA AS A RESOURCE TO ENHANCE SHORT TERM TRAFFIC COUNT PROGRAMS

This chapter broadens the investigation of AADT estimation practice by assessing the viability of integrating a new data source, passively-collected vehicle probe data, into conventional traffic monitoring practice. It seeks to answer the third objective question: *What attributes of passively-collected probe data can be used to improve short duration count programs?*

The analysis explores multiple relationships between passively-collected probe data and conventional continuous count data. The relationships are evaluated to identify trends with respect to temporal variability, spatial variability, and vehicle classification data. It contributes to the thesis theme by assessing how the relationships between probe data and conventional traffic data produce opportunities to enhance AADT estimation practice.

The material in this chapter is submitted for publication to the Canadian Journal of Civil Engineering and reprinted with permission of co-authors Matthew Lesniak, Louis-Paul Tardif, and Jonathan Regehr. The chapter is self-contained with its own abstract, introduction, and conclusion; references are provided at the end of the thesis. The thesis author conducted the analysis and literature review, interpreted results, and prepared the manuscript.

4.1 ABSTRACT

Traffic monitoring practice depends on point-based data collection devices. Annual average daily traffic (AADT) is a fundamental traffic statistic in infrastructure design, planning, and management. Passively-collected probe data have emerged as a potential alternative for providing widespread data collection. This article explores the potential of integrating speed-based probe data and traditional traffic volume data in Manitoba, Canada, by analyzing the relationships between them.

The results indicated that mean travel speed appeared to be a poor predictor of traffic volumes, as it did not deviate from the free flow speed within the observed volume range. The quantity of probe data observations showed moderate correlation with traffic volume in some areas (R-squared up to 0.65). At nearly all sites, the correlation was stronger between observed probes and truck traffic volume. These findings imply that probe data can be used in conjunction with traffic data by providing unique applicability in truck traffic monitoring.

4.2 INTRODUCTION

Traffic monitoring programs provide input data to highway and infrastructure design applications by measuring and estimating the volume, speed, and classification of vehicles using roadways. Annual average daily traffic (AADT) is the most common traffic volume statistic. AADT describes the expected number of vehicles using a facility for a single day in a given year. Resource limitations constrain the means by which agencies measure or estimate AADT on large road networks. Such constraints lead to uncertainties (errors) in reported AADT statistics or the absence of AADT estimates on certain portions of the network. Given these shortcomings, researchers and practitioners have explored novel methods and technologies to estimate traffic volumes – particularly AADT. This article explores the use of passively-collected probe data as a resource for improving traffic volume estimates at short term count sites.

Traditionally, traffic monitoring practice uses short term count programs to provide network-wide coverage with lower resource requirements than permanently installed devices. By definition, short term counts have a duration of less than one year, though most range from a few hours to a few days (AASHTO, 2009; FHWA, 2016b; Regehr et al., 2017). Since these counts do not encapsulate a full year of data, they are prone to biases in estimating daily traffic volumes due to the variability of traffic throughout the year (e.g., traffic on a summer weekend may be abnormally high compared to the annual average). These biases are typically corrected by applying temporal adjustment factors that are generated using full-year data. In this way, a short term count can be adjusted for seasonal effects to produce a more reliable AADT estimate. The annual average estimates are preferred as they are assumed to have captured the periodicities of traffic volumes by day-of-week and month.

4.2.1 Research Objectives and Scope

The primary objective of this article is to assess the strength and form of relationships, if any exist, between probe-based speed data and conventional site-specific traffic data. This objective supports a broader goal of using probe-based data to supplement conventional traffic monitoring programs. The development and testing of specific models and approaches to achieve this broader goal are beyond the scope of this research but are recommended as potential next steps for future work based on the findings herein.

The geographic scope of the research is the highway network in Manitoba, Canada, specifically those locations that are continuously monitored by permanent traffic count sites (PTCS). The study period encompasses hourly data from 2018. Probe-based speed data are provided by Transport Canada from HERE Technologies™, a third party probe data analytics company. Conventional traffic data are obtained from the Manitoba Highway Traffic Information System (MHTIS).

4.2.2 Literature Review

Annual average daily traffic is the most commonly used traffic volume statistic. AADT is a key input in numerous infrastructure applications (AASHTO, 2009, 1993; Chen and Xie, 2016; FHWA, 2016b; Fu et al., 2017; Regehr et al., 2017). It summarizes a year's worth of traffic volume into a simple statistic that is comprehensible and widely applicable. Consequently, traffic monitoring agencies place high priority on estimating AADT throughout a network. For example, the U.S. Federal Highway Administration (FHWA) requires annual estimates of AADT as part of its Highway Performance Monitoring System. While no equivalent legislation exists in Canada, most provincial traffic monitoring programs prioritize the production of AADT statistics (Regehr et al., 2017).

Numerous technologies and techniques exist to monitor traffic and estimate AADT. Agencies balance the benefits and shortcomings of these technologies and techniques to monitor traffic throughout a road network. Conventionally, two general approaches have emerged: (1) deployment of permanently-installed and continuously operated equipment (i.e., continuous counts) to capture traffic variability over time; and (2) deployment of temporarily-installed and/or portable equipment to obtain short term samples of traffic data (i.e., short term counts) for broad geographic coverage (FHWA, 2016b; Regehr et al., 2017). Both approaches collect site-specific traffic data.

Continuous counts are those that are conducted for an entire year. Often, these counts make use of permanently-installed devices on or near the roadway. Continuous counts are resource-intensive, making them unsuitable for covering dense or vast road networks in their entirety. A continuous record of count data at a site enables AADT calculations, assuming that the data exist for the full counting period (Grande et al., 2017; Jessberger et al., 2016), and allows for the production of seasonal factors for calculating AADT at short term count sites.

Two methods are commonly employed for calculating AADT from continuous count data. The first is the simple average, wherein the AADT is taken to be the mean of all daily traffic volumes for the study year. The simple average produces an accurate estimate of AADT in cases where little or no data are missing (FHWA, 2016b; Grande et al., 2017; Jessberger et al., 2016). However, if significant portions of data are missing, the AADT may be biased due to the variability of traffic volumes. The second method, referred to as the AASHTO method in the Traffic Monitoring Guide (FHWA, 2016b), groups all daily traffic volumes by weekday and month to account for missing days of data. Equation 4.1 shows the AASHTO formula for calculating AADT of a certain vehicle classification (FHWA, 2016b). Note that the classification of vehicles is not a necessary step in calculating AADT, generally.

$$AADT_c = \frac{1}{12}\sum_{m=1}^{12}\left[\frac{1}{7}\sum_{j=1}^{7}\left(\frac{1}{n_{jm}}\sum_{i=1}^{n_{jm}} VOL_{ijm,c}\right)\right] \tag{4.1}$$

Where:

VOL_{ijm} = total traffic on i^{th} occurrence of j^{th} day of week within m^{th} month;

i = occurrence of a particular day-of-week in a particular month;

j = day-of-week (1 to 7);

m = month-of-year (1 to 12);

n_{jm} = amount of times day j occurs in month m with available traffic data; and

c = FHWA vehicle classification. (*optional)*

Short term traffic counts are those that are conducted for less than the full year. Typically, these span from a few hours to one week in duration. Short term counts are a cost-effective way of collecting traffic data on extensive road networks. However, the natural variability in traffic, as well as seasonal and daily trends, limit the use of average daily traffic volumes as surrogates for AADT (Regehr et al., 2017). Instead, short term counts are adjusted to account for traffic variability when estimating AADT (FHWA, 2016b). This is done by assigning short term counts to factor groups (or traffic pattern groups), which comprise a set of continuous count sites that exhibit similar traffic characteristics.

Gadda et al. (2008) provide a comprehensive review of several error sources associated with converting short term traffic counts into AADT. They make recommendations for how best to mitigate estimation errors, including the use of multiple seasonal counts, counting on weekdays, and improving the process by which short term counts are assigned to factor groups. Milligan et al. (2016) further quantify these errors in the context of road safety performance measures. They find that 48-hour counts substantially reduce error, as compared to 24-hour counts, but that multiple counts have little effect on the overall accuracy of estimates. Tsapakis et al. (2012) provide alternatives to the assignment method for short term count programs. Bagheri et al. (2014) incorporate Bayesian statistics with historical data to estimate AADT. Some projects have applied advanced algorithms to improve AADT estimates, such as artificial neural networks (Gecchele et al., 2013; Sharma et al., 2002).

On very large networks, even the relatively cost-effective short term count program is infeasible for covering the entire network (Wang et al., 2013). Aiming to capture classification data further intensifies this issue. The FHWA (2016b) and TAC (2017) recommend that agencies collect classification data at 25 to 30% of their short term sites, at minimum, leaving room for flexibility based on resource constraints and traffic data needs. Paramita et al. (2020) developed a tool to design an appropriate classification count program based on multiple agency inputs and desired outputs. Their tool is applied to Manitoba’s traffic monitoring program as a case study. The problem of capturing traffic on an entire network is particularly noteworthy in urban areas, where traffic conditions change frequently in space and time (Regehr et al., 2017). This has led to the advent of alternative traffic monitoring technologies and techniques that leverage newly available data.

Passively collected data is perhaps the strongest candidate for enhancing traffic monitoring practice (Cambridge Systematics Inc. and Massachusetts Institute of Technology, 2018). These data are collected by other means and for other purposes, but often reflect certain traffic patterns and thus may be a resource for traffic monitoring programs. For example, cell phones’ call detail records (CDRs) have been investigated for estimating traffic volumes (Calabrese et al., 2013; Montero et al., 2019; Zhao et al., 2016). Unfortunately, the spatial granularity of cell towers and the relatively low uptime of cell phone activity limits the effectiveness of these as a replacement for traditional methods (Becker et al., 2013). Zhang and Chen (2020) use probe data to enhance statewide AADT estimates by deriving annual average daily probe volumes and betweenness centrality from probe speeds. Other works have sought to combine CDR data with other sources, though not to estimate AADT (Toole et al., 2015; Wu et al., 2015).

There are now multiple organizations that purchase passively collected probe data and repurpose it for traffic analyses. At least two studies have directly assessed the efficacy of such programs. Streetlight Data® worked with the Minnesota DOT to develop and test the beta version of its traffic volume analysis program (Turner, 2017). They found a wide range of estimation errors, particularly on low volume roads, and identified the technology as promising but with a need for improvement. The Louisiana Transportation Research Center (LTRC) (Codjoe et al., 2018) assessed Streetlytics®' product for AADT estimates. Again, the technology showed promise but produced significant estimation errors that were exacerbated on low volume roads. However, the LTRC recommends continued use of Streetlytics data, with stipulations, which suggests that the promise of full network coverage has benefits that outweigh the inaccuracy costs.

This article extends past attempts to merge traditional methods with passively collected data. Specifically, it investigates potential options for integrating probe-based speed data into a traditional traffic monitoring program (in this case, the program in Manitoba, Canada). It uniquely considers vehicle classification data in rural environments as they relate to probe data.

4.3 METHODOLOGY

This article investigates potential relationships between conventional traffic monitoring methods and passively-collected probe data. This section describes the databases used for the research and the analysis methods applied.

4.3.1 Data

Traffic data are provided by the MHTIS. The data provided are obtained, by hour, from 85 permanently-installed traffic count sites (PTCS) across Manitoba on provincially controlled highways. Note that each PTCS measures traffic by direction, and so there are 170 PTCS-direction pairs of data available. However, if data are missing from a site for a significant portion of the year, AADT cannot be estimated.

Transport Canada provided probe data sourced from HERE Technologies' Traffic Analytics data set. HERE Technologies collects probe data from multiple sources, including commercial and non-commercial vehicles. The data used in the analysis are speed-based probe data, aggregated by hour and road segment. Note that these are post-processed data, where HERE Technologies cleans and prepares the speed data using their own proprietary methods. While the use of post-processed data places certain constraints on the analysis, it nevertheless facilitates a pragmatic assessment of the utility of a readily-available commercial data product for enhancing short term traffic count programs. Only hours with at least one available probe device are included in the database, meaning that hourly speed statistics exist for every link if at least one probe is measured during that period. The attributes considered in the exploratory analysis follow:

- *Mean speed (km/h)*: This attribute represents the arithmetic mean of speed observations. It is calculated by hour for each road segment.
- *Free-flow speed (km/h)*: This attribute represents the estimated unimpeded travel speed of traffic. It is estimated by HERE Technologies using speed observations during off-peak hours and is assumed to be constant for each road segment.
- *Probe count*: This attribute represents the number of probe devices detected. It is measured by hour for each road segment.
- *Functional classification*: This attribute represents the type of road segment. It is defined by HERE Technologies on a scale from 1 to 5, where 1 represents the road segments with the heaviest traffic.

Both MHTIS data and probe data are provided for the entirety of calendar year 2018. The analyses require that the site-specific MHTIS data be mapped to the same road segments as the link-based probe data. Road segments are defined by HERE Technologies based on an assumption of homogeneous traffic conditions. MHTIS uses a linear referencing system that differs from that of the probe data. GPS coordinates were used in a GIS environment to find the concurrent probe data links. In this way, each MHTIS PTCS was mapped to a single corresponding probe data link. One limitation of this method is that the probe data links are variable in length, based on changes in roadway conditions. This variability is lost when conducting one-to-one pairing of MHTIS PTCS with probe data links.

4.3.2 Methods

This article explores the relationships between commercially-available (post-processed) probe-based speed data and conventional traffic data collected at continuous count sites. Specifically, it examines the relationships between probe vehicle speed or volume and site-specific traffic volume and classification over multiple periods. The analytical methods proceed sequentially as described in the following paragraphs. The next section contains additional analysis details.

Based on previous research, the analysis first explores the question: *Is there a relationship between mean travel speed (as measured by probe data) and traffic volume (as measured at a PTCS)?* Traffic flow theory suggests that mean travel speed (space mean speed) and traffic flow rate are related (Kong et al., 2009; Mahmassani et al., 2013). As commonly depicted by the fundamental diagrams of traffic flow, when the number of vehicles using a facility reaches some critical flow rate, the mean travel speed starts to deteriorate. Flow rate describes the number of vehicles using a facility over some period, often expressed in terms of an equivalent hourly rate. Likewise, traffic volume describes the number of vehicles per unit time that use a facility (measured, for example, in vehicles per hour or vehicles per day). It follows that traffic volumes may have some relationship with detected speeds, since both flow rate and volumes describe the quantity of vehicles over time. Consequently, the analysis examines the relationships between traffic volumes and mean recorded speeds for hourly and daily periods.

The classical Greenshields' model suggests that the relationship between mean travel speed and traffic flow rate is parabolic, expressed mathematically as given by Equation 4.2:

$$q = k_j v - \left(\frac{k_j}{v_f}\right) v^2 \tag{4.2}$$

where:

q = traffic flow rate (veh/h)

k_j = jam density of the facility (veh/km)

v = mean travel speed (km/h)

v_f = free-flow speed of the facility (km/h)

Note that the jam density and free-flow speed of a facility are assumed to be constant.

However, other models have shown that mean travel speed remains nearly constant relative to the flow rate (i.e., a horizontal line) in uncongested conditions (Hall et al., 1992). Preliminary analysis of the traffic data available from MHTIS predominantly revealed free-flow traffic conditions (i.e., the capacity of the roads greatly exceeds the demand for service on these roads).

