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Development of Accurate and Reliable Annual Average Daily Traffic Factoring Methods

Li Zhao, Ph.D., P.E.
Research Assistant Professor
Department of Civil &
Environmental Engineering
University of Nebraska-Lincoln

Mahyar Madarshahian, Ph.D.
Graduate Research Assistant
Department of Civil &
Environmental Engineering
University of Nebraska-Lincoln

Amirmohammad Sadeghnejad
Graduate Research Assistant
Department of Civil &
Environmental Engineering
University of Nebraska-Lincoln

Nathan Huynh, Ph.D.
Professor
Department of Civil &
Environmental Engineering
University of Nebraska-Lincoln

Nebraska Department of Transportation Research
Headquarters Address
1400 Nebraska Parkway
Lincoln, NE 68509
ndot.research@nebraska.gov
(402) 479-4697
https://dot.nebraska.gov/business-center/research/

Nebraska Transportation Center
262 Prem S. Paul Research Center at Whittier School
2200 Vine Street
Lincoln, NE 68583-0851
(402) 472-1932
http://ntc.unl.edu

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Li Zhao, Ph.D., P.E.
Research Assistant Professor
Department of Civil & Environmental Engineering
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Mahyar Madarshahian, Ph.D
Graduate Research Assistant
Department of Civil & Environmental Engineering
University of Nebraska-Lincoln

Amirmohammad Sadeghnejad
Graduate Research Assistant
Department of Civil & Environmental Engineering
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Nathan Huynh, Ph.D.
Professor
Department of Civil & Environmental Engineering
University of Nebraska-Lincoln

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Accurate estimation of Annual Average Daily Traffic (AADT) is essential for the Nebraska Department of Transportation (NDOT) to support planning, design, safety evaluation, asset management, and federal reporting requirements. Because continuous traffic monitoring is not feasible at every roadway location, NDOT relies on short-term traffic counts that are expanded to annual values using temporal adjustment factors (TAFs). The selection of appropriate temporal factors directly affects the reliability of AADT estimates and, consequently, the quality of transportation investment decisions. NDOT's current practice primarily relies on month-of-the-year–based adjustment factors, with additional day-of-week considerations. While this approach follows national guidance, the performance of alternative temporal adjustment structures has not been systematically evaluated under Nebraska-specific traffic conditions. Differences in seasonal variation, holiday effects, and roadway functional characteristics may influence the accuracy of various temporal aggregation levels. Therefore, a comprehensive assessment of candidate temporal adjustment factors was necessary to determine the most accurate and reliable approach for estimating AADT from short-term counts in Nebraska. The objective of this project was to evaluate multiple temporal adjustment factor structures and identify the most suitable options for NDOT's roadway functional groups. Eleven temporal adjustment factor structures were evaluated, ranging from monthly to daily and week-based configurations. Performance was assessed using error-based metrics that compare estimated AADT values against ATR-derived annual averages. To support implementation, this project developed an Excel-based tool that incorporates the three recommended temporal adjustment factors. The tool automates data formatting, factor calculation, AADT estimation, and error evaluation. It is designed to be user-friendly and compatible with NDOT's existing workflow, minimizing implementation barriers. The tool allows engineers to select among the recommended factor options depending on data availability and operational needs.
The findings of this study provide NDOT with a data-driven basis for improving AADT estimation practices. Adoption of the recommended temporal adjustment factors, particularly in combination with 48-hour short-term counts when feasible, can enhance the reliability of AADT values used in planning, safety analysis, and funding allocation decisions. The accompanying implementation tool further facilitates practical application of the research results.</td></tr>
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List of Abbreviations

AADT: Annual Average Daily Traffic

ATR: Automatic Traffic Recorder

CV: Coefficient of Variation

DOW: Day of Week

DM: Day of the Month

DMY: Day of all Months of the Year

DW: Day of the Week

DWM: Day of all Weeks of the Month

DWMY: Day of all Weeks of all Months of the Year

DWY: Day of all Weeks of the Year

DY: Day of the Year

FHWA: Federal Highway Administration

IQR: Interquartile Range

MAPE: Mean Absolute Percentage Error

MY: Month of the Year

NDOT: Nebraska Department of Transportation

TAF: Temporal Adjustment Factors

WM: Week of the Month

WMY: Week of all Months of the Year

WY: Week of the Year

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Disclaimer

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Executive Summary

Accurate estimation of Annual Average Daily Traffic (AADT) is essential for the Nebraska Department of Transportation (NDOT) to support planning, design, safety evaluation, asset management, and federal reporting requirements. Because continuous traffic monitoring is not feasible at every roadway location, NDOT relies on short-term traffic counts that are expanded to annual values using temporal adjustment factors (TAFs). The selection of appropriate temporal factors directly affects the reliability of AADT estimates and, consequently, the quality of transportation investment decisions.

