Methodology to Characterize Ideal Short-Term Counting Conditions and Improve AADT Estimation Accuracy Using a Regression-Based Correcting Function

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Abstract: Transportation agencies' motor vehicle count programs tend to be well established and robust with clear guidelines to collect short-term count data, to analyze data, develop annual average daily traffic (AADT) adjustment factors, and to estimate AADT volumes. In contrast, bicycle and pedestrian traffic monitoring is an area of work for most transportation agencies. In most agencies, there are a low numbers of counting sites and limited agency experience to manage a city-wide or state-wide system of collecting, processing, and using nonmotorized data. Short duration counts are used to estimate longer duration volumes such as AADT. Because bicycle or pedestrian short-term counts vary dramatically over time and significantly more than motorized vehicle counts, the direct application of motorized vehicle AADT estimation methods may be inadequate. The goal of this paper is to present a methodology that will enhance, if needed, existing AADT estimation methods widely employed for motorized vehicle counts. The proposed methodology is based on the analysis of AADT estimation errors using regression models to estimate a correcting function that accounts for weather and activity factors. The methodology can be applied to any type of traffic with high volume variability but in this research is applied to a permanent bicycle counting station in Portland, Oregon. The results indicate that the proposed methodology is simple and useful for finding ideal short-term counting conditions and improving AADT estimation accuracy. **DOI: 10.1061/(ASCE)TE.1943-5436.0000663.** © *2014 American Society of Civil Engineers.*

Author keywords: Annual average daily traffic (AADT) estimation; Sampling error; Short-term counts; Bicycle data.

Introduction and Motivation

Motor vehicle count programs are well established and robust; however, bicycle traffic monitoring is incipient. There is only a small number of established permanent counting sites and limited agency experience to manage a state-wide system of nonmotorized data. From a planning point of view, a key measure of traffic volumes is annual average daily traffic (AADT). AADT represents average daily volume over an entire year at a specific location or facility. The applications of AADT values are numerous and range from safety analysis to prioritization of investments.

There are two primary procedures for calculating motorized AADT from permanent, 365-day, 24-h counting stations, also referred to as automated traffic recorders (ATR): one is a simple sum of all daily volumes for one year divided by the number of counting days in that year; the other is an average of averages (FHWA 2012). The AADT calculation for averages of averages from continuous counts comes from the "AASHTO Guidelines for Traffic Data Programs," prepared in 1992 (AASHTO 1992). One outcome of the method to calculate the average of averages is estimates for day of week (DOW) factors for each month of the year. That is, 84 factors are estimated: Seven factors for each DOW for each of the 12 months of the year. The procedure for the AASHTO method of determining AADT using continuous counts is as follows:

1. Calculate the average for each DOW for each month to derive each monthly average DOW;
2. Average each monthly average DOW across all months to derive the annual average DOW; and
3. The AADT is the mean of all of the annual average DOW.

The formula for the AASHTO method for determining AADT is

$$\mathrm{AADT} = \frac{1}{7}\sum_{i=1}^{7}\left[\frac{1}{12}\sum_{j=1}^{12}\left(\frac{1}{n}\sum_{k=1}^{n}\mathrm{VOL}_{ijk}\right)\right] \tag{1}$$

where VOL = daily traffic for day k, of day of the week i, and month j; i = day of the week; j = month of the year; k = index to identify the occurrence of a day of week i in month j; n = the number of occurrences of day i of the week during month j.

Agencies' motor vehicle count programs tend to be well established, robust, and operate with clear guidelines. In general, the programs consist of sets of permanent count stations used to develop AADT factors and a short-term counting program which uses these factors to estimate AADT volumes. Typically, for motorized counts, employing both DOW and monthly seasonal factors is sufficient to estimate AADT volumes using short-term counts. However, transportation agencies find that the estimation of bicycle or pedestrian AADT volumes from short-term counts is less accurate, because pedestrian and bicycle counts vary dramatically over time —in most cases significantly more than motorized vehicle counts. For example, Table 1 compares data from a major commute freeway (Interstate 84) and the most important (by volume) commute bicycle facility (Hawthorne Bridge, with over a million and a half

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Note. This manuscript was submitted on August 9, 2013; approved on January 14, 2014; published online on March 7, 2014. Discussion period open until August 7, 2014; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Transportation Engineering***, © ASCE, ISSN 0733-947X/04014014(8)/$25.00.