As a second step, and based on recent findings by Zhang and Chen (2020), the analysis considers another question: *Is there a correlation between the count of vehicle probes and traffic volume?* Traditional traffic monitoring practice uses sampling to overcome resource limitations in collecting traffic data. Probe vehicles represent a form of vehicle sampling that is parallel to the principles of sampling in space or time (that is, sampling must be conducted carefully and/or accounted for when producing AADT estimates). If the penetration rate of probes within the total traffic stream is constant, there should be a strong, linear correlation between probes detected and total traffic volume. As an exploratory analysis, this step assesses this relationship by reporting the coefficient of determination (R-squared), but does not attempt to test the significance of the relationship or propose a linear model.

Findings from the foregoing analysis lead to further questions. *What spatial and temporal patterns are evident in the relationship between the count of vehicle probes and traffic volumes? And, what impact does vehicle classification have on the observed relationships?* Spatially, the analysis considers the location of the PTCS relative to major highways and urban centres. Temporally, the analysis considers hourly and daily periods, and groups data by day of week and month of year (based on findings from the literature review). Finally, the analysis filters traffic data to consider only truck traffic. In this case, truck traffic refers to any vehicle that fits into FHWA vehicle class 5 or higher (FHWA, 2016b). Again, results of the correlation analyses are reported using the R-squared statistic.

4.4 RESULTS AND DISCUSSION

The analyses described in this section utilize vehicle probe data provided by HERE Technologies and continuous count traffic data for a total of 170 PTCS-direction pairs in Manitoba. Of these, 145 satisfied the requirement for producing an AADT estimate using 2018 traffic data and applying Equation 4.1 (i.e., they measured traffic volumes for at least one entire day for every combination of day-of-week and month). Missing data were attributed to temporary equipment malfunctions at the PTCS during the study year. Only the locations with valid AADT estimates were featured in the analysis.

4.4.1 Speed-volume relationship

The first test for a relationship between the probe data and traffic data considered the mean travel speed, provided hourly by road segment, and the total traffic measured at the corresponding MHTIS PTCS. Figure 4.1(a) shows this relationship, aggregated for all studied sites. In this case, speed is shown as the dependent variable. Mean speed is depicted as a percentage of free-flow speed to normalize data across multiple sites. The results show that, regardless of hourly traffic volume, mean travel speeds as a percentage of free-flow speed are randomly distributed around the free-flow speed. Further, the data show considerable variance, especially at low volumes, and are roughly normally distributed around the mean.

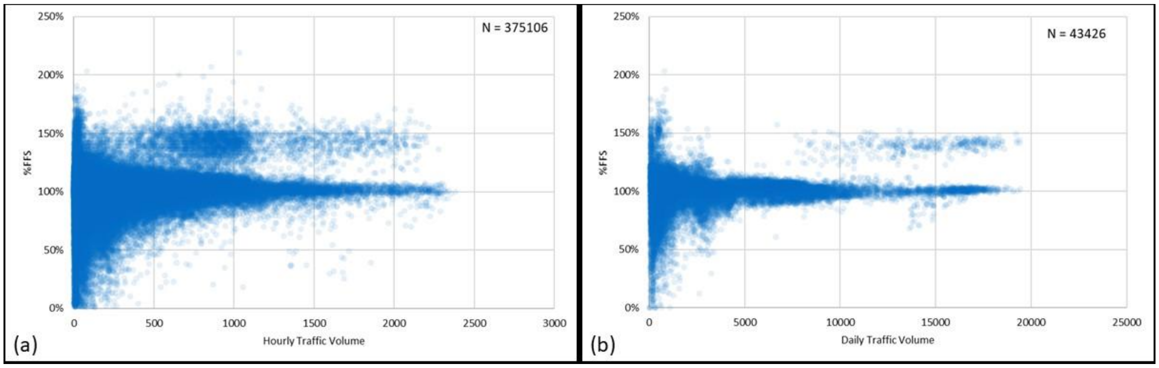

Figure 4.1: Relationship between mean travel speed (expressed as percentage of free-flow speed, FFS) and (a) hourly total traffic and (b) daily total traffic

This process was repeated to check for a relationship at the daily time scale, as shown in Figure 4.1(b), where daily mean travel speed is taken to be the average of hourly mean travel speeds, weighted by the number of observations per hour, over an entire day. The results provide some clarity on the speed-volume relationship. Specifically, summing the hourly volumes to produce daily equivalents reduces the amount of variance around the free-flow speed, though at very low volumes the problem persists. Regardless, the resultant conclusion is the same for both base time units – no matter the recorded volume, the mean travel speed is randomly distributed around the free-flow speed and the expected mean travel speed does not vary. This is consistent with the assumption that the traffic data represent uncongested conditions. As volumes get higher, the variance in mean travel speed is reduced.

A series of outliers are apparent at roughly 140% of the free-flow speed. These observations all come from one site in northern Manitoba, whose reported free-flow speed is 64 km/h, which is well below expected travel speeds on a rural highway. This suggests that there is a systematic reduction in speed at this site during the off-peak hours, which are used to produce the free-flow speed, and that a majority of the traffic operates at higher speeds.

As described earlier, traffic flow theory suggests that mean travel speed and traffic flow rate are related, where very high demand (i.e., high traffic flows) creates congested conditions on a facility and reduces the mean travel speed. This analysis considered the assumption that traffic volumes, which represent an aggregate of instantaneous flows, could be applied in the same way. The observed data support this theory by exemplifying part of the expected parabolic relationship between speed and flow. However, the observed traffic volumes on the Manitoba highway network seldom reach saturated flow conditions. It is likely that the recorded volumes are not high enough to meaningfully reduce travel speed for an entire hour or day. Thus, the observed speed-volume relationship agrees with traffic flow theory, but there is no reduction of traffic speeds and no meaningful speed-volume relationship to infer from the available data.

4.4.2 Probe count-volume correlation

The second test for a relationship between probe data and traffic volume data considered the proportion of probe vehicles to total traffic, or the penetration rate of probe vehicles in the traffic stream. Figure 4.2(a) shows this relationship, at an hourly time scale, across all studied sites. The hourly scatter plots feature a considerable amount of noise, similar to the speed-volume data. However, unlike the speed-volume data, there is no random distribution around the mean – implying that some correlation is plausible.

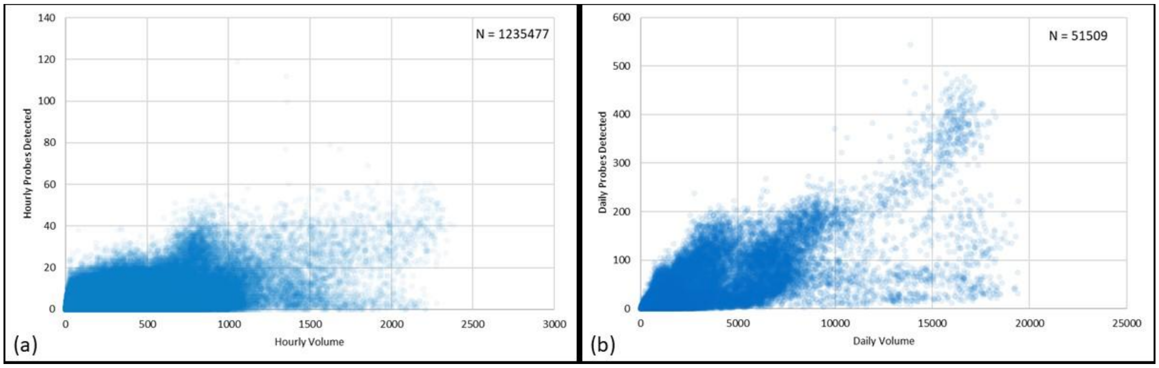

Figure 4.2: Relationship between (a) hourly probe counts and hourly total traffic volumes and (b) daily probe counts and daily total traffic volumes

Traffic volumes and probe counts were also examined at a daily time scale. Figure 4.2(b) shows the relationship between daily traffic volumes and probe vehicle counts, aggregated for all study sites. Again, summing hourly data into daily equivalents starts to provide more clarity on the underlying relationships. In this case, multiple clusters of data emerge that were not evident at the hourly level. The two clusters on the bottom-right and top-right of the figure represent data from two sites on Winnipeg's Perimeter Highway. The traffic volumes at these sites are high relative to the other studied sites, and exhibit different probe count-volume behaviour. This suggests that the probe count-volume relationship may vary with roadway characteristics, similar to the concept of traffic pattern groups that is common in traffic monitoring.

Indeed, when considering individual sites, as shown in Figure 4.3, patterns emerge more clearly. Two sites, labeled A and B, are used to illustrate the findings from the analysis.

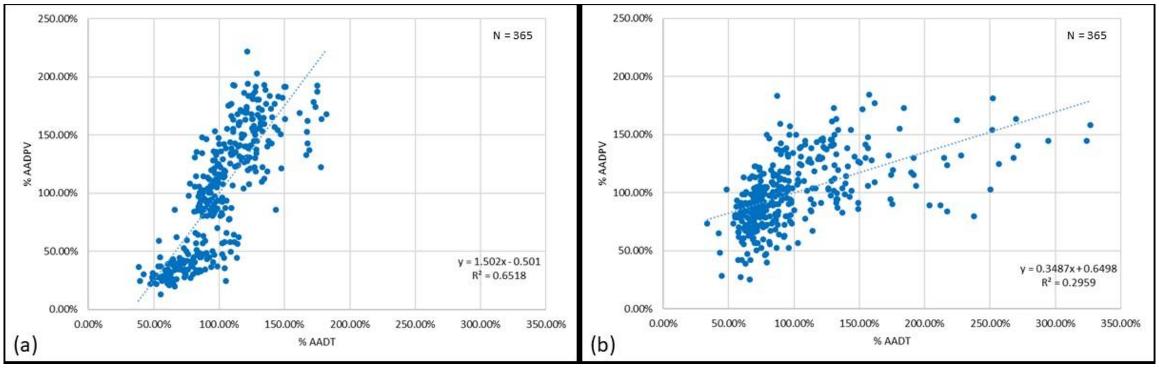

Figure 4.3: Relationship between AADPV and AADT at (a) site A and (b) site B

- Site A is located on Winnipeg's south Perimeter Highway (PTH 100). The AADT at this site is roughly 14,000 vehicles per day with a 50-50 directional split. Traffic at this site exhibits typical commuter traffic behaviour, with peaks in the morning and afternoon on weekdays, and generally lower traffic volumes on weekends. Seasonally, the traffic at this site is highest in the summer, with the monthly average daily traffic (MADT) in July reaching 127% of AADT.
- Site B is located on the Trans Canada Highway (PTH 1). The AADT at this site is roughly 7,800 vehicles per day with a 50-50 directional split. Traffic at this site exhibits high weekend traffic and no clear hourly peaks. Seasonally, the traffic at this site is very high in the summer (MADT peaks in August at July is 163% of AADT) and low in the winter (MADT in January is 61% of AADT).

These figures normalize the input data against annual average daily values. The analysis assumes that the traffic periodicities underlying the AASHTO method for estimating AADT are applicable to probe vehicle counts, based on the findings of Zhang and Chen (2020). In this way, annual average daily probe vehicles (AADPV) are estimated for all sites by applying Equation 4.1.

These two sites are both located near the southeast corner of Winnipeg and are 34 km apart. Despite their close proximity, they exhibit different relationships between probe counts and total traffic volumes (as shown by the R-squared statistics). Notably, the traffic data at site A has a relatively strong correlation with probe data (R-squared = 0.652) while at site B the correlation is weaker (R-squared = 0.296). Thus, the probe count-volume relationship likely exists, but external factors affect the nature of this relationship at different sites.

4.4.3 Variation in probe count-volume correlations

The analysis continued, post hoc, by investigating the causes for varied probe count-volume behaviour at different sites. The analyses shown in Figure 4.3 were replicated for all sites with a valid AADT estimate. Figure 4.4 shows the resultant R-squared statistic for each correlation conducted using probe count and volume data. The figure also shows major highways in Manitoba, designated as classes 1, 2, or 3 in the 5-class scheme provided in the probe data.

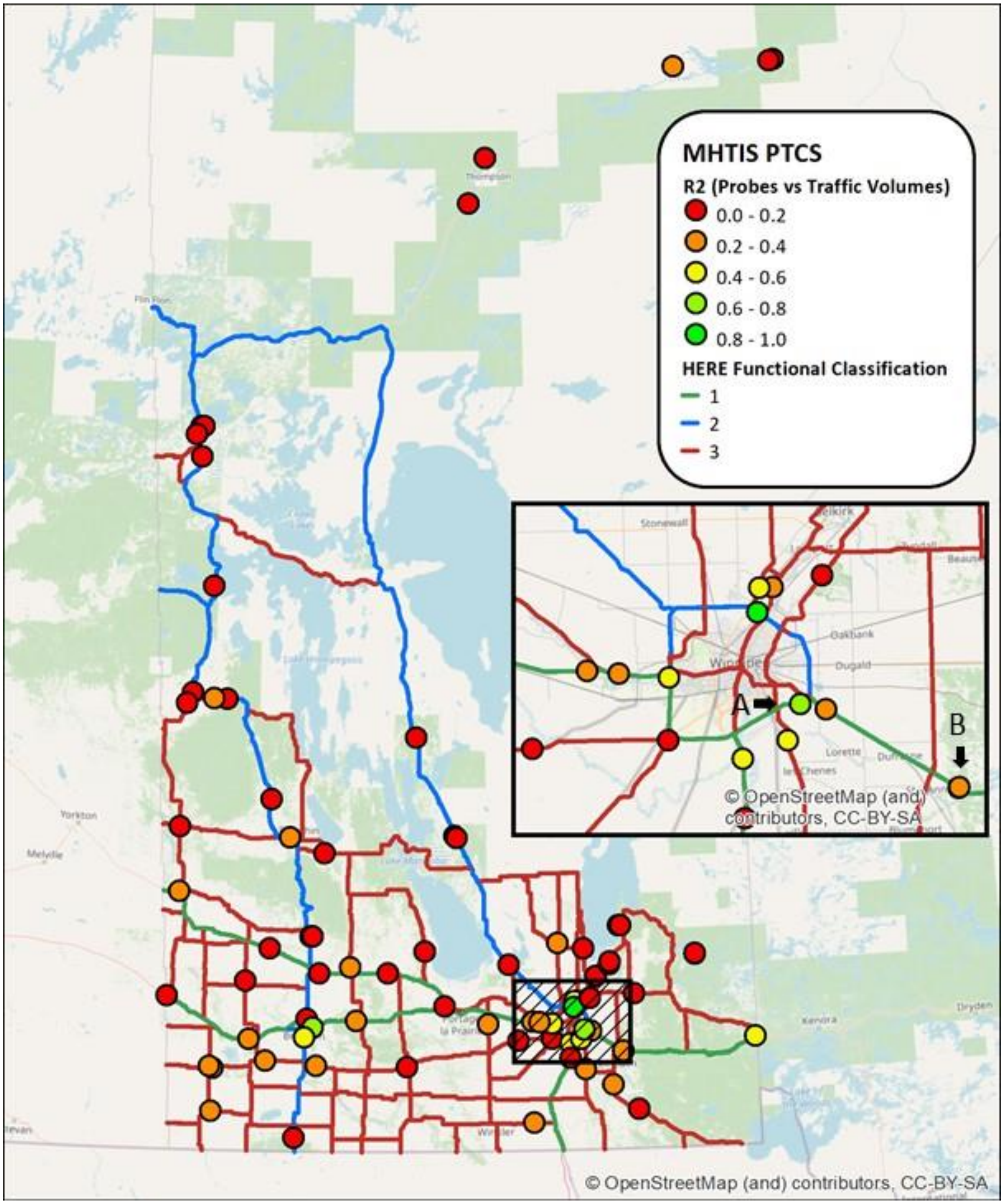

Figure 4.4: Results from correlation analysis of probe count and total traffic volume for all sites in Manitoba

The resultant R-squared statistic is below 0.4 for 128 of the 145 studied site-directions. The exceptions to this predominantly occur at sites around Winnipeg and Brandon – the two largest urban centres in Manitoba. The results imply that the probe count-volume relationship does vary in space. Seemingly, proximity to urban centres has a positive influence on the correlation. This also helps to explain the visible outlier clusters in Figure 4.2, where unique probe count-traffic relationships are apparent. Given that spatial relationships were apparent in the data, the analysis continued by analyzing temporal relationships as well.