NDOT's current practice primarily relies on month-of-the-year–based adjustment factors, with additional day-of-week considerations. While this approach follows national guidance, the performance of alternative temporal adjustment structures has not been systematically evaluated under Nebraska-specific traffic conditions. Differences in seasonal variation, holiday effects, and roadway functional characteristics may influence the accuracy of various temporal aggregation levels. Therefore, a comprehensive assessment of candidate temporal adjustment factors was necessary to determine the most accurate and reliable approach for estimating AADT from short-term counts in Nebraska.

The objective of this project was to evaluate multiple temporal adjustment factor structures and identify the most suitable options for NDOT's roadway functional groups. The study utilized 2023 hourly traffic volume data from 47 Automatic Traffic Recorder (ATR) stations across three roadway groups: Rural Highways, City Streets, and County Roads. A cross-validation framework was implemented to simulate short-term count conditions using both 24-hour and 48-hour durations. In addition, short-term count stations located near ATR sites were used to confirm practical applicability.

Eleven temporal adjustment factor structures were evaluated, ranging from monthly to daily and week-based configurations. Performance was assessed using error-based metrics that compare estimated AADT values against ATR-derived annual averages. The analysis yielded the following key findings:

- 48-hour short-term counts consistently produced more accurate AADT estimates than 24-hour counts across all roadway groups.
- Week-based temporal adjustment structures generally outperformed traditional month-based factors.
- Highly granular daily factors demonstrated increased variability, particularly on lower-volume roadways.
- Performance varied slightly by roadway functional class; however, several factor structures demonstrated consistent stability across groups.

Based on overall performance across roadway groups and count durations, the following three temporal adjustment factors emerged as the most accurate and reliable options:

1. Week of the Year × Day of the Week

2. Week of the Year

3. Day of the Year

These factors consistently ranked among the top-performing alternatives and demonstrated strong robustness across seasonal conditions. Compared to the current month-of-the-year-based approach, the recommended factors reduced estimation error and provided more stable performance across functional classifications.

To support implementation, this project developed an Excel-based tool that incorporates the three recommended temporal adjustment factors. The tool automates data formatting, factor calculation, AADT estimation, and error evaluation. It is designed to be user-friendly and compatible with NDOT's existing workflow, minimizing implementation barriers. The tool allows engineers to select among the recommended factor options depending on data availability and operational needs.

The findings of this study provide NDOT with a data-driven basis for improving AADT estimation practices. Adoption of the recommended temporal adjustment factors, particularly in combination with 48-hour short-term counts when feasible, can enhance the reliability of AADT values used in planning, safety analysis, and funding allocation decisions. The accompanying implementation tool further facilitates practical application of the research results.

Chapter 1 Introduction

1.1 Background

Annual Average Daily Traffic (AADT) represents the average number of vehicles traveling past a roadway location per day over the course of a year. AADT is one of the most fundamental traffic performance measures used by transportation agencies for planning, roadway design, safety analysis, pavement management, congestion assessment, and funding allocation. Accurate AADT values are essential for both statewide decision-making and federal reporting requirements.

The Nebraska Department of Transportation (NDOT) is responsible for collecting, maintaining, and reporting traffic data in accordance with Federal Highway Administration (FHWA) guidelines. As part of the Highway Performance Monitoring System (HPMS), NDOT must submit annual AADT estimates for roadway segments across the state. These values are used not only for federal compliance, but also to support state-level infrastructure investment, safety screening, and long-range transportation planning.

While permanent Automatic Traffic Recorder (ATR) stations provide continuous data at select locations, it is not feasible to operate ATRs at every roadway segment due to equipment costs, maintenance requirements, staffing needs, and infrastructure limitations. Therefore, NDOT relies extensively on short-term traffic counts, typically collected over 24- or 48-hour periods, which are expanded to annual values using temporal adjustment factors (TAFs). The selection and performance of these adjustment factors directly influence the accuracy and reliability of estimated AADT values.

1.2 Current NDOT Practice

NDOT currently applies temporal adjustment factors that are primarily based on the month of the year, with additional consideration of day-of-week variation. This approach aligns with established national guidance and provides a practical framework for expanding short-term counts to annual averages. The method has been implemented consistently over time and is integrated into NDOT's traffic data workflow.