Table 1. Percent of AADT by Month and Vehicle Type, 2012

Month of year	Bicycles, Hawthorne Bridge (%)	Motor vehicles I-84 (%)
January	72	96
February	85	99
March	78	100
April	107	102
May	126	102
June	96	103
July	115	103
August	135	101
September	137	100
October	112	101
November	82	96
December	55	96

counted bicycles per year) in the Portland, Oregon, metropolitan area from 2012. The monthly volume variability is significantly higher for the bicycles, especially when warmer and colder months are compared.

The motivation for this research work stems from the need of transportation agencies, in this case the Oregon Department of Transportation, or ODOT, to develop AADT estimation procedures that build upon existing agency knowledge and practices to estimate motorized AADTs. For example, it is more cost-effective to use existing traffic monitoring staff and exploit the opportunities and synergies for coordinated short-term data collection efforts (e.g., simultaneous deployment of motorized vehicle traffic and bicycle tube counters) wherever this is possible. The goal of this research is to develop a methodology that will enhance, if needed, existing AADT estimation methods widely employed for motorized vehicle counts. The methodology can be applied to any type of traffic with high volume variability; in this research the application of the methodology is demonstrated using bicycle count data. In addition, it is necessary that the new methodology be practical, simple, and take advantage of the AASHTO DOW/monthly factors. The starting point of the proposed methodology is the estimation of the 84 DOW/monthly AASHTO factors, which can be readily estimated by the agency's traffic monitoring staff. If more accuracy is needed, the proposed methodology develops a correcting function that can be applied to any day of the year. The next section presents a literature review and specifies the contribution of this paper to the extant body of work.

Literature Review

One of the major differences between motor vehicle and nonmotorized traffic demand fluctuations is the influence of weather and seasons on travel behavior. While weather can influence motor vehicle traffic, nonmotorized traffic is more sensitive to changes in weather. Bicyclists and pedestrians are more exposed to the weather elements than motor vehicle drivers. In inclement weather, bicyclists and pedestrians may decide to use another mode of transportation.

Numerous studies have found that weather conditions do have a significant effect on bicycling and pedestrian traffic volumes; early studies go back to the 1990s (Niemeier 1996; Nankervis 1999). The significant effect of weather on bicycling volumes has been confirmed across many cities and countries such as the Netherlands (Thomas et al. 2009); Montreal, Canada (Miranda-Moreno and Nosal 2011); Melbourne, Australia (Phung and Rose 2007); Boulder, Colorado (Lewin 2011); Minneapolis, Minnesota (Wang et al. 2014); rural Vermont (Flynn et al. 2012); and Portland, Oregon (Rose et al. 2011). In all the cited studies, rain and temperature were key weather factors, and in some windy places it is possible that wind intensity is also a significant factor. The literature suggests that bicyclists' sensitivity to weather varies across locations (Ahmed et al. 2012; Miranda-Moreno and Nosal 2012), e.g., the same amount of rainfall has a smaller effect on bicycle volume in rainy Portland than in sunnier Brisbane (Ahmed et al. 2012). This finding strongly suggests that AADT adjustment factors must reflect local weather, population preferences, sensitivity to weather, and activity factors that drive the demand for bicycle trips.

There are many studies that aim to estimate bicyclists' volume using linear or log-linear regression models. For example, Lindsey et al. (2007) and several of the already mentioned studies looked at the effect of weather on bicycle volumes (Niemeier 1996; Nankervis 1999; Miranda-Moreno and Nosal 2011; Phung and Rose 2007; Lewin 2011; Wang et al. 2014; Rose et al. 2011; Ahmed et al. 2012). There has also been work on negative binomial count regression models (Wang et al. 2014; Miranda-Moreno and Nosal 2012; Nordback 2012) and time series models (Thomas et al. 2009; Gallop et al. 2012). Some studies have, in addition, looked at the effect of neighborhood, sociodemographic, built environment, and street characteristics using regression models (Hankey et al. 2012).

There are fewer studies that focus on bicycle AADT estimation. One of the most relevant to this research is the work of El Esaway et al. (2013). This work used bicycle count data from the City of Vancouver, Canada. El Esaway et al. (2013) tested the addition of factors based on weekend versus weekday volumes, road class, and weather variables. It was found that precipitation adjustment factors improved bicycle AADT estimations and decreased error by 3 to 8%. Although factoring for weather conditions was recommended, it was mentioned that it is necessary to group weather into general categories. It was found that creating adjustment factors for more than one weather variable can lead to an excessive number of factors. For example, the study simplified precipitation into just two categories: wet and dry weather. *Wet weather* was defined as daily rain over 5 mm and *dry weather* was anything less than 5 mm.