The temporal variations were tested by comparing the variance in traffic at each site to the variance in probe counts. To illustrate, Figure 4.5 shows the traffic variations at sites A and B by day of week. The values used in these graphics are the proportion of average daily traffic for the weekday (e.g., all daily counts on Mondays) relative to the annual average value (i.e., AADT for traffic and AADPV for probe counts). A third measure is shown for truck-only traffic, based on potential relationships between probe counts and truck traffic, explored in the final part of the analysis. Error bars indicate one standard deviation of the data in both directions.

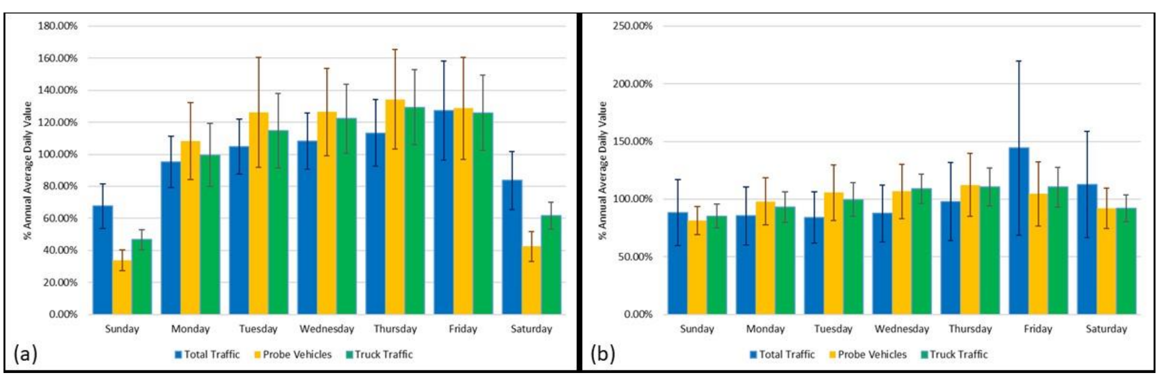

Figure 4.5: Day of week traffic ratios for (a) site A and (b) site B

The results show that probe counts differ significantly from total traffic in terms of daily variation. Probe counts are disproportionately low on weekends, compared to total traffic. This is a trend that is more common to trucks and other commercial vehicles that tend not to operate on weekends, so trucks are included in the figures for comparison. The variance on weekends is also disproportionately low. This contrasts with traffic data, particularly in near-urban areas like the sites shown, where weekday traffic is more stable. The similarities between probe counts and a subset of total traffic (i.e., trucks) provide impetus for the final component of this analysis.

4.4.4 Probe count-truck volume correlation

The prior analyses on probe count-volume data were repeated using filtered traffic data that only included truck traffic. Note that vehicle classification data are only available at certain PTCS that automatically classify vehicles into the FHWA 13-class scheme (FHWA, 2016). In this case, trucks encompass all vehicles of class 5 and above. In order to be used in the analysis, truck traffic data at each site must be sufficient for calculating annual average daily truck traffic (AADTT) using the AASHTO formula (Equation 4.1, stipulating that only vehicles class 5 and above are included). In total, 48 sites contained valid data for the analysis and a total of 89 site-direction pairs were used. Figure 4.6 shows this relationship, aggregated for all sites with valid truck data, using hourly and daily time scales.

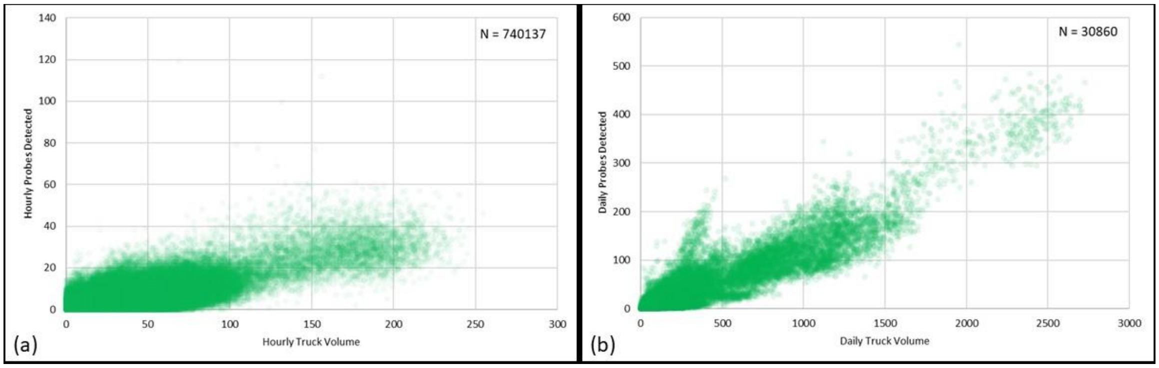

Figure 4.6: Relationship between (a) hourly probe counts and hourly truck traffic volumes and (b) daily probe counts and daily truck traffic volumes

The results show a clearer linear relationship between truck traffic volume and the probe count. The noise and clustering that were apparent in the total traffic data are considerably reduced when filtering the data into only trucks. To illustrate, Figure 4.7 shows this relationship at sites A and B, with both axes normalized against annual average daily values at those sites. Note that the correlation is very strong at site A (R-squared = 0.873, compared to 0.652 for total traffic) and is also stronger at site B than it was for total traffic (R-squared increased from 0.296 to 0.589). This process was repeated at each site with valid data, using the R-squared statistic to represent the relative strength of the linear correlation. Figure 4.8 shows how this relationship varies across Manitoba.

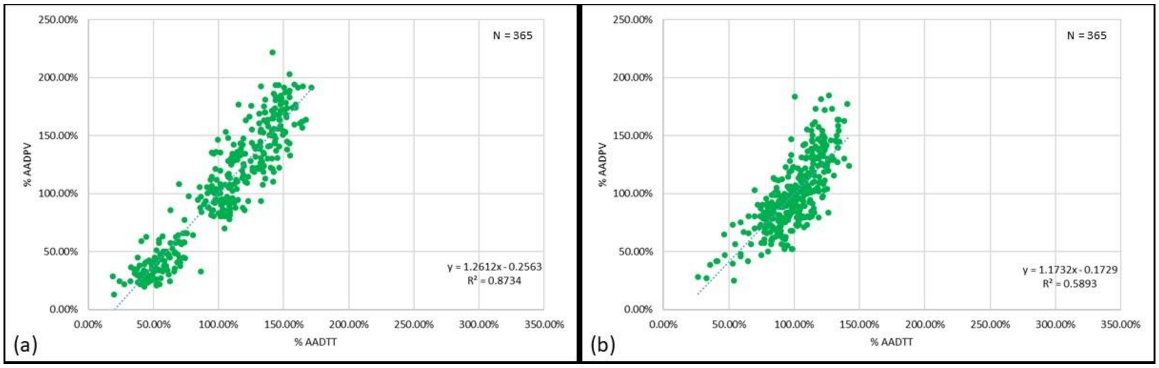

Figure 4.7: Relationship between daily truck volumes and probe counts at (a) site A and (b) site B

The province-wide results corroborate the earlier findings. Probe count data are shown to have a stronger linear correlation with truck traffic than total traffic at most sites in the province. 39 of the 89 site-directions tested yielded an R-squared statistic of 0.6 or greater (19 of the 48 sites satisfied this condition when considering data for both directions). Once again, the correlation around urban centres is very strong. Further, the correlation is very strong along the class 1 roads (i.e., on major highways). These routes serve high levels of inter-provincial truck trips, which are likely captured by HERE Technologies as probe vehicles. Conversely, roads that are not on major truck routes tend to show very poor correlation between probe count and truck volumes (in addition to the established weak correlations between probe count and total traffic). Thus, the probe count-truck traffic correlation is shown to exist and has a spatial relationship that is a function of the truck traffic patterns at those sites.

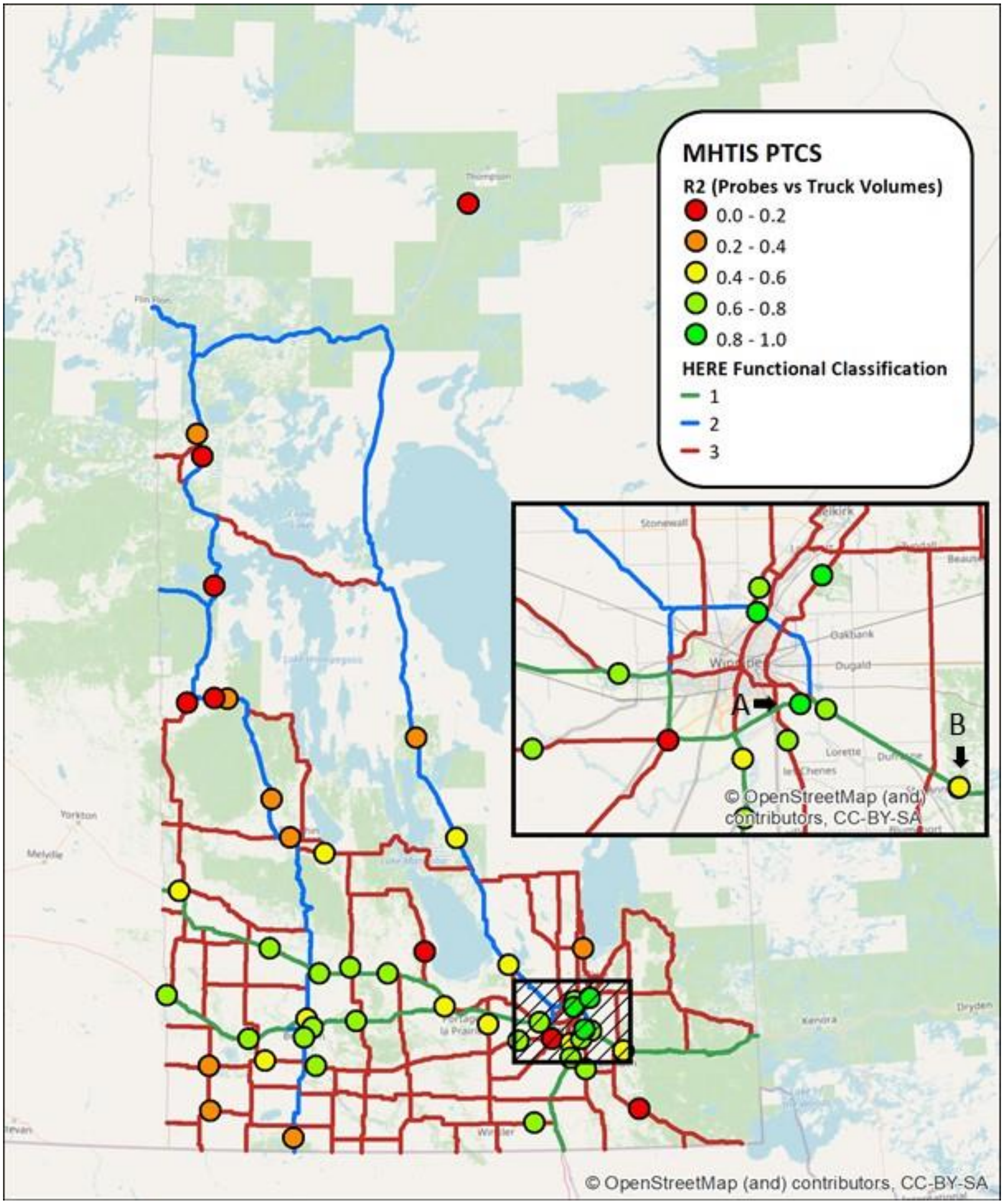

Figure 4.8: Results from correlation analysis of probe count and truck traffic volume for all sites in Manitoba

Generally, R-squared values exceeding 0.6 can be considered strong (60% of the variance in the dependent variable can be explained by variance in the independent variable). However, the value of the R-squared statistic is application-dependent. Lower R-squared values may be considered to be valuable if the alternatives are insufficient or non-existent, whereas very high R-squared values may be considered weak in cases where strong models already exist. When considering truck traffic (in this case, a binary classification), the available alternatives for collecting network-level classification data are known to be poor (Paramita et al., 2020).

4.5 CONCLUSION

4.5.1 Findings

Reliable AADT data are fundamental for numerous civil engineering applications. This article explored the potential for a new resource – passively-collected probe data – to supplement conventional traffic monitoring practice for generating network-wide estimates of AADT.

Generally, the quality of traffic data may be enhanced by implementing techniques that improve (1) the accuracy of estimates and/or (2) the precision of estimates. Past research has benchmarked such values in the context of network-level AADT estimates (Milligan et al., 2016; Sharma et al., 2002). However, probe data are highly pervasive in space and time – data are available for the entire year on an entire network. Moreover, post-processed data products generated by probe data are increasingly available from commercial providers. Thus, the spatial coverage provided by probe data offers a third dimension by which data quality from short term count programs may be enhanced.

Based on the available data, the results suggest that mean travel speed cannot be used to predict traffic volumes on Manitoba highways. These highways carry relatively low traffic volumes in comparison to their roadway capacity, and so the mean travel speed is almost always near the free-flow speed, regardless of the hourly or daily volume measured. In terms of traffic flow theory, the demand is too low to ever reach breakdown conditions at any of the measured sites. Thus, the expected parabolic relationship between speed and traffic flow is not apparent in the results. A lower capacity or busier roadway may exhibit the expected decline in mean travel speed that would allow for inferences about the speed-volume relationship, which could be the focus of future research.

Observations of traffic flow suggest that speed variance should be relatively high when volumes are low, since vehicles are free to travel at their desired speed (Blandin et al., 2012). As volumes increase, individual drivers are constrained by surrounding traffic, so the speed variance decreases. While the results presented in this article agree with this expectation, this agreement is likely influenced by sampling issues. The lower volume sites, generally, have fewer available probes. Thus, the resultant speed estimates at low volume sites are generated from a relatively small sample size and exhibit higher variance than the data at higher volume sites.