However, traffic patterns are influenced by multiple temporal dimensions, including weekly cycles, seasonal trends, holidays, and special events. Month-based aggregation may not fully capture short-term fluctuations or intra-month variability. Furthermore, traffic characteristics can vary across roadway functional classes, potentially affecting the performance of different temporal adjustment structures.

To date, the performance of alternative temporal adjustment factor configurations has not been systematically evaluated under Nebraska-specific traffic conditions. As a result, it is unclear whether the current month-based approach provides the most accurate and stable AADT estimates across all roadway groups.

1.3 Research Gap

Numerous temporal adjustment factor structures have been proposed in the literature, including week-of-year factors, day-of-year factors, and hybrid combinations that incorporate multiple temporal dimensions. While these approaches have shown potential in other jurisdictions, their applicability and relative performance in Nebraska remain uncertain.

Traffic in Nebraska exhibits seasonal variation, holiday-related fluctuations, and functional-class-specific characteristics that may influence the effectiveness of different temporal aggregation levels. Without a comprehensive comparative evaluation, the relative advantages of alternative factor structures cannot be determined.

A systematic, data-driven assessment of candidate temporal adjustment factors using statewide ATR data is therefore necessary to identify the most accurate and reliable approach for estimating AADT from short-term counts.

1.4 Objectives

The objective of this study is to evaluate multiple temporal adjustment factor structures and determine the most suitable options for estimating AADT from short-term traffic counts in Nebraska. Specifically, the study:

- Evaluates eleven temporal adjustment factor configurations;
- Compares performance across three roadway functional groups;
- Assesses estimation accuracy using both 24-hour and 48-hour count durations; and
- Develops an implementation-ready Excel-based tool incorporating the top-performing factors.

Through this evaluation, the study aims to provide NDOT with evidence-based recommendations to enhance the accuracy, reliability, and practical implementation of AADT estimation practices.

Chapter 2 Literature Review

The estimation of AADT from short-duration traffic counts has historically relied on temporal adjustment factors derived from permanent count stations. One of the earliest structured implementations of this approach was presented by Drusch (1966). These principles were subsequently formalized in national guidance. The Federal Highway Administration's Traffic Monitoring Guide (TMG) outlines the structure of statewide traffic monitoring systems and emphasizes the use of permanent Automatic Traffic Recorder (ATR) stations to develop seasonal and day-of-week adjustment factors. According to the TMG, short-term counts are expanded to AADT using factors derived from continuous monitoring sites that capture predictable seasonal, weekly, and daily traffic variation. This approach enables agencies to meet Highway Performance Monitoring System (HPMS) reporting requirements while maintaining practical monitoring costs.

2.1 Traditional Temporal Adjustment Factors

Since the mid-1980s, numerous methods have been developed to improve the accuracy of AADT estimation, ranging from traditional factor-based techniques to modern machine learning approaches. Much of the existing research has relied on a limited set of traffic adjustment factors (TAFs), such as month-of-year and day-of-week, or has avoided them altogether by employing black-box or alternative data-driven models. However, only a few studies have comprehensively examined a broad range of TAFs or systematically compared their relative performance under controlled conditions. This review summarizes the major methodologies, assesses their strengths and limitations, and highlights this gap as an important opportunity for further advancement in AADT estimation practices.

Three primary research areas address AADT estimation: converting short-term traffic counts into annual estimates, projecting future traffic volumes using historical data, and transferring traffic information from one site to another through spatial extrapolation (Lowry and Dixon 2012). In this project, the focus is on the first area, which involves converting short-term counts into annual estimates. The FHWA guidelines (Federal Highway Administration 2016) describe three primary procedures for computing Annual Average Daily Traffic (AADT): the simple average method, the traditional AASHTO average-of-averages method, and a recently developed modified hourly-based approach. The formula recommended by AASHTO is described in the following Equation:

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

where:

VOL = daily traffic for day k, of day-of-week i and month of the year j,

k=1 when the day is the first occurrence of that day of the week in a month, and

n = number of days of that day of the week during that month.

The simple average method computes AADT as the arithmetic mean of all available daily volumes within a year. While easy to implement, it can introduce bias when data are missing, especially if missing periods correspond to specific traffic patterns (e.g., seasonal peaks). To address this issue, the traditional AASHTO method calculates AADT using an average-of-averages approach. It first computes average traffic for each day of the week within each month and then averages these values across months and days. This method explicitly accounts for weekday and monthly representation and generally performs better than the simple average when data are incomplete. However, it requires complete daily records and may introduce slight bias because it equally weighs months and days regardless of differences in the number of days per month.