Dowds and Sullivan (2011) tested another method of weather-based factoring developed in Vermont that addressed seasonal and day-of-week adjustments. Additional adjustment factors were developed for each day of the week in each seasonal aggregation period, either by month or season. This method takes into consideration weather variables such as temperature, rainfall and snowfall, and clusters segments of the year into similar yearly weather patterns. In this Vermont example, six different seasonal clusters were identified. Adjustment factors were then calculated for each DOW and each aggregation period. This method produced 84 adjustment factors and another 42 adjustment factors; one factor for each day of the week and for each of the six clusters. However, the use of the 42 season-based factors did not result in substantially different estimates of AADT than the use of the 84 DOW/monthly factors.

Unlike the work of El Esaway et al. (2013) and Dowds and Sullivan (2011), the methodology proposed in this paper does not require the predefinition of weather categories, clusters, or thresholds (e.g., rainfall below or above 5 mm). The regression-based correcting function proposed in this research selects the most relevant variables that have not been accounted for by the 84 DOW/monthly factors; in addition, there is no need to predifine hard thresholds or groups. The correcting function is a function of the characteristics of the day of the count (and previous days if there are lagged variables) and includes not only weather variables (e.g., rain and temperature), but also activity or usage-based variables (e.g., holiday or school day) without adding new factors. In addition, the correction function allows for an incremental approach since it is built on top of the well-established DOW/monthly factors approach. It is important to note that the method does not add new factors, regardless of the number of variables that are significant to reduce AADT estimation errors.

Another line of research relevant to this work has focused on analyzing the relationship between short-term data collection durations and the bicycle AADT error or sampling error (Nordback et al. 2013). The results from this study, using data from Colorado, found that the optimal short-term count duration with the least error was one week of counts. The average error for one week of counts was 22%. Average error for AADT estimated from counts less than one week had average error of as much as 60%. Durations longer than one week gave estimates with fewer errors but with diminishing returns. Similar results were found in a previous AADT estimation research applied to motorized counts; motor vehicle AADT errors from 24-h counts averaged at about 15% (Gadda et al. 2007). Both Gadda et al. (2007) and Nordback et al. (2013) recommended that short-term counts be conducted when variation in counts is lowest. The next section describes the bicycle data used in this research and estimates AADT estimation errors by month and DOW.

Initial Data Analysis

The bicycle count data set was obtained from the city of Portland's bike tube counters on the Hawthorne Bridge and paired with weather data from the National Weather Service and other calendar data related to United States federal holidays and active school periods. The Hawthorne Bridge is located immediately adjacent to downtown Portland and within five blocks of a university campus (Portland State University, or PSU). It connects the dense, prewar housing stock on the east side of Portland with the central downtown core. Though there are other bridges with bicycle infrastructure, the connections and location make the Hawthorne the key facility in the bridge network. PSU is a large attraction center in the downtown area. It has more than 29,500 students and a bicycle mode share of 13%.

Daily 2012 count data were used for AADT factor estimation and analysis. These bicycle volume data were used to estimate daily and monthly factors. Plots of hourly and day of week volumes were created in order to display trends, which revealed a clear commute pattern. The annual average bicycle traffic (AADT) is 4,440; the annual average weekday bicycle traffic is 5,118; and the annual average weekend bicycle traffic is 2,744. The weekday average volumes are almost double the weekend average volumes.

This section analyzes the effect of counting duration and conditions on AADT estimation errors. Note that the same data used to compute the factors are also used to estimate the error in AADT estimation from applying those factors. If these factors were applied to another location (as one would do in using a permanent count station to estimate AADT at a short-term count locations) much higher errors would be expected than those reported here.

Two types of conditions are studied: time of the year/week and count duration. The authors define AADT estimation error as the ratio between the residual or estimated difference (difference between estimated and actual AADT) and the actual AADT; to facilitate interpretation of the numbers in this section, the authors employ error percentage [Eq. (2)]. Note that errors can be positive (overestimation) or negative (underestimation). When summing the estimated AADT errors over a period of time, the errors tend to cancel each other out, and the sum can be equal to zero. Hence, when comparing error estimations over a period of time, it is then better to use the absolute percentage error. In this section when comparing different AADT estimations, the authors employ the mean absolute percentage error (MAPE) metric [Eq. (3)]

$$e_i = \frac{\widehat{\mathrm{AADT}}_i - \mathrm{AADT}}{\mathrm{AADT}} 100 \tag{2}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{abs}(e_i) \tag{3}$$

i = any day whose AADT has been estimated; $\widehat{\mathrm{AADT}}_i$ = estimated AADT applying the daily and monthly AASHTO factors to day i; n = total number of days i grouped for the MAPE estimation; $\mathrm{abs}(x)$ = absolute function of number x

The MAPE by day of the week is shown in Table 2 and by month in Table 3. Data in Table 2 and an analysis of traffic volumes by time of day and day of the week indicate that the bicycle traffic is predominantly utilitarian (commuters). Estimated AADT, or $\widehat{\mathrm{AADT}}_i$, is calculated after applying the daily and monthly factors for each day i of the year. As expected, middle days during the week and warmer months tend to perform better in terms of MAPE. The last column of the tables includes the associated traffic; it seems that there is a correlation between higher traffic volumes and lower MAPE.