Probe vehicle volumes show more promise in being able to support volume estimation processes. The general upward trend in probe vehicle counts with total traffic volumes implies some correlation between them. Intuitively, as traffic volumes increase, so too should probe vehicle observations. However, the majority of sites showed very weak linear correlations between probe counts and total traffic volumes. This indicates variability in the probe penetration rate when using passively-collected probe data. The results show that the proportion of probes to total vehicles is quite volatile. Since current traffic monitoring practice already implements multiple methods that are known to mitigate errors in AADT estimates (e.g., by employing traffic pattern groups and collecting multiple samples in a single year), there is a low likelihood that introducing passively-collected probe data would reduce existing errors with such weak correlations.

Probe vehicles are a sample of the total population. Thus, probe vehicle counts could be used to estimate traffic volumes if penetration rates were consistent. Instead, there is some expected noise and multiple apparent relationships in the data. Based on the results, the penetration rate varies in space and time. Moreover, the available probe count data more closely resemble a subset of traffic data – trucks. Indeed, the available probe count data showed strong correlation with truck traffic data, particularly in urban areas and on major highways, where trucks are more prevalent and contribute meaningfully to the pool of probe vehicles. This also helps to explain the modest improvements to correlation with total traffic around urban centres. Roads that are not on major truck routes show weak probe count truck volume correlation. These findings point to two conclusions regarding probe count and traffic volumes in Manitoba:

- Where trucks are meaningfully present within the traffic stream, it may be possible to use them as probes to reasonably estimate the truck traffic volume on road segments.
- The penetration rate of probes among non-truck traffic appears too inconsistent to reliably make inferences about traffic volumes.

At its outset, this article considered whether readily-available probe-based data could be used to support traffic monitoring practice by searching for relationships between probe-based speed data and conventional traffic volume data from Manitoba. The findings show that there are, at best, tenuous relationships between the available total traffic data and these probe data. However, the findings reveal potential for using probe counts for supplementing truck traffic volume estimates.

This potential has implications for civil engineering applications. Infrastructure design and management, in particular, depend on accurate traffic data. For example, truck volume data are a fundamental input to the design of pavements, bridges, and roadway geometry (AASHTO, 2008). Normally, classification data are sourced from fixed sensors or extrapolated from short term counts at strategic locations. The findings from the analysis presented in this article suggest that probe data could be used to develop reasonably accurate estimates of truck volumes on major trade corridors and in urban areas.

While the post-processed nature of the data inhibits conclusive statements about the reasons behind these findings, it appears that the type of sampled vehicles, the sampling variations in space and time, and the post-processing techniques influence the results. More generally, then, traffic monitoring professionals need to consider how best to balance the potential new value of probe-based data (despite uncertainties about the underlying sampling and post-processing approaches) with the opportunity to enhance a known weakness in traffic monitoring practice, namely, the estimation of system-wide truck traffic volumes. Further research is needed to better inform such decisions.

4.5.2 Limitations and future research

The findings from this article support future research on using probe data as an additional resource for conventional traffic monitoring practice. The most prudent extension appears to be the development of a model that could predict truck traffic volumes using probe data as an input. In this way, a traffic monitoring program could potentially improve the spatial coverage and accuracy of truck traffic volume estimates, based on the findings herein.

However, this analysis is limited in scope to Manitoba highways. Future work may extend the methodology to other provinces to verify whether the results are still applicable in other locales. Future work may also consider extending the temporal scope of the analysis to view the results over a multi-year analysis.

Truck traffic percentages vary in space and time, which lends to the need for improved truck traffic data collection. The analysis in this article was limited to using mixed-traffic probe data, as provided by HERE Technologies via Transport Canada. HERE Technologies also offers speed data using only trucks as probes. Unfortunately, by using post-processed passively-collected probe data, this analysis does not control which data sources are used as probes. This limitation would extend to the truck-only analysis where "trucks" would be defined by HERE Technologies, and this definition may be inconsistent with classification schemes used in highway traffic monitoring practice. Future research should consider repeating the analyses using truck-only probe data, if available, given the apparently strong correlation between conventionally measured truck traffic data and mixed-traffic probe data.

4.6 ACKNOWLEDGEMENTS

The financial support of Transport Canada and the Natural Sciences and Engineering Research Council of Canada (NSERC) are gratefully acknowledged.

The authors also gratefully acknowledge the financial contributions of Manitoba Infrastructure. The results and conclusions presented are those of the authors and no official endorsement by Manitoba Infrastructure is intended or should be inferred.

5 IMPACTS OF ROAD AND RAIL TEMPORAL TRAFFIC VARIATIONS ON GRADE CROSSINGS EXPOSURE, DESIGN, AND REGULATION IN MANITOBA

This chapter concludes the investigation of AADT estimation and applications by measuring the impacts of traffic variability on a particular traffic data application: grade crossings. It seeks to answer the final objective question: *How sensitive are grade crossing design and regulation to the known variability in traffic relative to average statistics (i.e., AADT)?*

The analysis tests the sensitivity of grade crossing regulations in Canada to detailed traffic volume distribution data, relative to average statistics.. It uses continuous count data and available rail data to artificially create variability in grade crossing exposure and compares these variations to regulatory limits. It contributes to the thesis theme by developing insights on the state-of-the-practice in a particular AADT application and proposes an alternative that explicitly considers temporal variability.

The material in this chapter is published in Transportation Engineering (Grande et al., 2020) and reprinted with permission of co-authors Garreth Rempel and Jonathan Regehr. The chapter is self-contained with its own abstract, introduction, and conclusion; references are provided at the end of the thesis. The thesis author conducted the analysis and literature review, interpreted results, and prepared the manuscript.

5.1 ABSTRACT

Transport Canada has recently published regulations and guidance for design considerations at grade crossings. Cross-product, or the product of average daily vehicles and trains, is one of several criteria that define warning system requirements. While based on readily available data, application of the cross-product may oversimplify the interactions between vehicles and trains at a crossing by failing to account for known temporal variations in both modes.

Through two analyses, this paper investigates the effects of temporal traffic variations on estimated grade crossing exposure and develops insights about alternatives to quantify this exposure. The first analysis considers the effect of daily road traffic variations on grade crossing exposure and compliance at 240 rural grade crossings. Nine of the studied crossings (4%) experienced at least one day for which the estimated single-day exposure indicated a need for an upgraded warning system, based on the cross-product criterion alone. Conversely, 91 crossings (38%) had warning systems that would be considered over-designed for the entire year. The second analysis considers the effect of hourly road and rail traffic variations on grade crossing exposure at 13 urban grade crossings by estimating hourly cross-product equivalents. Each of the eleven studied gated crossings featured at least seven hourly cross-product equivalents that exceeded the cross-product threshold for gated crossings.

The findings demonstrate that the cross-product may misrepresent vehicle-train interactions at a crossing by suppressing temporal variability in road and rail traffic. Consequently, these variations should be considered in design and prioritization decisions for reducing risk and delay at grade crossings.

5.2 INTRODUCTION

A grade crossing (also referred to as a road-railway crossing, level crossing, train crossing, or at-grade crossing) is the intersection where a road or path crosses one or more railway tracks at the same elevation (Transport Canada, 2014). Grade crossings are designed to mitigate safety risks and user delays. Their design, operation, and regulation must consider the physical and operational properties of motorized vehicles, trains, and non-motorized users (Lu and Tolliver, 2016; Oh et al., 2006; Sperry et al., 2017). Because of the safety and economic implications for all users, there is a need to better understand interactions occurring at grade crossings to improve grade crossing policy and engineering practice.

Grade crossing safety risk and potential user delays influence the type of treatment at the grade crossing. Generally, treatments are categorized as passive or active (Hsu and Jones, 2017; Wang et al., 2019). Passive crossings are controlled exclusively by non-activated systems, such as stop signs, crossbucks, and crossing ahead signs (FHWA, 2019). Active crossings feature electronic components to notify drivers of approaching trains. Active warning systems must at least have flashing lights but may also feature bells to audibly alert drivers and gates to physically impede vehicles from moving through a crossing when a train is present. Grade separations eliminate the interactions between road and rail traffic and are implemented when safety risks and/or user delays are expected to be unacceptably high. However, grade separation is significantly more expensive than at-grade design alternatives (Ghaffari Dolama et al., 2019).

Regulations dictate the types of design treatments required at grade crossings. Annual average daily traffic (AADT) and annual average daily rail movements (AADRM) are commonly used to determine the appropriate treatment for a crossing. AADT and AADRM describe the expected average daily total volumes of road and rail traffic, respectively, for a single day (i.e., 24-hour period). Transport Canada defines the product of these two values as a crossing's cross-product in their recently-enacted *Grade Crossings Standards* (Transport Canada, 2014). This concept exists in many other jurisdictions as well. The term "cross-product" is synonymous with "crossing exposure" (FHWA, 2019; National ALCAM Group, 2016) and "traffic moment" (Liang et al., 2018; Pyrgidis et al., 2016; SSB, 2010), although, in some cases, non-annualized average daily values are used instead. Regardless of the terminology, cross-product represents grade crossing exposure and acts as a surrogate for both safety risk and user delay (Nichelson and Reed, 1999). Grade crossing regulations, including those in Canada, define minimum design treatments in terms of cross-product thresholds, amongst other considerations.

Both AADT and AADRM are convenient measures of volume for their respective modes, but "flatten" variance in the underlying count data into a single representative (average) number. Transportation practitioners commonly use AADT as a measure of traffic volume (FHWA, 2016b; Regehr et al., 2017), despite the known traffic periodicities (by month, day-of-week, and hour) that influence its estimation and application (AASHTO, 2009; Grande et al., 2017). AADRM is an analogous measurement for trains. Normally, AADRM data are provided by railroad companies and are based on proprietary information. However, the analysis in this paper utilizes data collected by new sensors designed to detect rail movements, providing a unique data source for understanding temporal variations in train volumes that were previously unavailable.

This paper investigates the effects of temporal road and rail traffic variation on estimated grade crossing exposure (i.e., the cross-product) through two exploratory analyses. Specifically, the objectives of the paper are:

1. To identify the effects of daily road traffic variations on grade crossing exposure and compliance with specified cross-product thresholds (*Analysis 1*); and
2. To identify the effects of hourly road and rail traffic variations on grade crossing exposure and compliance with specified cross-product thresholds (*Analysis 2*).

The analyses offer insights about exposure at grade crossings in Manitoba, Canada, by measuring the degree of variability in exposure measures at grade crossings and relating the variations to regulatory criteria. The methods applied are generic and transferrable to other contexts within and outside of Canada. As in other Canadian provinces, recently updated federal regulations govern the design of grade crossings on all federally regulated properties in Manitoba. Thus, while the results of the research pertain specifically to the Manitoba context, the motivation for the analyses is evident nationwide.

The analyses leverage unique data available in Manitoba to characterize temporal variations for road and rail traffic. These data provide an opportunity to explore the decisions made within recent updates to federal grade crossing regulations. The research comprises two separate analyses to best utilize the available road and rail traffic data.

This paper comprises seven sections. Section 5.3 provides a summary of relevant literature. Section 5.4 outlines the analytical framework. Sections 5.5 and 5.6 describe the data, methods, and results of the two analyses, respectively. Section 5.7 discusses the findings of the analyses in the context of grade crossing policy and engineering practice. Finally, Section 5.8 presents concluding remarks.

5.3 BACKGROUND

5.3.1 Existing Grade Crossing Regulations

In Canada, the federal government regulates grade crossings on public and private roads. In 2014, Transport Canada released *Standards* which dictate minimum safety requirements for all grade crossings (Transport Canada, 2014). The *Standards* apply immediately to all new crossings, while existing crossings must be compliant with the *Standards* by 2021. Compliance rates with the former, voluntary, design standards ranged from 50% to 70% in a sampling exercise conducted by Transport Canada in 2011 (Canada Gazette, 2014). Consequently, most provincial and municipal jurisdictions have undertaken inspections of their grade crossings to determine whether they comply with the updated *Standards* and to prioritize required upgrades (Reimer et al., 2015).

The *Standards* specify warning system requirements based on the following criteria:

- Rail design speed,
- Number of lanes and tracks,
- Nearby sidewalks, paths, or trails,
- Nearby traffic control devices (such as signage and signalized intersections),
- Whether the crossing is private or public, and
- Forecast cross-product.

Given its relatively objective nature, the forecast cross-product has become a commonly used criterion for preliminary assessments of grade crossing compliance. The *Standards* feature two thresholds for the forecast cross-product at a grade crossing. Crossings whose forecast cross-product exceeds 2000 must feature an active warning system. If this number exceeds 50,000, the warning system must also feature gates. These specifications indicate that the cross-product influences the final design requirements of grade crossings. In some cases, a third threshold may be considered for grade separation. Some Canadian jurisdictions have reported 200,000 as a cross-product threshold for investigating the feasibility of grade separation (BC Ministry of Transportation and Infrastructure, 2014; City of Ottawa, 2017; Peel Regional Council, 2014; Town of Oakville, 2009; Town of Whitby, 2014); however, Transport Canada recommends consideration of grade separation when cross-product exceeds 1,000,000 and no formal grade separation thresholds exist in the *Standards*.

Internationally, grade crossing regulatory approaches vary by country. In the United States, the Federal Highway Administration (FHWA) prohibits grade crossings on fully access-controlled highways (FHWA, 2019). Additionally, passive control devices are federally regulated in the *Manual on Uniform Traffic Control Devices* (FHWA, 2012). Otherwise, the FHWA makes grade crossing design recommendations for additional crossing treatments, but state departments of transportation (DOTs) are ultimately responsible for regulating their crossings (FDOT, 2012; MDOT, 2017). The FHWA recommends passive, active, or gated warning systems based on measurable conditions at all crossings (e.g., crossing exposure, sight lines, and road and rail traffic speeds). In this way, the FHWA guidance makes recommendations akin to the mandated warning system requirements in the Canadian *Standards*. The FHWA also recommends consideration for grade separation where crossing exposure exceeds 1,000,000 in urban areas or 250,000 for rural areas (FHWA, 2019). Transport Canada has recently aligned with this recommendation in their *Grade Separation Assessment Guidelines*, which list cross-product exceeding 1,000,000 as a criterion for considering grade crossing separation (Transport Canada, 2019). Unlike the *Standards*, these guidelines are not required and are provided to jurisdictions as guidance. In some cases, models are used to prioritize crossings for upgrades. In Australia, modeled risk using the *ALCAM* tool selects the highest priority crossings (National ALCAM Group, 2016). Conversely, the Ministry of Transportation of Israel applies economic modelling to select grade separation candidates (Gitelman et al., 2006).

5.3.2 Characterizing Risk at Grade Crossings

Many jurisdictions employ hazard ranking systems to identify grade crossing candidates for potential upgrades (Sperry et al., 2017; Saccomanno et al., 2007). Ranking systems are categorized as either hazard index or crash prediction techniques. Hazard index techniques struggle to differentiate between many crossings with similar traffic and control conditions. This, in turn, leads practitioners to select from pools of crossings that are practically equivalent. Conversely, crash prediction methods estimate the frequency and severity of expected crashes at grade crossings. Moreover, crash prediction techniques produce a necessary input for economic analyses (Eluru et al., 2012; Fan et al., 2015; Haleem and Gan, 2015).