Recent evaluations identified two main limitations of the AASHTO method: (1) it excludes any day with missing hourly data, resulting in data loss and potential underestimation, and (2) it can introduce minor bias due to its averaging structure. To overcome these limitations, FHWA introduced a modified two-step hourly-based formulation. This method first computes Monthly Average Daily Traffic (MADT) using all available hourly (or sub-hourly) data, allowing partial days to be retained. It then calculates AADT by weighing monthly values according to the number of days in each month. This approach reduces bias, utilizes more available data, and provides more statistically reliable AADT estimates, particularly when hourly data are incomplete. The recommended procedure by FHWA is expressed mathematically below:

$$MADT_m = \frac{\sum_{j=1}^{7} w_{jm} \sum_{h=1}^{24} \left[\frac{1}{n_{hjm}} \sum_{i=1}^{n_{hjm}} VOL_{ihjm} \right]}{\sum_{j=1}^{7} w_{jm}}$$

$$AADT = \frac{\sum_{m=1}^{12} d_m MADT_{HP,m}}{\sum_{m=1}^{12} d_m}$$

Where:

$MADT_m$ = monthly average daily traffic for month m

VOL_{ihjm}= total traffic volume for the ith occurrence of the hth hour of day within jth day of week during the mth month

i = occurrence of a particular hour of day within a particular day of the week in a particular month (i = 1,…n_{hjm}) for which traffic volume is available

h = hour of the day (h=1,2,…24), or other temporal interval

j = day of the week (j=1,2,…7)

m = month (m=1,…12)

n_{hjm} = the number of times the hth hour of day within the jth day of week during the mth month has available traffic volume (n_{hjm} ranges from 1 to 5 depending on hour of day, day of week, month, and data availability)

w_{jm} = the weight for the number of times the jth day of week occurs during the mth month (either 4 or 5); the sum of the weights in the denominator is the number of calendar. days in the month (i.e., 28, 29, 30, or 31)

d_m = the weight for the number of days (i.e., 28, 29, 30, or 31) for the mth month in the particular year.

Figure 2.1 represent the overall view of three described methods.

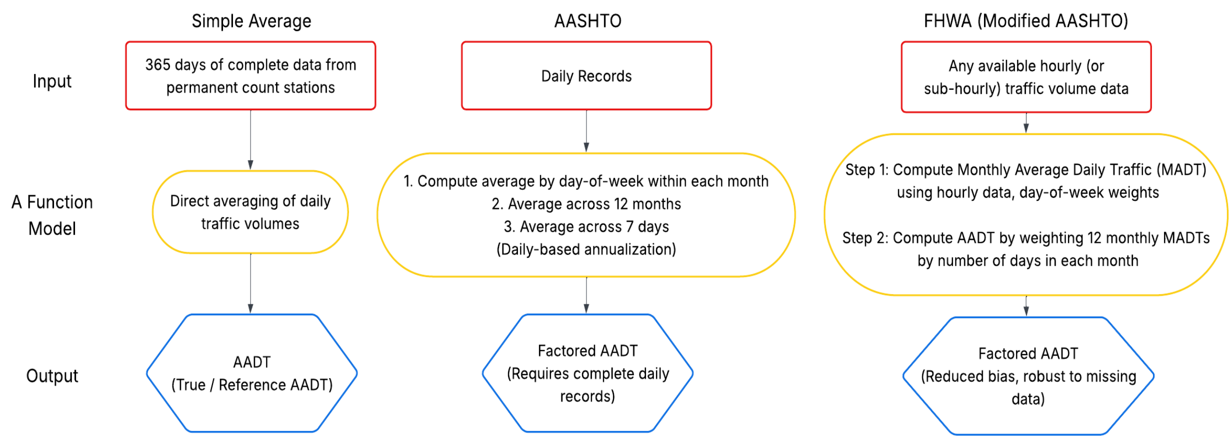


Figure 2.1 Conceptual framework of three commonly used models for AADT estimation

The HPSJB method, introduced by (Jessberger et al. 2016), was also developed to address key limitations of the traditional AASHTO AADT estimation procedure. As mentioned, the AASHTO method requires complete 24-hour data for any day included in the calculation; if even one hourly observation is missing, the entire day must be discarded. In addition, it equally weighs days of the week and months without fully accounting for differences in their frequency within a year, which introduces small systematic bias. The HPSJB method overcomes these limitations by utilizing available hourly data and incorporating hour-of-day, day-of-week, and month-of-year adjustments. As a result, it significantly reduces estimation uncertainty by 40% to 50% and improves overall AADT accuracy when data are incomplete.