Count data were missing for 20 days in the month of July. This may help explain the relatively high MAPE for a summer month like July. Because the Hawthorne Bridge traffic has a typical commuter profile (commuters to and from downtown Portland), it is not surprising that Sundays have the lowest traffic and the highest MAPE. Mondays also show a high MAPE, and this may be

Table 2. MAPE by Day of Week

Day of week	MAPE (%)	Average DOW traffic
Sunday	25.4	2,609
Monday	25.6	4,982
Tuesday	15.8	5,354
Wednesday	14.4	5,186
Thursday	16.6	5,272
Friday	15.4	4,796
Saturday	19.5	2,885

Table 3. MAPE by Month

Month	MAPE (%)	Average monthly traffic
January	26.4	3,199
February	14.5	3,790
March	22.0	3,463
April	13.6	4,738
May	20.9	5,574
June	15.2	4,249
July	19.9	5,126
August	10.3	5,999
September	8.1	6,065
October	22.3	4,970
November	23.0	3,656
December	31.2	2,456

explained by the high number of holidays that fall on a Monday; holiday counts tend to underestimate AADT significantly.

Weather effects and DOW characteristics are inherently incorporated into the 84 DOW/monthly factors. For example, in months when the weather is more comfortable, volumes will tend to increase and the factors account in part for this trend; similarly when considering weekdays versus weekend traffic volumes. Hence, it is not surprising that the 84 factors can produce very good estimations when short-term counts are performed in the warmer summer months and from Tuesday to Friday. It was mentioned in the literature review that motor vehicle AADT errors from 24-hour counts averaged about 15% (Gadda et al. 2007). Also note that the AADT estimation errors reported here are based on computing AADT at the same location from which the DOW/monthly factors were created. This results in lower error than would be expected if the same factors had been applied to any other location.

A posterior analysis of the days with high error (both positive and negative) indicates that days with adverse weather conditions and before, during, or after holidays or special events must be avoided for short-term counts. Other variables such as PSU or school class periods cannot be fully avoided because they take place over many weeks of the year, and it is better to adjust the counts.

One policy or strategy to reduce AADT estimation errors can be to count only on favorable days. This begs the question, "How can we define favorable days?" In addition, when scheduling traffic counting crews over a one- or two-month period, for example, it is certainly possible to avoid holidays, but it is not realistic to accurately forecast weather conditions more than a few days in advance. A more elaborate procedure is needed for circumstances such as (1) if more accuracy is needed, (2) to better identify and quantify the characteristics of favorable days, and (3) to better gauge the tradeoffs between short-term count duration and the sophistication of the AADT estimation methodology. A methodology to deal with these three issues is described in the next sections.

Regression Analysis of AADT Estimation Errors

As demonstrated in the literature review, there is a growing body of research analyzing the effects of weather on bicyclists' volumes or estimating regression models for bicycle or pedestrian volumes. However, to the best of our knowledge, there is no published research effort that has linked the usage of DOW/monthly factors, estimation errors, and the development of a correcting function that can be applied to reduce AADT estimation errors. The authors have developed a regression model where the dependent variable is the daily percent AADT error, e_i, [Eq. (2)], and the independent variables are weather factors and day characteristics associated with the demand for travel, such as holidays or school days. Because the methodology applies to a specific ATR, it is not possible to include spatial variables, such as neighborhood demographics, built environment, and sociodemographic or street type variables.

An additional and significant contribution of the method presented in this section is that the authors employ lagged variables and regression models that account for serial correlation. Lagged variables are important to explain the variability of the dependent variable when the recent past (e.g., the previous day's temperature or a holiday) affects present conditions (e.g., today's AADT estimation error). Accounting for serial correlation is important to properly estimate the regression coefficients. Count and error data do typically have high levels of serial correlation. Ignoring the serial correlation tends to artificially inflate the significance of the independent variables (e.g., showing that a variable is significant when in reality it is not).

Data Dictionary

Dependent Variable

e_i is the percent AADT error for each day. This is a continuous variable and can be positive or negative by measuring overestimation or underestimation, respectively.