Daily traffic volume and cross-product are ubiquitous measures used in predictive models. The USDOT prediction formula, often considered the industry standard (Saccomanno et al., 2007), incorporates average daily traffic and average train movements per day. The formula additionally includes the number of trains during daytime hours, supporting the use of hourly measurements. The relatively simple New Hampshire Hazard Index technique only considers the product of AADT, average daily train traffic, and a coefficient corresponding to the existing warning system. Some jurisdictions have modified this technique, though none have considered temporal variability (FHWA, 2019). The Peabody-Dimmick Formula, developed in 1941, predicts the expected number of accidents in a five-year window using the same inputs as the New Hampshire Hazard Index. Australia has modified this formula to estimate the exposure factor in its hazard index model (National ALCAM Group, 2016).

More recently, data mining techniques have gained popularity as an approach to predict safety performance at grade crossings. Crashes are rare and random occurrences, leading to issues when selecting parametric models to fit crash data (Lu and Tolliver, 2016; Oh et al., 2006; AASHTO, 2010; Lord and Mannering, 2010). By contrast, data mining techniques are non-parametric and focus on the relationships within the data, producing more accurate crash rate estimates regardless of the underlying data distribution (Iranitalab and Khattak, 2017; Lu et al., 2020; Yan et al., 2010; Yu et al., 2018; Zhou et al., 2020). However, the data mining techniques proposed in the literature focus solely on crash prediction and fail to consider the user delay implications of grade crossing exposure. Moreover, none of the studies in the literature explicitly consider the temporal variations of road and rail traffic volume, as is the focus of this paper.

Cross-product has historically had a pivotal role in the design and predicted safety and operational performance of grade crossings and remains prominent in recently issued grade crossing regulation and guidance. Despite this, previous research has disregarded the potential influence that known temporal variations in road and rail traffic volume have on crossing exposure and, by extension, on the safety and operational consequences that crossing exposure is used to predict. The analyses in this paper contribute new knowledge to address this gap in the state-of-the-practice by providing alternative considerations for grade crossing policy and engineering practice.

5.4 ANALYTICAL FRAMEWORK

The analytical framework applied in this paper extends the current practice for estimating average daily road traffic volume to estimate analogous measures of rail traffic volume. These volumes are used to develop cross-product measures as the arithmetic product of road and rail volumes. This section summarizes methods for estimating average daily road traffic and describes the analytical framework applied in this paper.

Highway traffic monitoring programs produce average traffic volume statistics from discrete traffic observations. As noted in Lord and Mannering (2010), aggregating discrete observations into coarse time periods (e.g., days or hours) assumes homogeneity within those time periods that may not exist, thus resulting in information loss and increased uncertainty.

The simplest method for determining the average daily road traffic volume (ADT) involves counting the number of vehicles passing a site for a multi-day period and dividing the total count by the number of days. At minimum, the duration of such a count should be 48 hours to calculate an average (FHWA, 2016b; Regehr et al., 2017). While simple, this method fails to consider the known periodicities in traffic volumes by day-of-week and month. Thus, the ADT is biased by the sampling period and duration of traffic volume counts. Longer counting periods tend to improve the reliability of estimating AADT using ADT (Milligan et al., 2016).

In practice, resource constraints inhibit an agency’s ability to continuously monitor traffic throughout a highway network. Consequently, most traffic monitoring programs implement short-duration sample counts to provide spatial coverage. Short-duration count data can be adjusted to estimate AADT using temporal adjustment factors. These factors are calculated from full-year data at continuous counting sites with assumed similarities in traffic characteristics. Equation 5.1 shows this formulation.

$$AADT_{hi} = VOL_{hi} \times M_h \times D_h \times A_i \times G_h \tag{5.1}$$

Where:

VOL_{hi} = total traffic observed during traffic count

M_h = the applicable seasonal (monthly) factor

D_h = the applicable day-of-week factor

A_i = the applicable axle-correction factor (if needed)

G_h = the applicable growth factor (if needed)

If a complete record of data is available for a year, the calculation of AADT at a continuous count site involves calculating the arithmetic mean of daily traffic volumes. However, interruptions in data collection (e.g., due to equipment malfunctions) are commonplace. The recommended practice applies the so-called AASHTO method (FHWA, 2016b) to account for missing data by considering the known periodicities in traffic volumes by day-of-week and month. Equation 5.2 shows the AASHTO method calculation.

$$AADT_c = \frac{1}{12}\sum_{m=1}^{12}\frac{1}{7}\sum_{j=1}^{7}\frac{1}{n_{jm}}\sum_{i=1}^{n_{jm}} VOL_{ijm,c} \tag{5.2}$$

Where:

VOL_{ijm} = total traffic on *i*th occurrence of *j*th day of week within *m*th month

i = occurrence of a particular day-of-week in a particular month

j = day-of-week (1 to 7)

m = month-of-year (1 to 12)

n_{jm} = number of times day j occurs in month m with available traffic data (1 to 5)

c = vehicle classification

The formulation involves the calculation of monthly average daily traffic (MADT) and average day-of-week traffic (ADWT) as steps to producing AADT.

Recently, a new formulation to calculate AADT has been recommended and validated (Grande et al., 2017; Jessberger et al., 2016), which uses an hourly rather than daily base time period. This two-step calculation produces AADT in a similar fashion to the AASHTO method, while improving precision and accuracy of results when data are removed. To summarize, the estimation of AADT involves one of several methods, which vary considerably in terms of the nature and extent of count data utilized and the calculation procedure applied. This complexity is not readily apparent in guidance used to estimate grade crossing exposure and risk. Yet, as will be explored in the subsequent sections, the validity of AADT and the known variability in the underlying traffic data may influence grade crossing design decisions and risk assessments. Moreover, despite the lack of documented practice, analogous issues arise when estimating average daily rail movements and these issues extend to the estimation and application of the cross-product.

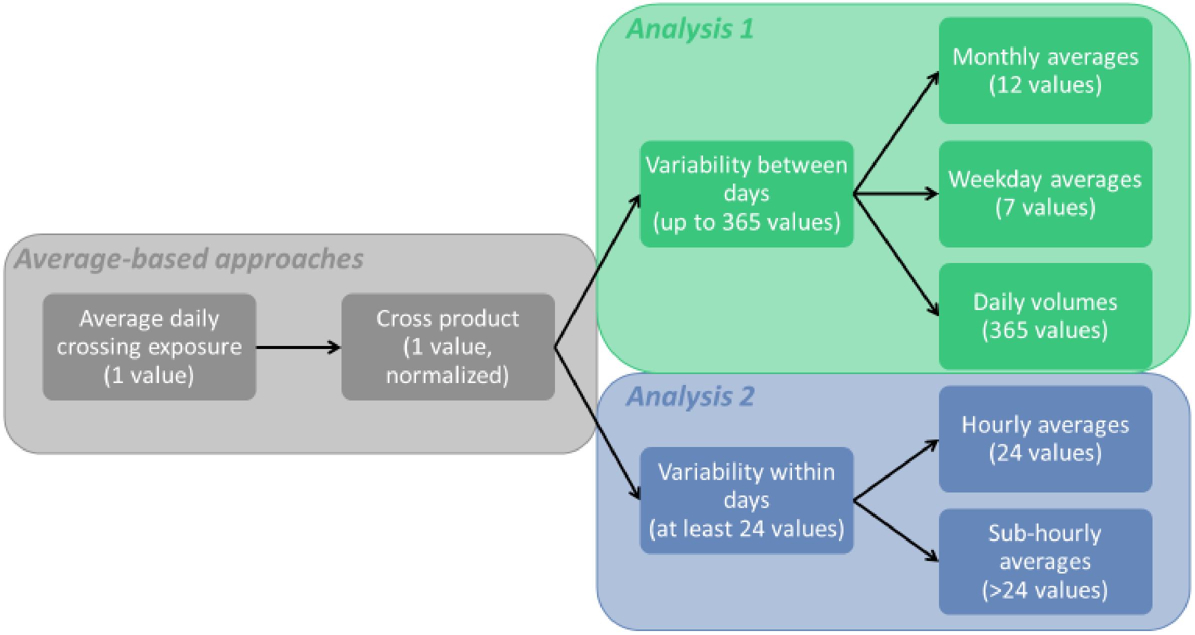

Figure 5.1: Potential measures of road or rail traffic exposure (values in parentheses represent the number of outputs from each method)

Figure 5.1 offers a visualization of the concepts explored in this paper. As depicted in the figure, practitioners can elect various measures to represent average daily road and rail traffic. Of the available methods, the ADT and ADRM are least capable of representing traffic volume periodicities and may misrepresent annualized conditions. The ALCAM (National ALCAM Group, 2016) is one example of an application that specifies the use of ADT (though, in practice, AADT could be used in place of ADT). Moving to the right, the more robust option recommended in the Canadian *Standards* and by FHWA utilizes AADT and AADRM to calculate grade crossing exposure, since they represent an annualized average and limit potential bias caused by missing data. These measures, however, are still averages and do not enable explicit consideration of the range of daily or sub-daily volumes at a grade crossing. Rather than relying on an annualized average, the practitioner may wish to understand the magnitude and nature of these periodicities – by month, by day-of-week, by hour, or at a sub-hourly temporal scale. Ultimately, road and rail traffic volumes could be decomposed into singular traffic events to examine microscopic interactions between vehicles and trains. This level of disaggregation is beyond the scope of this paper, as it may not provide practical value in system-wide grade crossing assessments given the relative difficulty of collecting per-vehicle and per-train data at a crossing.

The following two sections describe analyses designed to explore the effect of road and rail temporal traffic variation on cross-product. *Analysis 1* examines the effects of daily road traffic periodicities and *Analysis 2* examines the effects of hourly periodicities for both road and rail traffic. Both analyses present the products of road and rail traffic volume in terms of cross-product equivalents, that is, the cross-product that would be experienced at a grade crossing if the input road and rail traffic data represented the AADT and AADRM at that crossing, respectively. Specifically, *Analysis 1* utilizes a daily cross-product equivalent and *Analysis 2* utilizes an hourly cross-product equivalent. In this way, it is assumed that estimated crossing exposure can be related to the cross-product, its applications, and the relevant thresholds identified in the *Standards*.

5.5 *ANALYSIS 1*: DAILY VARIATIONS IN GRADE CROSSING EXPOSURE

Analysis 1 examines the effect of measured daily periodicities (by month and day-of-week) in road traffic volume on grade crossing exposure at a sample of rural grade crossings in Manitoba, Canada. For each crossing, the analysis produces a set of 366 daily cross-product equivalents using the input road traffic data and a constant AADRM. Daily variations in rail movements are unavailable at the rural grade crossings assessed. The analysis assesses compliance with the *Standards* by comparing these daily cross-product equivalents with relevant cross-product thresholds.

5.5.1 Methodology

Initial grade crossing data are obtained from Transport Canada's Grade Crossings Inventory (Transport Canada, 2018) for all grade crossings in Manitoba. The inventory provides the AADT, AADRM, existing warning system, and geographic coordinates for 22,820 grade crossings in Canada, 2299 of which are located in Manitoba. Spatial analysis software is used to identify grade crossings that are situated on provincially-owned highways in Manitoba (262 crossings meet this criterion). These crossings are then screened to remove all crossings that contain erroneous or incomplete data. This yields a set of 240 grade crossings in rural Manitoba for the analysis.

Manitoba's traffic monitoring program, the Manitoba Highway Traffic Information System (MHTIS), collects and disseminates traffic data on all provincial roads, including temporal traffic variation data (Grande et al., 2018). Raw data are not publicly available but aremade available for this research. Specifically, to support AADT estimation at short-duration count sites, the program assigns all locations on the provincial highway network to one of seven traffic pattern groups (TPGs). The seven TPGs were developed in an unpublished study in 2006 by applying Ward's minimum variance hierarchical clustering procedure (Ward, 1963). Each TPG comprises a set of continuous count sites with unique monthly, day-of-week, and hourly adjustment factors and characterizes the sites in terms of highway functionality and proximity to trip generators. Table 5.1 shows the range of monthly and day-of-week adjustment factors in each TPG and their distinguishing characteristics.

Table 5.1: Characteristics of Manitoba's traffic pattern groups

TPG	Monthly Factors (%)		Day-of-Week Factors (%)		Description
	Minimum	**Maximum**	**Minimum**	**Maximum**	
1	81	114	75	114	Routes in or near major urban centres
2	80	120	89	117	Routes serving longer-trip purposes to population centres
3	54	180	77	124	Routes serving longer-trip purposes to recreational destinations
4	83	114	79	114	Routes near rural population centres
5	72	141	93	122	Routes near population centres and recreational destinations
6	63	160	84	118	Routes connecting to recreational destinations
7	76	137	87	118	Routes in northern Manitoba

Analysis 1 uses spatial analysis software to associate each grade crossing with the road segment on which it is situated, as defined in the MHTIS linear referencing system. Each grade crossing is assumed to have the same traffic characteristics as the road segment to which it is associated. Further, each road segment adopts the TPG of the nearest traffic counting site (either short-duration or continuous). In this way, grade crossings are assigned TPGs using the MHTIS data. Table 5.2 summarizes the grade crossings used in the analysis by TPG assignment, existing warning system, and AADRM and AADT ranges.

Table 5.2: Characteristics of grade crossings used in analysis 1

Crossings by TPG		Crossings by Warning System		Crossings by AADRM		Crossings by AADT	
TPG	**Count of Crossings**	**Warning System**	**Count of Crossings**	**AADRM**	**Count of Crossings**	**AADT**	**Count of Crossings**
1	38	Passive	47	0 – 10	174	0 – 200	49
2	50	Active	131	11 – 20	23	200 – 400	34
3	6	Gated	62	21 – 30	35	400 – 800	44
4	118			> 30	8	800 - 1600	48
5	9					1600 – 3200	36
6	11					3200 – 6400	13
7	8					> 6400	16
Total	240	Total	240	Total	240	Total	240

Initially, daily volumes at all crossings are considered equal to the AADT at the grade crossing. The MHTIS TPG data are then used to simulate daily traffic variability through the assumption that the day-of-week and monthly factors can be used to predict daily volumes. Day-of-week and monthly factors are calculated, by TPG, as described in the *Traffic Monitoring Guide* (FHWA, 2016b). Equation 5.3 shows the method by which daily volumes are predicted at a given grade crossing, using the attributed traffic data.

$$DV_{n,G} = AADT \times M_{n,G} \times D_{n,G} \tag{5.3}$$

Where:

$DV_{n,G}$	= estimated daily traffic volume on the *n*th day of the year at a crossing in pattern group, *G*
$M_{n,G}$	= monthly factor, expressed as a proportion, for the *n*th day of the year in pattern group, *G*
$D_{n,G}$	= day-of-week factor, expressed as a proportion, for the *n*th day of the year in pattern group, *G*

This method produces a realistic estimate of daily traffic volume for all 366 days in 2016 by using factors derived from continuous traffic count data. Further, the method ensures that the AADT at the site (and, by extension, its cross-product) is unaffected by the simulated traffic variability. No further rail data are used in *Analysis 1*. Thus, the daily train volumes are assumed to be equal to the AADRM (i.e., the daily volumes of trains are assumed to be constant).

Finally, daily cross-product equivalents are produced. The actual cross-product at each site is the product of its AADT and AADRM. *Analysis 1* produces 366 cross-product equivalents at each site by multiplying the simulated daily traffic volume and daily train volume. The analysis investigates the frequency at which these daily cross-product equivalents deviate from the cross-product thresholds specified in the *Standards*. Compliance with the *Standards* is also considered. Note that the cross-product is only one of several criteria used to stipulate warning system requirements. Thus, a crossing could be over-designed according to the cross-product criterion, but could be adequately or even under-designed when considering criteria holistically.