A key question in AADT estimation research is how the duration of short-term counts and the selection of temporal adjustment factors influence estimation accuracy and reliability. A study utilized 14 years of Traffic Monitoring Analysis System (TMAS) hourly volume data collected from thousands of permanent monitoring stations across 32 U.S. states between 2000 and 2012 to evaluate AADT estimation methods (Krile et al. 2015). The evaluation considered 24- and 48-hour counts across same-year, two-year, three-year, and six-year cycles. The results indicated a median bias of approximately ±3% and minimal bias within the 95% confidence intervals; however, reduced precision was observed for shorter count durations and longer factoring intervals. Another study examined the use of prior-year month-of-year (MOY), day-of-week (DOW), axle correction, and growth factors to estimate AADT from short-term counts (Desai et al. 2014). The findings indicated no statistically significant loss of accuracy when applying these prior-year adjustment factors. A study evaluated AADT estimation using simulated 48-hour short-duration counts derived from continuous monitoring sites in Manitoba, Canada, to compare the conventional Traffic Pattern Group (TPG) assignment method with a data-driven assignment (DDA) approach (Grande et al. 2021). In both approaches, month-of-year (MOY) and day-of-week (DOW) temporal adjustment factors were applied to expand short-term counts to annual estimates; however, the procedures used to assign count sites to TPGs differed. The conventional method assigns sites to predefined TPGs based on roadway functional classification and surrounding land-use characteristics. In contrast, the DDA approach dynamically assigns sites by minimizing the absolute deviation among multiple short-duration

AADT estimates collected at the same location within a year. This optimization-based procedure is intended to better capture site-specific temporal traffic patterns that may not align with static group classifications. The results indicated that improper TPG assignments can introduce mean absolute percentage errors (MAPE) of up to 9%. The proposed DDA method reduced estimation error from 10.32% to 7.86%, demonstrating improved AADT accuracy through more representative temporal grouping. A study compared three methods for estimating AADT: the FHWA single-year method, the Tennessee DOT five-year simple average method, and a proposed Weighted-Factor Method (WFM) that accounts for variance across years (Monney 2020). Estimation accuracy was evaluated using mean absolute percentage error (MAPE). The results indicated that the WFM consistently produced the lowest MAPE values, often below 10%, outperforming both the Tennessee DOT and FHWA methods. The FHWA method exhibited the highest errors, reaching up to 12.2% in some cases.

Additional research has addressed specific contexts and methodological innovations in AADT estimation. A study examined methods to improve the assignment of short-term traffic counts to Seasonal Adjustment Factor (SAF) groupings to enhance estimation accuracy (Tsapakis et al. 2014). Using continuous count data from Ohio collected between 2002 and 2006, the study compared traditional functional classification with discriminant analysis (DA) and a weighted coefficient of variation (WCV) approach. The results indicated that directionally based assignments outperformed total volume analysis, and hourly time-of-day factors were found to be more influential than average daily traffic. The WCV method reduced mean absolute percentage error (MAPE) by 58% and the standard deviation of absolute error (SDAE) by 70%, while the DA approach achieved reductions of 35% and 60%, respectively.

International research has also contributed to methodological development. A study developed hourly, daily, and monthly adjustment factors for AADT estimation using 5.5 months (168 days) of automatic traffic count data collected on a suburban road in Colombo, Sri Lanka (AHAMED et al. 2019). The traffic counter was validated against manual counts, showing a small discrepancy of 49 vehicles. However, undercounting was observed during peak congestion periods due to the device's inability to detect vehicles traveling below 10 km/h, limiting its reliability under high-density traffic conditions.

2.2 Machine Learning and Data-Driven Models

Machine learning (ML) models estimate AADT with little or no reliance on traditional TAFs. These models often learn temporal patterns directly from data or use external predictors such as demographics or land use (Sharma et al. 1999).