Independent Variables

- Tmax_i: Daily maximum temperature in Fahrenheit registered in day *i*.
- $\mathrm{Tmax} > 70_i$: Degrees above 70°F for the daily maximum temperature registered in day *i*. If the maximum temperature falls below 70°F, the value is 0. For example, if maximum temperature is 75°F, the value of the variable is 5; if maximum temperature is 65°F, the value of the variable is 0.
- $\mathrm{Tmax} < 50_i$: Degrees below 50°F for the daily maximum temperature registered in day *i*. If maximum temperature exceeds 50°F, the value is 0. For example, if maximum temperature is 35°F, the value of the variable is 15; if maximum temperature is 65°F, the value of the variable is 0.
- $\mathrm{TempDev}+_i$: Positive deviation or difference between the maximum temperature registered in day *i* and the long-term average daily maximum temperature provided by NOAA (2013). For example, if the maximum temperature is 65°F and the long-term average for the day is 55°F, the value of the variable is 10; if the maximum temperature is 45°F, the value of the variable is 0.
- $\mathrm{TempDev}-_i$: Deviation or difference between the long-term average daily maximum and the maximum temperature in Fahrenheit registered in day *i*; for example, if the maximum temperature is 65°F and the long-term average for the day is 55°F, the value of the variable is 0; if the maximum temperature is 45°F, the value of the variable is 10.
- Precip_i: Daily precipitation in inches. (Note that precipitation contains more than just rainfall and includes, for example, drizzle or dew accumulation.)
- Tmax_i^2: The square of the daily maximum temperature in Fahrenheit registered in day *i*.
- Precip_i^2: The square of the daily total precipitation in inches. (Note that precipitation contains more than just rainfall and includes, for example, drizzle or dew contributions.)
- $\mathrm{Holiday}_i$: Dummy variable that is 1 if day *i* is a federal holiday; the variable is 0 otherwise.
- $\mathrm{PSU\ Hol.}_i$: Dummy variable that is 1 if day *i* is a weekend or a weekday when Portland State University is not in session for any of the fall, winter, or spring terms.

Previous research using Hawthorne Bridge data (Rose et al. 2011) has shown that the effect of temperature on bicycle volumes is not linear. The squared terms for temperature and precipitation are introduced to allow nonlinear effects. Similarly, $\mathrm{Tmax} > 70_i$ and $\mathrm{Tmax} < 50_i$ are introduced to detect the effect of extreme temperatures on AADT estimation errors (50°F and 70°F were chosen because they are approximately equal to the 25th and 75th percentile, respectively). The $\mathrm{TempDev}_i$ variables also attempt to measure the effect of extreme temperatures.

In addition, the significance of lagged variables was also tested. For example, $\mathrm{Holiday}_{i-1}$ is a dummy variable that is 1 for the day $i-1$ if the day i is a federal holiday; the variable is 0 otherwise.

The variable $\mathrm{Holiday}_{i-1}$ is employed to test if there is a significant change in AADT errors the day before a holiday. Similarly, Tmax_{i-1}, $\mathrm{TempDev}_i$, and Precip_{i-1} (and their squares or extreme temperatures) were included in the analysis. In all the models, some of the temperature parameters are significant at the $p \leq 0.05$ level and even lagged temperature variables are significant in some cases. However, in the autoregressive models the temperature lagged variables are estimated with $p > 0.10$. An examination of the data shows that unusually cold or hot days are serially correlated.

Regression Results

The final regression model is shown in Table 4. Alternative specifications for temperature were tested, including nonlinear terms for both high and low temperatures. Only the final model was included in the paper based on the model that better fits the data with fewer parameters [Akaike's information criterion (AIC)] as well as model stability. Stability was measured by the change in the estimated coefficients when a variable was removed. It is worth noting that several alternative model specifications produce models whose AIC were very close (within 1%).

Only independent variables that were significant at the $p \leq 0.05$ level are included in the final model and shown in Table 4. It is possible to observe that there are two significant lagged variables: precipitation and holiday. Precipitation also has linear and quadratic significant variables. The only significant temperature variable is associated temperature above 70°F (linear increase above 70°F). To facilitate the interpretation of the coefficients, they are expressed as a percentage in Table 5.

The interpretation of PSU Hol.$_i$ is that, on average and removing the effect of the other significant variables, performing a one-day count on a day without significant PSU activity *underestimates* AADT, estimated using only daily and monthly DOW/monthly factors, by 9.4% (the coefficient is *negative*). In all cases, the interpretation of the coefficient should be accompanied by the qualifying words "on average and removing the effect of the other significant variables." For the sake of brevity, the authors have removed these qualifying words when interpreting the remaining coefficients.