5.5.2 Results

As discussed earlier, the *Standards* specify ranges of cross-product values suitable for each type of grade crossing warning system. Crossings with a cross-product exceeding 2000 must have an active warning system to comply with the cross-product criterion. Similarly, crossings with a cross-product exceeding 50,000 must additionally feature gates. Thus, if a passive crossing has a cross-product exceeding 2000, it is considered under-designed with respect to the cross-product criterion. This is also true of non-gated crossings whose cross-product exceeds 50,000. Conversely, if a gated crossing has a cross-product below 50,000, it is considered over-designed with respect to the cross-product criterion (this is also true of active crossings with cross-products below 2000).

The analysis revealed that, of the 240 crossings examined, two were actually under-designed (i.e., their actual cross-product exceeded the cross-product threshold specified by the *Standards* for the crossing's existing warning system. The remaining 238 crossings were compliant with the cross-product criterion in the *Standards*. Of these, 112 crossings featured a warning system that would be considered over-designed with respect to the cross-product.

Extending this logic, *Analysis 1* yielded 366 daily cross-product equivalents rather than the singular cross-product for each crossing. Table 5.3 summarizes the results of the analysis. Each column indicates the number of crossings that would be considered under or over-designed for the condition listed in the top of the header row. Results are broken down by TPG. The table reveals the following findings:

- Nine crossings featured at least one day in which the daily cross-product equivalent exceeded the specified cross-product threshold (i.e., the crossing would be considered under-designed on that day). The number of under-designed crossings decreased as the number of days considered increased, with no crossing exceeding the specified cross-product threshold for all 366 days.

- Ninety-one crossings had warning systems that would be considered over-designed (conservative) for all 366 days of the year (i.e., the daily cross-product equivalent was always less than the minimum applicable threshold). The number of over-designed crossings increased as the number of days considered decreased. Over half (135) of the crossings had warning systems that would be considered over-designed for at least one day.
- All crossings that are either over- or under-designed for a portion of the year are properly designed with respect to the cross-product criterion for the remaining days (i.e., no crossing is over-designed for some days and under-designed for others). Ninety-six crossings were neither over- nor under-designed for all 366 days of the year.
- A crossing's assigned TPG does not appear to influence the likelihood that a crossing is under- or over-designed for some portion of the year.

Table 5.3: Number of Crossings Under- and Over-Designed When Comparing Daily Cross-Product Equivalents to Specified Thresholds in the Canadian Standards

	At least 1 day		**At least 10% of days**		**At least 50% of days**		**All 366 days**		
	Over-designed[1]	Under-designed[2]	Over-designed[1]	Under-designed[2]	Over-designed[1]	Under-designed[2]	Over-designed[1]	Under-designed[2]	Total
PG1	23	1	21	1	16	1	14	0	38
PG2	28	0	28	0	23	0	19	0	50
PG3	4	2	4	2	4	0	4	0	6
PG4	62	2	56	2	53	1	47	0	118
PG5	7	0	7	0	6	0	3	0	9
PG6	5	3	4	1	4	0	2	0	11
PG7	6	1	5	0	5	0	2	0	8
Total	**135**	**9**	**125**	**6**	**111**	**2**	**91**	**0**	**240**

[1] Over-designed means that, for the condition listed above, the crossing's cross-product is less

than the minimum cross-product threshold for the existing warning system as specified in the *Standards*.

[2] Under-designed means that, for the condition listed above, the crossing's cross-product exceeds the maximum cross-product threshold for the existing warning system as specified in the *Standards*.

To illustrate further, Figure 5.2 shows the daily cross-product equivalents at two crossings. The crossing depicted in (a) is a gated crossing in TPG 2. For 116 days, the daily cross-product equivalent at this crossing is below the minimum cross-product threshold for a gated crossing (i.e., 50,000), which implies that the installed warning system is over-designed for those 116 days with respect to the cross-product criterion. The crossing depicted in (b) is a passive crossing in TPG 3. For 61 days, the daily cross-product equivalent at this crossing exceeds 2000, which implies that the installed warning system is under-designed for those 61 days.

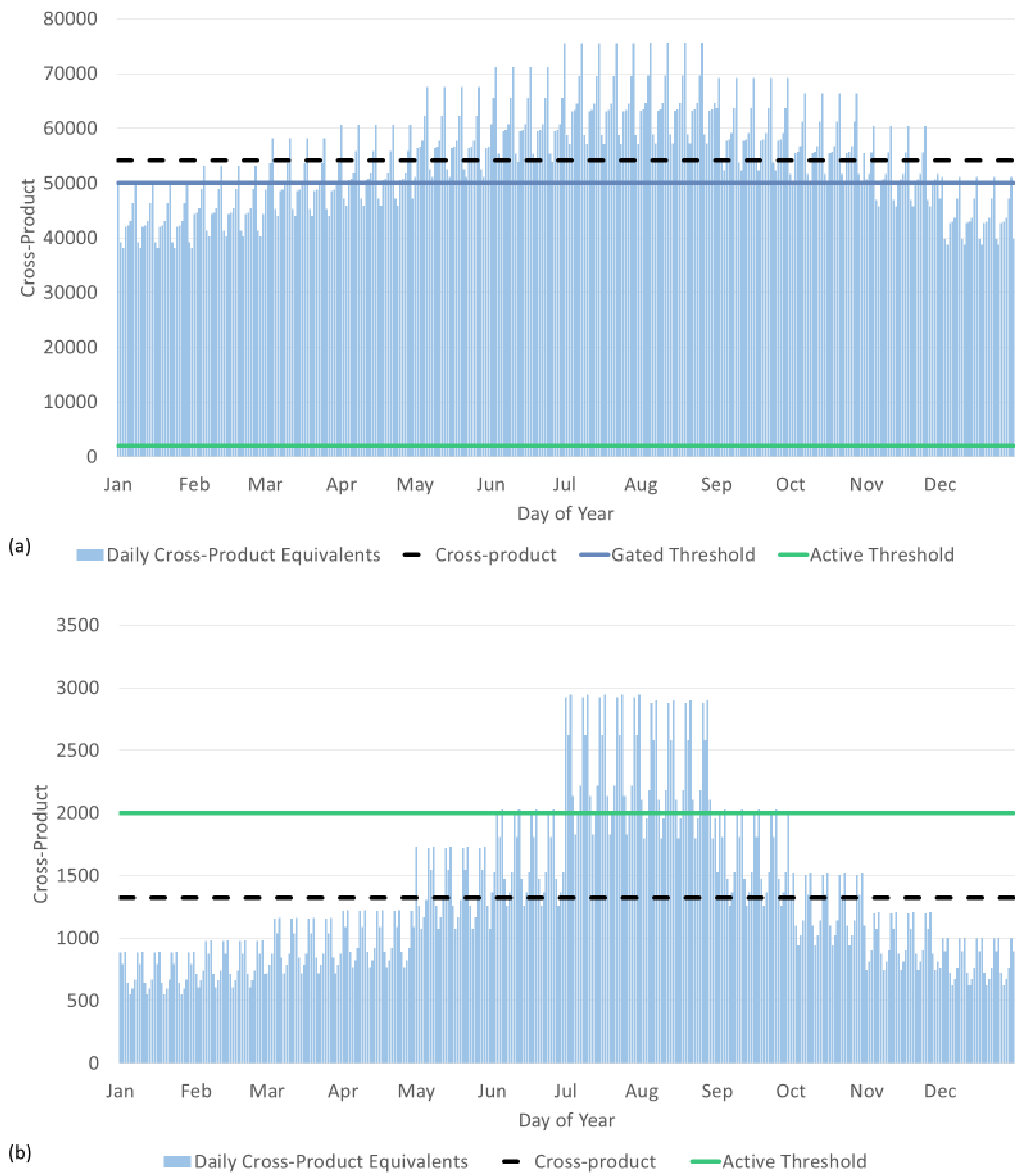

Figure 5.2: Daily cross-product equivalents for samples sites located in (a) traffic pattern group 2 and (b) traffic pattern group 3

5.6 *ANALYSIS 2*: HOURLY VARIATIONS IN GRADE CROSSING EXPOSURE

Analysis 2 examines the effect of hourly road and rail traffic variations on grade crossing exposure at thirteen grade crossings in Winnipeg, Manitoba, Canada. The analysis produces 24 hourly cross-product equivalents for each crossing and assesses compliance with the *Standards* by comparing these equivalents with relevant cross-product thresholds.

5.6.1 Methodology

Rail traffic data are collected using TRAINFO® sensors installed at the thirteen grade crossings in Winnipeg. Figure 5.3 depicts the crossings that are used for the analysis (data for crossing *A* were omitted from the analysis due to missing road traffic data). These sensors detect and log time stamps for crossing occupancy events (i.e., when a train occupies the crossing and blocks road traffic) and clearances (i.e., when the crossing re-opens to road traffic after the train passes). The analysis assumes that each crossing occupancy represents a single train movement (i.e., a through train movement or switching movement) at a crossing, thus ignoring cases of occlusion or improper activations. No special considerations are made for observations during specific portions of the day (e.g., for daytime versus nighttime occupancies). Sensor installation periods were inconsistent at each crossing; thus, data availability varies between crossings. A full year of data are available at eleven of the thirteen crossings.

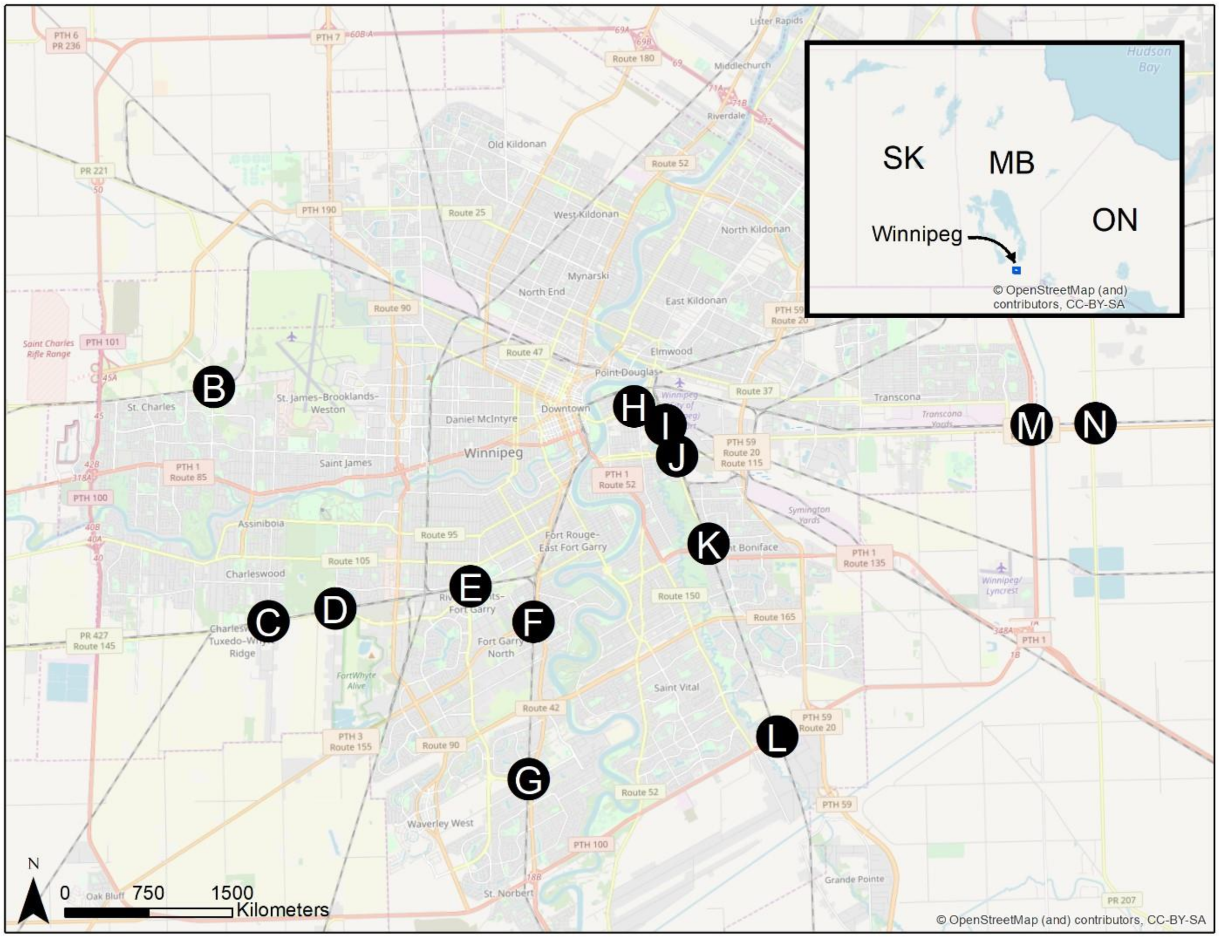

Figure 5.3: Locations of TRAINFO sensors used to detect train movements in Winnipeg, Manitoba, Canada

Road traffic volume data (i.e., AADTs) are obtained from Transport Canada's *Grade Crossing Inventory* (2018) for the thirteen studied crossings. Three of these crossings (*L*, *M*, and *N*) exist on provincial highways. The remaining ten exist on municipal roads. Hourly temporal adjustment factors are obtained from Regehr et al. (2012) for municipal roads and from the MHTIS for provincial roads.

Crossing occupancy data are used to estimate rail traffic volumes. Average daily rail movements at each crossing are calculated as the simple average of rail movements per day. Twenty-four hourly occupancy factors are calculated at each crossing as the ratio of occupancies which began in each hour to the total number of occupancies at the site. This process aligns the rail and road traffic data and enables calculations at sites without a full-year record of rail data.

Twenty-four hourly cross-product equivalents are calculated at each crossing. Each equivalent represents the cross-product that would occur at the selected crossing if its hourly road and rail traffic persisted for the entire day. These cross-product equivalents combine the effects of within-day traffic variability and the interactions between two modes at grade crossings. Equation 5.4 shows the formula used to calculate hourly cross-product equivalents.

$$XP_{h,c} = (AADT_c \times TF_{h,c}) \times (AADRM_c \times OF_{h,c}) \times 24^2 \tag{5.4}$$

Where:

$XP_{h,c}$ = hourly cross-product equivalent for hour, *h*, at crossing, *c*

$AADT_c$ = annual average daily traffic at crossing, *c*

$TF_{h,c}$ = traffic factor for hour, *h*, and crossing, *c*

$AADRM_c$ = annual average daily rail movements at crossing, *c*

$OF_{h,c}$ = occupancy factor for hour, *h*, and crossing, *c*

The analysis investigates the frequency at which these hourly cross-products deviate from the cross-product thresholds specified in the *Standards* and those used in practice in Canada and the United States.