A study by Khan et al. (2018) developed machine learning models, specifically Support Vector Regression (SVR) and Artificial Neural Networks (ANN), to estimate AADT from short-term traffic counts across different roadway functional classes. Using ATR data from South Carolina, the study compared the performance of the proposed models with traditional regression-based and factor-based methods. The results indicated that the SVR model outperformed the ANN model as well as conventional regression and factor-based approaches in terms of estimation accuracy. A study proposed an interpretable machine learning framework to estimate Annual Average Daily Traffic (AADT) on low-volume roads, where reliable traffic data are often limited (Das and Tsapakis 2020). Using multiple data sources, including the U.S. Census and the American Community Survey, the model was applied to roadway networks in Vermont to identify the key factors influencing traffic volume. The findings showed that population density and Work Area Characteristics (WAC) density were the most influential variables in predicting AADT. When compared to traditional linear regression approaches, machine learning models, particularly the random forest model, demonstrated substantially improved predictive performance. The coefficient of determination (R^2) increased from 0.45 to 0.77, indicating a much stronger model fit. The framework also produced practical decision rules for different functional classes of low-volume roadways, which can support improved traffic monitoring, safety analysis, and the development of Safety Performance Functions (SPFs). Although the study acknowledged limitations related to sample size and model interpretability, the results suggest that machine learning approaches can offer a cost-effective and more accurate alternative for estimating AADT on low-volume roadway networks. A recent study proposed a power-function-based Long Short-Term Memory (LSTM) model to estimate AADT using hourly and daily traffic observations without relying on traditional temporal adjustment factors such as month-of-year or day-of-week (Han 2024). Instead of applying predefined adjustment factors, the model learned seasonal patterns and temporal trends directly from time series data. The results showed substantially lower estimation errors compared with SARIMA, Prophet, and standard LSTM models, with a mean absolute error of 0.025 compared to values ranging from 0.117 to 0.158 for the alternative methods. Similarly, another study applied Random Forests, deep neural networks, and generalized linear mixed models that incorporated socio economic and roadway characteristics to estimate AADT (Chen et al. 2019). The findings reported notable improvements in estimation accuracy without relying on traditional temporal adjustment factors.

Other work has integrated ML into factor-based frameworks. For example, Tsapakis and Schneider (2015) applied a supervised learning approach using Support Vector Machines (SVM) to assign short-term traffic counts to seasonal adjustment factor (SAF) groups for AADT estimation. Using permanent traffic recorder data for training, the Gaussian kernel-based SVM significantly outperformed traditional and discriminant analysis methods, improving AADT accuracy by up to 65% and reducing absolute percentage error by 73.7%. The results also show that combining daily traffic and hourly factors enhances model performance compared to using hourly factors alone. Additionally, directional volume-based analysis yielded lower assignment errors than total volume-based analysis. Overall, the findings highlight the effectiveness of SVM-based models in improving AADT estimation accuracy through more reliable factor assignment. Decision-tree-based stratification also improved accuracy, cutting median absolute percentage errors by 41% compared to conventional schemes (Tsapakis et al. 2022). Support vector regression (SVR) consistently outperformed ANN, regression, and factor-based methods, with MAPE in the range of 9–14% across multiple studies (Castro-Neto et al. 2009; Chowdhury et al. 2019; Khan et al. 2018).

2.3 Probe-Based and Third-Party Data Approaches

Parallel to ML, probe-based and third-party data have emerged as alternatives to direct counts and factor-based methods. These methods leverage GPS data, mobile device location data, and third-party traffic datasets. A study demonstrated that satellite and aerial imagery can be used to generate AADT estimates and, when combined with traditional methods, may improve accuracy while reducing reliance on costly ground-based traffic monitoring systems (McCord et al. 2003). A Federal Highway Administration study further showed that GPS and Location Based Services data, when integrated with a gradient boosting model, achieved a mean absolute percentage error of 8.11 percent and a correlation coefficient of 0.99 (Schewel et al. 2021). These results outperformed the conventional temporal adjustment factor approach based on 48-hour counts. Similarly, another study used StreetLight Data to estimate AADT and reported comparable performance, with a mean absolute percentage error of approximately 14.6 percent and near zero mean count error for corridors with AADT values above 5,000 vehicles per day (Tsapakis et al. 2021). Kernel-weighted GPS approaches (Chang and Cheon 2019) and random forest models incorporating annual average daily probes and betweenness centrality (Zhang and Chen 2020) have further enhanced estimation accuracy, with reported R^2 values reaching as high as 0.97.

These studies collectively underscore the growing effectiveness of probe-based and third-party data approaches in producing accurate AADT estimates, often outperforming traditional methods while eliminating the need for conventional adjustment factors. However, they raise questions about data access, licensing costs, and long-term consistency.

2.4 Regression, Clustering, and Spatial Models

A third stream of research focuses on regression and clustering-based methods, often applied to rural or low-volume roads. These studies replace fixed TAFs with regression or spatial clustering frameworks that implicitly capture temporal variation.