Table 4. Regression e_i versus Daily Condition Variables

Variable	Coefficients	Standard error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.054	0.014	3.968	0.000	0.027	0.081
PSU Hol.$_i$	−0.094	0.037	−2.563	0.011	−0.166	−0.022
Holiday$_{(i-1)}$	−0.506	0.059	−8.571	0.000	−0.622	−0.390
Holiday$_i$	−0.205	0.059	−3.476	0.001	−0.321	−0.089
Precip$_{(i-1)}$	−0.105	0.038	−2.770	0.006	−0.179	−0.030
Precip$_i$	−0.483	0.074	−6.496	0.000	−0.630	−0.337
Precip$_i^2$	0.199	0.056	3.559	0.000	0.089	0.309
Tmax$_i(> 70)$	0.008	0.003	2.810	0.005	0.002	0.013

Note: Correlation coefficient $\rho = 0.46$.

Table 5. Regression Coefficients as Percentage

Variable	Regression coefficients (%)
Intercept	5.4
PSU Hol.$_i$	−9.4
Holiday$_{(i-1)}$	−50.6
Holiday$_i$	−20.5
Precip$_{(i-1)}$	−10.5
Precip$_i$	−48.3
Precip$_i^2$	19.9
Tmax$_i(> 70)$	0.8

The effect of the variable holiday is even more dramatic. Performing a one-day count on a federal holiday on average *underestimates* AADT by a 50.6% (the coefficient is *negative*). Furthermore, there is a lagged effect of the variable holiday, because performing a count a day before a federal holiday will result in an AADT value that is on average *underestimated* by 20.5%. It is likely that the dramatic influence of holidays is largely due to the strong commute pattern at this location. It is expected that locations with recreational patterns would behave differently.

Precipitation has an important effect on AADT estimation errors. Because a lagged variable is significant, one inch of rain (on the previous day) on average tends to *underestimate* AADT by 10.5% if monthly and daily factors are applied to (today) a one-day volume. Because the squared term is significant, for a given day the effect of rain on AADT error is nonlinear. For example, if the total measured precipitation for today is one-half inch, AADT is underestimated on average 19.2%; if today's rain is one inch, AADT is underestimated on average 28.4%. The maximum effect of rain is reached when rain is equal to 1.22 in. and AADT is underestimated by 29.4%. As a reference, only 0.75% of the days in a year exceed the 1.22 in. amount.

Temperature (above 70°F) is the only temperature coefficient that was significant at a $p \leq 0.05$ level. The interpretation of the temperature variable is related to the *value* of the maximum temperature above 70°F. For example, if the maximum temperature on the day of the count is 80°F, AADT is likely to be overestimated by 8% on average; if the maximum temperature reaches 90°F, estimating bicycle AADT using DOW/monthly factors will overestimate AADT by 16% on average.

Finally, the model is technically described as an autoregressive model of order one (1) or AR(1); in this model the serial correlation coefficient is 0.46 (a positive correlation coefficient can vary from +1 to 0). This positive correlation indicates that conditions and estimation error present the day before do effect today's estimation error. For example, if the error yesterday was highly negative (AADT underestimation), then on average today's error will tend to be negative too. On the other hand, if yesterday's error was positive (AADT overestimation), then on average today's error will tend to be positive too.

It is worth mentioning that AR(2) models were also estimated but the additional term does not improve the results according to AIC; the correlation between percent AADT errors decreases rapidly as the number of lags increases. The final model passed the Ljung-Box and Breusch-Godfrey tests for serial correlation.

In the next section, the performance of the correcting function is presented followed by a succinct summary of the proposed methodology to select count duration and improve the AADT estimation process.

Correcting Formula Performance

Employing the estimates of the final regression model shown in Table 4, it is possible to formulate a correcting function $f(x_i)$ that is a linear combination, where x_i is the vector of parameters that represent the significant variable values (e.g., rain or holiday) for any given day i and lagged days and variables that were significant in the final model. The newly corrected AADT estimation is shown in Eq. (4)

$$\widehat{\mathrm{AADT}}_i' = \frac{\mathrm{VOL}_i}{\mathrm{AASHTO}_i * [1 + f(x_i)]} \tag{4}$$

where $\widehat{\mathrm{AADT}}_i'$ = estimated AADT on day i using the correcting formula; VOL_i = volume of bicycle traffic on day i (a one-day count); AASHTO_i = AASHTO DOW/monthly factor for day i; $f(x_i)$ = value of the correcting function for day i.