5.6.2 Results

Analysis 2 estimated hourly cross-product equivalents for thirteen grade crossings using available road and rail traffic data. Figure 5.4 shows the number of hourly cross-product equivalents for each studied crossing that exceeded the displayed cross-product values. Note that the minimum abscissa value is 2000, which aligns with the active warning system daily cross-product threshold specified in the *Standards*. The two non-gated crossings, *B* and *I*, had the lowest hourly cross-product equivalents; neither had a single hourly cross-product equivalent exceeding 75,000. Of the 11 gated crossings, most exhibited cross-product equivalents that exceeded 2000 for all 24 hours (crossing *K* being the exception). Crossing *E* was the only crossing whose hourly cross-product equivalents all exceeded 25,000.

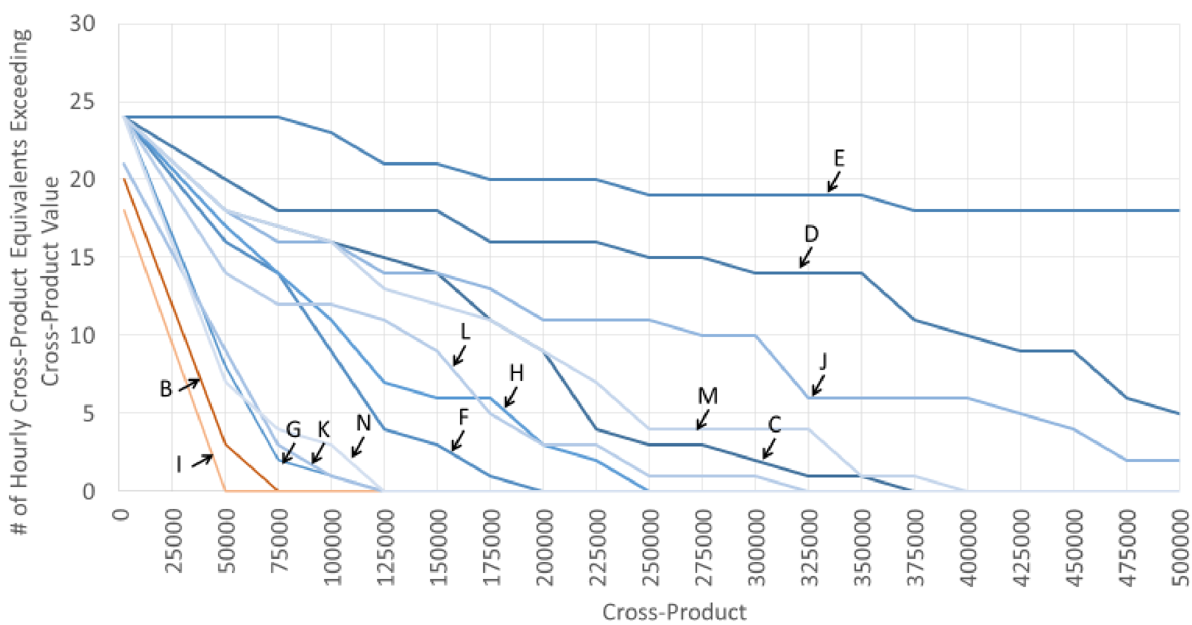

Figure 5.4: Number of hourly cross-product equivalents exceeding select cross-product values by crossing

Certain cross-product thresholds are considered in current grade crossing policy and practice. Table 5.4 shows the number of hours at each crossing where the hourly cross-product equivalents exceeded four specific thresholds:

1. 2000 – According to the *Standards*, a crossing with a cross-product above 2000 must have an active warning system.
2. 50,000 – According to the *Standards*, a crossing with a cross-product above 50,000 must have a gated warning system.
3. 200,000 – According to Canadian literature but not specified by the *Standards*, a crossing with a cross-product above 200,000 may be a candidate for grade separation.
4. 1,000,000 – According to FHWA and Transport Canada guidelines (FHWA, 2019; Transport Canada, 2019) but not specified in the *Standards*, an urban crossing with a cross-product above 1,000,000 should be considered for grade separation.

Highlighted values in the table represent the number of hourly cross-product equivalents which exceeded the cross-product threshold identified. All crossings were compliant with the *Standards* with respect to cross-product. However, two (crossings *D* and *E*) would be considered as potential candidates for grade separation if considering the state of the practice in some Canadian jurisdictions. Only crossing *E* surpasses the 1,000,000 cross-product threshold for grade separation according to Canadian and American guidelines.

Table 5.4: Crossing Conditions and Number of Hourly Cross-Product Equivalents above Specified Thresholds

Crossing Conditions					Number of Hourly Cross-Product Equivalents Above Cross-Product Thresholds			
Crossing	**Warning System**	**AADT**	**AADRM**	**Cross-Product**	**> 2000 (Active)**	**> 50000 (Gated)**	**> 200,000 (Separated)**	**> 1,000,000 (Separated)**
B	Active	10248	2.24	22994	20	**3**	0	0
C	Gated	4941	31.81	157 189	24	18	**9**	0
D	Gated	10975	30.80	338 061	24	20	**16**	0
E	Gated	33675	35.22	1 185 526	24	24	**20**	**15**
F	Gated	24518	3.22	78956	24	16	0	0
G	Gated	21700	2.21	47999	24	8	0	0
H	Gated	31992	3.23	108 197	24	17	**3**	0
I	Active	1496	5.94	8889	18	0	0	0
J	Gated	24400	7.66	186 801	24	18	**11**	0
K	Gated	7348	4.45	32684	21	9	0	0
L	Gated	16340	4.99	96600	24	14	**3**	0
M	Gated	7480	21.79	162 987	24	18	**9**	0
N	Gated	2460	16.46	40471	24	7	0	0

The results for two crossings provide particularly relevant insights. Crossing *E*, a gated crossing, featured the highest hourly cross-product equivalents. Its actual cross-product exceeds 1,000,000 and 15 hourly cross-product equivalents exceeded this number. Figure 5.5(a) shows the hourly cross-product equivalents for all 24 hours at crossing *E*. The hourly cross-product equivalents exceeded the actual cross-product at this location for twelve hours (i.e., exactly half of the day). The largest differences between hourly cross-product equivalents and actual cross-product occurred at 4:00 pm, when the hourly cross-product equivalent was 99% higher than the crossing's actual cross-product, and at 3:00 am, when the hourly cross-product equivalent was 93% lower than the actual cross-product. In the case of crossing *E*, even the lowest hourly cross-product equivalent exceeded the thresholds for active and gated warning systems.

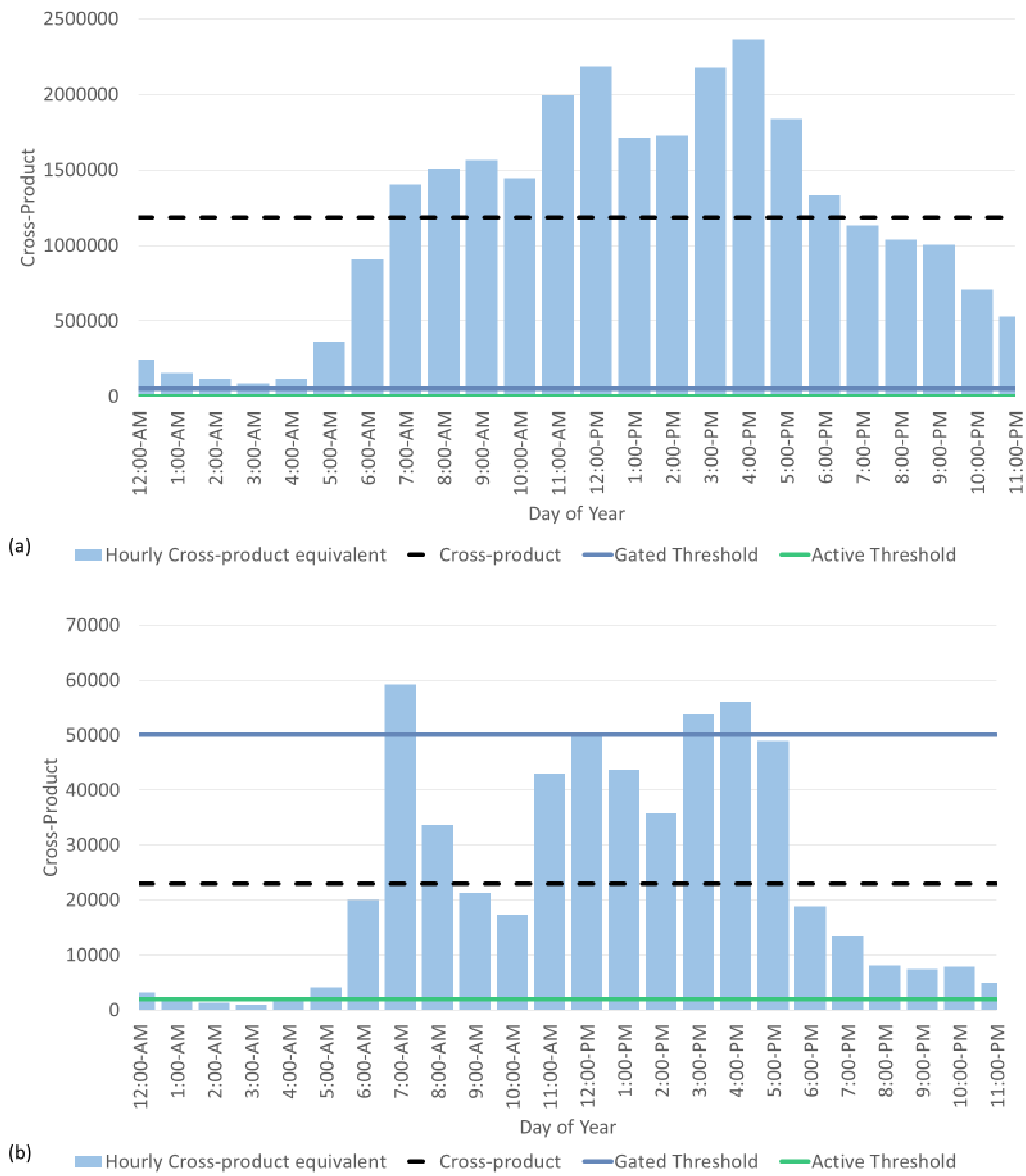

Figure 5.5: Hourly cross-product equivalents for (a) crossing E and (b) crossing B

Crossing *B* is an active crossing that experienced high variance in hourly cross-product equivalents, as shown in Figure 5.5(b). Peaks in the morning and mid-day were principally associated with hourly peaks in road traffic, while train traffic was more evenly distributed throughout the day. The hourly cross-product equivalents during these hours suggest a potential need for a gated warning system, but for most hours in the day the hourly cross-product equivalents were below the threshold for gated systems. In addition, the hourly cross-product equivalents at crossing *B* were below the actual cross-product for 15 hours. The hourly cross-product equivalents demonstrated wider variation at this crossing than at crossing *E*, peaking at 157% of the actual cross-product at 07:00 am. Three hourly cross-product equivalents were above the gated system threshold (07:00 am, 3:00 pm, 4:00 pm), some were only above the active system threshold (e.g., from 5:00 pm to the end of the day), and others fell below the active system threshold (e.g., in the night time hours after midnight).

5.7 DISCUSSION

The analyses in this paper sought to demonstrate the effects of temporal variations on grade crossing exposure and compliance. Cross-product, or the product of AADT and AADRM, is the most common measure of exposure at a grade crossing. While cross-product is simple to calculate and apply, it is hard to understand and its units lack real-life meaning. Moreover, the use of average values for road and rail traffic volumes neglects the effect of temporal variations. These patterns are well-known in the road traffic sector and are the foundation of AADT calculations. Rail traffic, conversely, has less predictable patterns due to the nature of its operation; rail movement schedules are predominantly controlled by the rail operator and not subject to the travel tendencies of the public. Consider the contrived scenario in which a crossing experiences high daytime and low nighttime road traffic volumes, but low daytime and high nighttime rail traffic volumes. In this case, the crossing could be designed based on a cross-product that does not accurately reflect vehicle-train interactions at the crossing.

Analysis 1 considered the daily variability in road traffic, a well-known and quantifiable phenomenon. The results illustrated the possibility for crossings to experience daily road traffic conditions that would warrant a more aggressive warning system – though this occurred rarely in the study. Only 9 of the 240 crossings studied were identified as being under-designed with respect to the cross-product criterion. Conversely, many of the studied crossings were apparently over-designed with respect to the cross-product. This result is expected, as cross-product is only one of multiple criteria used to define warning system requirements in the *Standards*. If another criterion governs the design at a crossing, then the warning system may seem over-designed when considering only the cross-product criterion. The relative rarity of under-designed crossings and the observed propensity for over-design, with respect to cross-product alone, demonstrates general compliance with regulations and conservatism in design.

Two principal limitations influence the results of *Analysis 1*. First, the analysis assumed no variation in daily rail traffic at each crossing. This assumption was necessary, due to the data available, but does not preclude the conclusion that daily variability in traffic – even in only one mode – can affect the selection of an appropriate warning system. More detailed information about rail traffic variations would enable a detailed examination of the interactions between road and rail traffic at the crossing. Second, the analysis assumed that hourly traffic variability had no bearing on the cross-product equivalents. This assumption is consistent with the use of cross-product, as defined in the *Standards*, which also disregards the effects of within-day traffic variability.

Analysis 2 addressed the two foregoing limitations by considering cross-product equivalents generated by hourly traffic data for both road and rail traffic. The analysis showed that, by accounting for hourly traffic variations expressed as hourly cross-product equivalents and comparing these values to the thresholds defined in the *Standards*, all crossings featured vehicle-train interactions that could warrant the need for different warning systems through an average day. Consequently, hourly cross-product equivalents at these crossings represent an alternative measure by which to assess warning system requirements.

Like the cross-product, hourly cross-product equivalents measure the exposure or interactions between two modes at shared infrastructure (i.e., grade crossings). However, unlike cross-product, hourly cross-product equivalents encapsulate the within-day variability of two modes that do not share the same temporal variability. There are no current guidelines, nor best practices, for the number of hours in a day that a warning system should be designed to accommodate. In the most conservative case, a warning system selection could consider a crossing's peak hour or highest hourly cross-product equivalent. Alternatively, a pragmatic approach could consider the existing warning systems at the studied crossings and the number of hours for which the cross-product equivalents exceed each threshold. For example, Figure 5.4 illustrates that all of the studied gated crossings have at least seven hourly cross-product equivalents exceeding the gated crossing threshold of 50,000. Further, crossing *B* has only three hourly cross-product equivalents exceeding 50,000 and is not gated. Thus, based on this limited evidence, a crossing could be required to have a gated warning system if seven hourly cross-product equivalents exceed the gated threshold. Alternatively, the hourly cross-product equivalents presented in this work could be used to support prioritization decisions.

Analysis 2 used a relatively small sample size compared to *Analysis 1*. Crossings were selected based on data availability, with the locations of TRAINFO sensors defining the study sample. Three of eleven crossings have a cross-product below the gated threshold of 50,000 and all crossings are compliant with the *Standards* (with respect to the cross-product criterion). However, one crossing (*E*) would be considered for grade separation based on Transport Canada's *Grade Separation Assessment Guidelines*. Fittingly, this crossing has been upgraded to a grade separated crossing since the analysis for the research concluded. Another crossing (crossing *D*) would require separation if using 200,000 as a threshold, as some Canadian jurisdictions have done.