Explanatory variables play a crucial role in regression modeling. Population, vehicle ownership, number of households, and employment levels as key factors influencing roadway AADT (Neveu 1983). Numerous studies have applied ordinary linear regression models to estimate AADT using socioeconomic and roadway characteristics. These models commonly incorporated variables such as population, employment, vehicle ownership, number of lanes, functional classification, land use, and access to major facilities (Crouch 2000; Fricker and Saha 1986; Cheng 1991; Mohamad et al. 1998). Collectively, these studies demonstrate the widespread use of traditional regression approaches for AADT prediction.

A multiple linear regression model was developed to estimate Annual Average Daily Traffic (AADT) on paved county roads in Indiana using limited short-term traffic counts (Mohamad et al. 1998). From 11 candidate variables, four significant predictors were identified: location (urban/rural), accessibility, county population, and arterial mileage. After applying a log transformation, the final model was validated using independent data and produced a low mean squared prediction error (MSPR = 0.051), indicating good predictive accuracy. These results support the model's practical use for county-level traffic estimation. A study applied geographically weighted regression methods to estimate AADT, allowing model parameters to vary locally rather than being assumed constant across the entire study area as in ordinary regression analysis (Zhao and Park 2004). This localized modeling approach provides greater flexibility in capturing spatial differences in traffic patterns. Another study introduced a spatial regression framework that incorporates both explanatory variables and spatial dependence among traffic monitoring locations (Eom et al. 2006). The underlying premise is that traffic volume at one location is influenced by volumes at nearby locations. Spatial correlation was modeled using geostatistical techniques, including semivariogram modeling and universal kriging, which enable the interpolation of traffic volumes at sites without observed traffic counts. The findings indicated that prediction accuracy was higher in urban areas, such as Raleigh, where monitoring stations are more closely spaced and spatial correlation is stronger. In contrast, rural and collector roadways showed less improvement due to the sparse distribution of monitoring locations.

More recent research compared several modeling approaches, including multiple linear regression, random forest, and neural networks, to estimate minor road AADT at intersections using HPMS and Census data (Wu and Xu 2019). Based on cross validation results, a logarithmic multiple linear regression model was selected as the preferred approach due to its stable and robust performance. Other examples include the Multivariate Spatial Clustering (SMVC) model by Hasan and Oh (2020) which used seasonal and weekly adjustment factors derived from cluster-specific profiles, reducing MAPE to 5.0% for summer weekdays. Combining K-prototypes clustering with SVR improved accuracy (MAPE = 14.5%) compared to

Random Forest or Ordinary Least Squares alone (Sfyridis and Agnolucci 2020), while incorporating weather and activity variables into factor-based methods reduced one-day count errors from 19.1% to 15.6% (Figliozzi et al. 2014). Other regression-based efforts (Raja et al. 2018; Apronti et al. 2016; Pan 2008) highlighted the mixed performance of statistical models without TAFs, with R^2 ranging from 0.16 to 0.80 and MAPE exceeding 30% for heterogeneous urban roads.

Chapter 3 Data Preparation and Preliminary Analysis

This chapter describes the data sources, processing steps, and initial analyses conducted to support the evaluation of alternative TAFs for AADT estimation. Because the objective of this project is to determine the most appropriate temporal factor for short-term count expansion by functional class, careful preparation of the ATR data is required prior to hypothesis testing.

The chapter first introduces the study area and the roadway functional classes included in the analysis. It then describes the ATR data used as the ground truth for annual traffic volumes. A short-term count sampling framework is presented to generate subsets of data that replicate how AADT is estimated in practice from limited-duration counts. Next, preliminary analyses in terms of systematic data cleaning and quality control procedures are described to address missing, inconsistent, or erroneous hourly traffic counts. Finally, exploratory traffic pattern analysis is conducted to characterize temporal variation across functional classes and to provide a preliminary assessment of the suitability of candidate TAFs.

3.1 ATR Functional Classification

Functional classification plays a central role in this study because traffic patterns differ systematically by roadway type. Higher functional classes generally serve longer-distance travel and freight movement, with stronger weekday commuting patterns and lower seasonal fluctuation. Lower functional classes may exhibit more pronounced seasonal variation, recreational traffic effects, and local activity influences. Since AADT temporal adjustment factors are derived from historical traffic patterns, grouping ATR stations by functional class provides a consistent framework for evaluating factor performance.

This study focuses on Nebraska state highway facilities managed by the NDOT, excluding Interstate highways and local functional roads. Consistent with the project scope, the analysis includes Federal Highway Administration (FHWA) functional classes 2 through 6.