In Eq. (4), the value of the correcting function $f(x_i)$ can be interpreted as follows: if the value of the correcting formula is negative for day i (e.g., because there was heavy rain), the estimated value $\widehat{\text{AADT}}_i'$ will be higher than that solely using the DOW/monthly factors.

Count Duration and Sample Size Error

The results presented in the previous sections assumed 1-day count durations. If the count duration is extended, AADT estimation errors tend to decrease because a one-day or special weather condition anomaly can be averaged out across more days. In addition, the longer the count, the less likely that a condition persists over the entire period of time. For example, it is more likely to have two days with heavy rain than 10 consecutive days of heavy rain.

The results presented in Table 6 show the distribution of absolute AADT error values as a function of count duration. The meaning of the column labels is

- 1-day: MAPE distribution estimated assuming 1-day counts in the 2012 year, i.e., applying the corresponding factors to estimate AADT each day.
- 3-day: MAPE distribution estimated assuming 3-day counts in the 2012 year, i.e., applying the corresponding factors to estimate AADT each Tuesday, Wednesday, and Thursday.
- 5-day: MAPE distribution estimated assuming 5-day counts in the 2012 year, i.e., applying the corresponding factors to estimate AADT Monday to Friday.
- 7-day: MAPE distribution estimated assuming 7-day counts in the 2012 year, i.e., applying the corresponding factors to estimate AADT over a whole week.
- 10-day: MAPE distribution estimated assuming 10-day counts in the 2012 year, i.e., applying the corresponding AADT factors from Tuesday to Thursday of the next week.
- 14-day: MAPE distribution estimated assuming 14-day counts in the 2012 year, i.e., applying the corresponding factors to estimate AADT for two whole weeks.

The results shown in Table 6 show the error when AADT is estimated using the AASHTO DOW/monthly factors without the correcting formula. They indicate that for the Hawthorne Bridge data, the mean error is approximately 19% but only 15% if only the seven warmest months are analyzed (comparable to the 15% mean observed for motorized by Gadda et al. 2007). The estimation error (MAPE) can be also reduced by extending the count duration from 1 to 3 days (Tuesday to Thursday). It is noticeable that 3-day counts outperform counts done for durations of 5, 7, and 10 days. This can be explained by the lack of weekends and the presence of the more stable high-volume days of the middle of the week. This finding is potentially significant for the design of cost-effective sampling strategies in areas where traffic is predominantly utilitarian (commuting). Future research efforts are needed to validate this finding across different urban areas.

It is important to notice that in all cases, the mean is always larger than the median and that the distribution is not symmetrical around the mean. Removing the five coldest months improves the results, but even if a mean error of 15% is acceptable, one out of four times the MAPE will be larger than 25% for a 1-day count.

Correcting Formula Results

If the correcting formula is applied, Table 7 is obtained. In all cases, the errors are reduced and the mean error for 1-day counts is reduced to 15% considering all the months of the year. Furthermore, the reduction in the 3rd quartile is almost 8% while the reduction in the 1st quartile is almost 2%. Hence, the greater benefit of applying the correcting formula is in reducing the AADT estimation errors in days that tend to highly overestimate or underestimate AADT values. This is a desirable distribution of the improvement in AADT estimation. The performance of 3-day counts also improves significantly after applying the correcting formula. In particular, 3-day counts outperform all the other count durations with the exception of the 14-day counts.

Comparing the results of Tables 6 and 7, it is clear the AADT estimation errors can be reduced by (1) reducing the sampling error (increasing count duration), (2) improving the sophistication of the AADT estimation process, or (3) being more selective in terms of the timing of the counting. For example, 1-day counts in the seven warmest months of the year after applying the correcting formula outperform 3-day, 5-day, and 7-day counts using only the DOW/monthly factors and sampling anytime throughout the year.

Proposed Methodology

The steps proposed in this research to characterize ideal short-term counting conditions and improve AADT estimation accuracy are the following:

1. Select a permanent counting station.
2. Estimate AASHTO AADT DOW/monthly factors
3. Apply the DOW/monthly factors to estimate AADT estimation errors.
4. Estimate AADT errors as a function of count duration (sampling error). Analyze the tradeoffs between duration costs and admissible errors.
5. Evaluate whether the short-term-count AADT estimation errors are within the range admissible for the agency. If the answer is yes, to go Step 9. Otherwise go to Step 6.