Overall, the results of the two analyses reveal two issues with the current use of cross-product. First, cross-product is meant to serve as a surrogate for crossing safety and user delay. However, in terms of safety, using the average assumes constant conditions at the crossing. Crashes do not necessarily occur on average days; they occur at specific times, on specific days, in specific months. Making inferences about risk at crossings based on averages carries this assumption into the models being used. The results from these analyses show that crossing conditions can vary by day or by hour. Second, cross-product is also used as a surrogate for user delay. *Analysis 2* reveals that a disproportionate number of vehicles interact with trains at peak hours, and that variance in train traffic has the potential to compound these peaks. By extension, microscopic analysis of vehicle-train interactions at a crossing may lead to more refined estimates of user delay (Rempel, 2018).

Methodologically, both *Analyses 1* and *2* revert to the use of averages, as measured by daily and hourly cross-product equivalents. This is a limitation of the available data and reflects the strength of averages in summarizing results. However, the impetus for the research is the unspecified weakness of averages in representing traffic variability—a phenomenon that often follows predictable patterns. The critical distinction is that both analyses ‘unpack’ AADT and AADRM to better characterize train-vehicle interactions while providing comparison cases to the current state of practice. Future work may quantify the magnitude and frequency with which actual rail traffic deviates from the hourly and daily averages. These deviations are expected to play a major role in the inadequacy of averages to characterize rail movements.

Figure 5.6 visualizes the theoretical range of road and rail traffic data inputs by their temporal resolution. The cross-product (as currently defined) sits on the low end of both spectra. *Analysis 1* disaggregated AADT into estimated daily values instead, while *Analysis 2* did the same for hourly road and rail volumes. Detailed traffic data are becoming increasingly available, making analyses such as these more plausible. Agencies must decide what level of detail is appropriate for a range of applications. The results of the analyses imply that cross-product inadequately represents the vehicle-train interactions at a crossing. Daily cross-product equivalents are a useful tool to observe the range in daily exposure that can be seen at a crossing over a year. This would be further strengthened by detailed rail data, which were not widely available for the rural crossings tested in *Analysis 1.* Hourly cross-product equivalents are an apparent opportunity to differentiate between sites with similar cross-products. These could be implemented as an additional step in selecting crossings for upgrades or closures, after using the cross-product as an initial screening step. Further disaggregation of road and rail traffic data into per vehicle and/or per train data would reveal further details about vehicle-train interactions and help identify outliers from the average or general cases normally assessed by the cross-product.

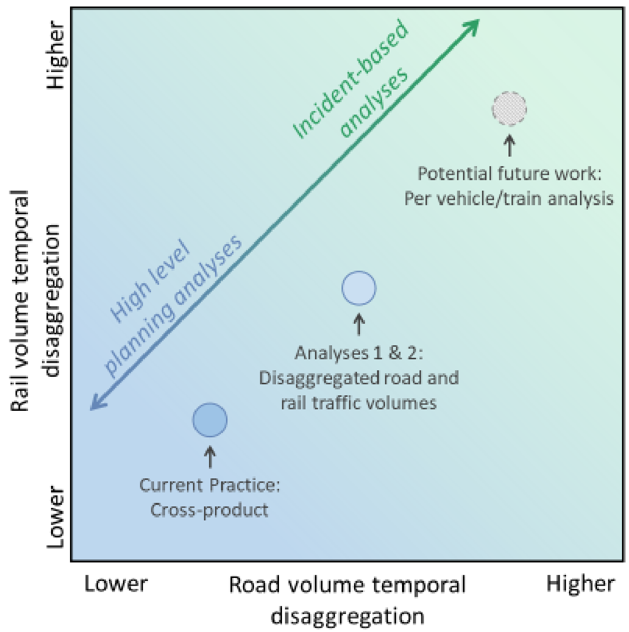

Figure 5.6: Spectrum of temporal resolutions in input road and rail traffic data

5.8 CONCLUSION

This paper investigated the effects of temporal variations in road and rail traffic on grade crossing warning system regulation and compliance. This is timely because of the recent changes to Canadian grade crossing regulations. Cross-product, or the product of average daily vehicles and trains at a crossing, is one measure used in the Canadian *Standards* to determine warning system requirements. Averages are simple and conveniently summarize data, but they also flatten the variability within the data into a single value. This paper used known variations in road and rail traffic to partially undo this flattening effect and explore its influence on regulatory conditions.

Analysis 1 varied road traffic volumes at rural grade crossings using known daily road traffic patterns for an entire year. Daily train volumes were assumed to be constant. The findings demonstrated that daily road traffic variations generate sufficiently large variations in the daily cross-product equivalent to warrant a change in the warning system required at the crossing, when applying the cross-product thresholds specified in the *Standards*.

Analysis 2 considered hourly road and rail traffic variations within an average day and compared hourly cross-product equivalents to the cross-product thresholds specified in the *Standards*. Hourly road traffic factors and crossing occupancy data were used to create hourly cross-product equivalents at the 13 studied crossings. All of these crossings were compliant with the *Standards* and two were potential candidates for grade separation based on the state of the practice in some Canadian jurisdictions, though only one surpasses the cross-product threshold stipulated in Transport Canada's *Grade Separation Assessment Guidelines*. Each of the 11 gated studied crossings featured at least seven hourly cross-product equivalents above the cross-product threshold for gated crossings.

On aggregate, the findings demonstrated that the cross-product, as currently defined, potentially oversimplifies vehicle-train interactions at a crossing, thereby misrepresenting the safety risks and delays associated with these interactions. Consequently, there is an apparent need to consider temporal traffic variability when modelling risk and operational delay at grade crossings, specifying grade crossing warning system requirements through guidance and standards, and prioritizing grade crossing upgrades. Specifically, the cross-product should be supplemented with detailed temporal traffic data, where available, and new criteria should be developed to select appropriate crossing treatments using these data.

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6 CONCLUSIONS

This concluding chapter of the thesis summarizes the key findings and discussion points from each of the foregoing research projects and ties them into the connecting themes of the thesis. A list of recommended future research topics follows, including those presented in the earlier chapters and topics derived from the connecting themes in this thesis. Finally, the last subsection provides a succinct set of concluding remarks on the benefits and shortcomings of AADT in light of known temporal and spatial traffic volume variability, thus satisfying the purpose of the research.

6.1 SUMMARY OF KEY FINDINGS

In Chapter 2, truck traffic data in Manitoba, Canada were used to estimate the effects that two systematic changes to AADT calculations had on the accuracy and precision of estimates. The use of truck traffic data, specifically, was selected to test these changes in conditions where traffic volumes were lower and tended to have different periodicities from total traffic. In this case, implementing a weighted average to account for the numbers of days in each month removed a clear, systematic bias in the AASHTO method of approximately 0.1% when considering up to 15 days of missing data (Scenario 3). Using hourly periods rather than daily units had little impact on the accuracy of the calculations but did reduce the width of the 95% confidence interval by 0.5%. The FHWA method, which incorporates both of these changes, was therefore the most accurate and precise formulation tested.

The AASHTO and FHWA methods to calculate AADT from continuous count data assume that the hourly, weekday, and monthly variations in traffic volumes are periodic. This allows for consistent treatment of missing data and has been shown to reduce errors, relative to a simple average approach that ignores those periodicities. Chapter 2 shows the improvements to AADT estimates, in terms of both precision and accuracy, when using the various formulations. Given the data used, the best tested method (the FHWA formula) reduced the width of the 95% confidence interval from 2.23% to 1.64% of AADT in the most robust test of missing data and reduced the mean absolute error (bias) from 0.38% to 0.24% of AADT. While these improvements are relatively modest, the FHWA provides the added benefit of calculating hourly, weekly, and monthly traffic factors as intermediate steps when estimating AADT. These factors are required for the expansion of short duration traffic count data into AADT estimates.

In Chapter 3, short duration count data were simulated using continuous count data in Manitoba, Canada. These simulated data were used to benchmark the expected ranges of errors produced when using short duration count data to estimate AADT. The results showed that, on average, the absolute percent error was 6.40% when using traffic adjustment factors from pre-assigned groupings. These errors grew to over 10% when using data from unassigned sites, which was expected due to the nature of the unassigned sites (they tend to have traffic patterns that do not align with the existing groupings).

Similarly to continuous count data, AADT estimates produced using short duration count data leverage knowledge of traffic periodicities to improve performance. By convention, short duration count data require temporal adjustment factors, developed from traffic pattern groups, to estimate AADT. The results from the case study conducted as part of Chapter 3 benchmark the errors produced using this conventional method. As expected, the accuracy and precision of AADT estimates using short duration count data were worse than those using continuous count data (mean absolute error was 6.40% compared to 0.24% and the 95% confidence interval width was 33.95% compared to 1.64%), even when incorporating simulated data losses to the continuous count data. When considering only the previously unassigned sites, the novel assignment method proposed as part of Chapter 3 reduced the mean absolute error from 10.32% to 7.86% (i.e., it reduced the assignment error by 2.46%).

Chapter 4 presented multiple tests for correlation comparing conventional traffic data with speed-based probe data available in Manitoba, Canada. Among these, the strongest correlation was found when relating truck traffic volume and probe observations. Specifically, sites around urban centres and on highways that served interprovincial trips produced R-squared values of up to 0.9. Truck traffic data are generally more difficult to obtain than total traffic data, since there are additional resources required to produce classification data. Given the relative difficulty in obtaining truck traffic data, the results from this analysis show that probe data may be a promising tool to supplement conventional traffic monitoring practice. Future research is required to develop a model that validates and utilizes this relationship. However, it is envisioned that speed-based probe data could also be used to broaden the spatial coverage of reliable truck traffic estimates in a way that is more cost-effective than the current state of the practice. Since this relationship only applies to certain contexts (i.e., near urban centres and along major interprovincial routes), there remains the potential for future research investigating probe data traffic groups, similarly to the traffic patterns that are explored in Chapters 3 and 5 of this thesis.

Finally, Chapter 5 disaggregated AADT and AADRM into periodic averages (by hour, weekday, or month) to evaluate the sensitivity of grade crossing design and regulation to the expected variations in traffic. The results showed that, in the rural Manitoba setting, the day-to-day variability in traffic can cause some sites to experience traffic volumes that would suggest the site belonged to a different regulatory range. For example, a non-gated site may have high daily traffic volume in the summer, resulting in a single-day cross-product that exceeds the threshold for gated crossings. Overall, 135 of the 240 crossings tested showed that this was true for at least one day in the study year while assuming a constant AADRM.

The analysis in Chapter 5 also assessed 13 crossings in the urban setting of Winnipeg, Manitoba. This analysis considered the hourly variations in road and rail traffic volumes to build hourly cross product equivalents – or the expected cross-product that would be experienced if the hourly road and rail traffic conditions persisted for an entire day. In two cases, the hourly cross-product equivalents exceeded the regulatory thresholds for their existing warning system treatment. These equivalents were presented as an alternative means for assessing the exposure at a grade crossing.

This research provides insights on AADT and, more generally, traffic volumes, through a series of related investigations. These insights can be categorized as those that contribute to knowledge of AADT at a site and those that contribute to knowledge of the effects of traffic variability at a site. The literature reveals numerous examples of efforts to improve the accuracy of AADT estimates, including those presented in Chapters 2 and 3 of this thesis. The improved accuracy in AADT estimates are relatively modest when compared to the variability in traffic volumes between or within days, as seen in Chapter 5. Most often, practitioners focus on the average (i.e., AADT) because it is common, convenient, and ingrained into many of the applications that use traffic data (e.g., the cross product). However, there are well-known traffic volume periodicities that are lost when reporting AADT. Paradoxically, these periodicities are ingrained in AADT production processes.

More generally, applications that use AADT, but fail to consider the periodicities in traffic that are explored in this thesis, are vulnerable to the impact those periodicities have on the application context—whether it relates to regulatory compliance, infrastructure design, or safety and operations. Conversely, the demonstrated consideration of these periodicities, as with the hourly cross-product equivalents introduced in Chapter 5, provides evidence that practitioners may benefit from a more explicit representation of the distribution of traffic volume in time and space. Such an approach could be similarly applied to other AADT use cases to determine the extent to which such benefits might occur in other transportation applications.

6.2 FUTURE RESEARCH

Future research topics are presented in each chapter that extend the findings of each individual work. To summarize, these recommendations are:

- To test the accuracy and precision of each AADT estimation formula, presented in Chapter 2, for longer periods of data loss (i.e., greater than 15 days).
- To test the applicability of the data-driven assignment method, presented in Chapter 3, in other regions and over multi-year spans.
- To test the validity of dynamic traffic pattern group assignments relative to static assignments over multi-year spans.
- To test the correlation between speed-based probe data and truck traffic on major highways in provinces outside of Manitoba.
- To develop a model that estimates AADT by integrating passively-collected probe data and conventional traffic data.
- To test the validity of cross-product equivalents, presented in Chapter 5, using detailed rail and traffic data (i.e., per-vehicle records).

More broadly, the previous subsection discussed the discrepancy between modest improvements to AADT estimates and relatively large variability in traffic volumes over time. Research into improving AADT estimation procedures is ongoing. It is unclear, however, how valuable this knowledge is in the context of traffic data applications. For example, employing the data-driven assignment method developed in Chapter 3 is shown to potentially reduce errors by roughly 2.5% of the true AADT, on average. Meanwhile, the daily traffic variations at a single site can be in excess of 100% of the AADT, as shown in Chapters 4 and 5. This reveals a potential avenue for future research: to investigate the elasticity of multiple traffic data applications to AADT inputs. This would reveal the relative value of allocating resources to refining AADT estimates.

A similar direction for future research could focus on revising traffic data applications themselves. This thesis has shown that AADT estimates are not always easily comparable. There are multiple methods and technologies available to collect traffic data and produce AADT estimates, each of which has their own underlying assumptions, strengths, and weaknesses. Further, identical AADT estimates may also summarize traffic with different underlying traffic patterns that, paradoxically, were likely used when generating the AADT estimates. However, many applications, like the use of the cross-product to assess grade crossing performance as explored in Chapter 5, require AADT as an input. As shown for this application, there is merit in revising the fundamental application of AADT in various transportation engineering and planning contexts to consider the spectrum of traffic volumes experienced at sites or the measured periodic tendencies of traffic by hour, weekday, or month.

6.3 FINAL REMARKS

AADT is the fundamental statistic to describe traffic volume. It is easy to understand, conveniently summarizes traffic volume at a site, and is widely applied thanks to this simplicity. However, the research presented in this thesis highlights critical limitations of AADT. Specifically:

- AADT estimates may be produced using different source data with inherent effects on the accuracy of the estimates (e.g., comparing AADT estimates using short duration count data with those using continuous count data).
- AADT estimates may be produced using different formulations, each of which may bias the resultant estimates by imposing their own built-in assumptions to the AADT calculation (e.g., calculating AADT using the simple average or the AASHTO method makes different assumptions about any missing data).
- The only traffic characteristic that AADT expresses is the average daily traffic (i.e., it does not represent the natural, measurable periodicities in traffic volumes that are experienced at a site).

In conclusion, the research finds that, while AADT estimates are convenient to calculate and ubiquitously applied, there is a need to better disclose the source data and methodologies used to produce AADT estimates to avoid misuse and false assumptions about comparability. Further, AADT summarizes the traffic at a site into a single average volume, which fails to express the periodical traffic variability at a site known to influence various transportation applications.

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