Table 6. Absolute Error as a Function of Count Duration

Time period	Statistic	1-day	3-day	5-day	7-day	10-day	14-day
January to	Mean (%)	19.1	13.0	13.2	12.8	10.9	9.0
December	SD (%)	16.6	12.3	11.2	9.7	8.3	7.2
(all year)	1st quartile (%)	6.4	2.4	4.7	5.0	1.6	2.3
	Median (%)	14.9	9.2	9.4	10.8	9.6	8.1
	3rd quartile (%)	27.2	18.8	21.3	19.8	18.5	12.6
April to	Mean (%)	15.4	8.4	9.8	10.8	9.3	7.8
October	SD (%)	14.6	7.6	7.5	7.7	9.2	7.8
(7 months)	1st quartile (%)	4.6	2.2	3.8	4.5	1.1	1.9
	Median (%)	10.6	6.7	8.7	9.1	7.6	3.0
	3rd quartile (%)	25.4	18.1	20.4	19.9	15.9	13.0

Table 7. Absolute Error after Applying the Correcting Formula

Time period	Statistic	1-day	3-day	5-day	7-day	10-day	14-day
January to	Mean (%)	15.6	10.7	10.5	10.3	9.1	8.4
December	SD (%)	16.2	12.3	11.4	9.9	8.7	7.2
(all year)	1st quartile (%)	4.6	4.6	3.6	4.3	3.7	4.2
	Median (%)	11.2	7.0	7.0	7.3	6.8	6.6
	3rd quartile (%)	19.8	9.5	10.4	11.3	10.4	7.6
April to	Mean (%)	11.9	8.3	8.0	8.6	8.2	7.9
October	SD (%)	10.8	6.1	5.7	5.5	4.5	4.3
(7 months)	1st quartile (%)	4.1	4.2	3.8	4.3	5.0	5.6
	Median (%)	8.2	6.8	5.9	7.2	7.3	6.6
	3rd quartile (%)	18.4	8.9	8.3	11.4	9.7	8.0

6. Select the days with highly positive or negative AADT estimation error. Find the day of week, month, and weather (e.g., rain) or activity (e.g., holiday) variables that are associated with highly positive or negative AADT estimation errors.
7. Produce a correcting function after estimating a regression model using the estimated errors (from Step 3) as the dependent variable and the variables identified in Step 6 as the independent variables. Explore nonlinear effects and lagged variables; correct for any potential estimation problems such as serial correlation, heteroscedasticity, and others, as needed.
8. From the analysis of the results of Steps 6 and 7
   a. Find the optimal conditions for short-term counts,
   b. Identify most favorable days/months characteristics, and
   c. Evaluate the new tradeoffs between count durations and AADT estimation errors.
9. Select a suitable combination of short-term count duration, timing, and estimation method.

Within a state-wide counting program, a correcting function would need to be estimated for each permanent data collection station, especially those stations with high daily count variability or AADT estimation sampling errors. Unless there are significant changes in travel patterns, the correcting function can be estimated annually or less frequently, if sampling errors are steady or decrease over time.

The authors emphasize that the proposed methodology improves only sampling errors. There is another type of error associated with assuming that the permanent counter distribution of volumes is also applicable to short-term counting stations. This type of error, also known as classification error (Gadda et al. 2007), is outside the scope of this research. Given the higher variability of bicycle and pedestrian counts, it may be reasonable to speculate that these errors could be significant for bicycle and pedestrian factoring methods.

Conclusions

With increasing bicycle ridership in Portland, Oregon, and across the country, the ability to improve estimates of AADT values for nonmotorized travel is important to city, county, and state agencies that build and manage transportation facilities. This paper proposes a new methodology, based on the analysis of AADT estimation errors: (1) to reduce sampling errors, (2) to improve the sophistication of the AADT estimation process, and (3) to be more selective in terms of the timing of the counting. The proposed methodology is suitable for any type of traffic with high volume variability; this paper demonstrated the method successfully applied to bicycle counts. Unlike previous work in the AADT estimation literature, the proposed method does not rely on the predefinition of weather categories, clusters, or thresholds. The methodology uses a correcting function that accounts for the characteristics of the day of the count (and previous days, if there are lagged variables) and includes not only weather variables like rain and temperature, but also activity or usage based variables like holidays or school days.

The correction function was shown to significantly improve the accuracy of the AADT estimation process for 1-day and 3-day counts for our test case. It is reasonable to expect that the method can be extrapolated to other short-term count location and ultimately could reduce short-term count costs without compromising AADT estimation accuracy. In addition, the proposed methodology allows for an incremental approach, since it is built on top of the DOW/monthly factors.

Future research efforts can apply the proposed methodology to other data sets with predominantly nonutilitarian traffic such as recreational travel, and in areas with different urban and transportation system characteristics.

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