These typically include principal arterials (non-Interstate), minor arterials, major collectors, and minor collectors. Therefore, for each ATR station included in the study, the following attributes were compiled:

- Functional classification (FHWA class 2–6)
- Geographic location
- Rural or urban designation
- Directional configuration and lane information (for additional reference)

All permanent traffic count data collected by ATR across the State of Nebraska were provided by NDOT, which comprises a total of 52 ATR stations. Nebraska's roadway network includes a diverse mix of urban arterials, rural highways, and low-volume county roads, each exhibiting distinct traffic characteristics and seasonal patterns.

To ensure that the TAFs capture differences in traffic patterns, the analysis was performed separately by roadway functional classification. NDOT determined multiple functional groupings to represent relatively homogeneous traffic characteristics, and these groupings were used consistently for the development and evaluation of TAFs. Specifically, the ATR stations studied in this project (only FHWA classes 2–6) were organized into three functional classes:

- Urban Arterials: including 13 ATR stations, marked as Group O. This group consists of urban roads, major city streets (urban), or highways handling higher traffic volumes.
- County Roads: including 9 ATR stations, marked as Group C. This group consists of low-volume county roads (rural), typically with moderate traffic and limited access.

- Rural Highways: including 30 ATR stations, marked as Group R. This group includes rural highways with AADT ≥ 500 vehicles, typically serving as regional connectors across less populated areas.

The geographic distribution of all the 52 ATR stations across Nebraska can be found in Figure 3.1. The stations are displayed by functional grouping, using different colors to distinguish Urban Arterials (Group O, 13 ATRs), Low Volume County/Rural Roads (Group C, 9 ATRs), and Other Rural Highways (Group R, 30 ATRs).

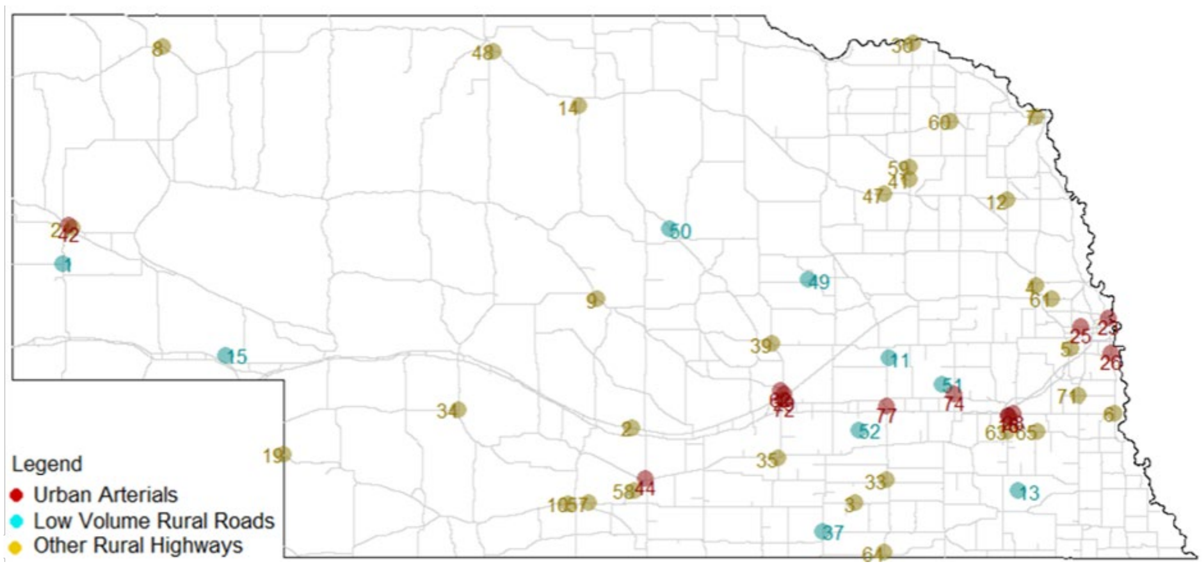


Figure 3.1 Locations of ATRs in different road functional classes

Figure 3.1 shows that ATR coverage is distributed statewide, with stations located in both eastern and western Nebraska. A higher concentration of stations appears in the eastern portion of the state, particularly near major population centers and along primary highway corridors. Western Nebraska includes fewer stations, but they are spatially distributed to capture traffic patterns along key regional routes. Urban arterial stations are primarily located within or near metropolitan areas, reflecting higher traffic density and urban travel demand. Low volume rural road stations are more dispersed, typically located in sparsely populated regions to represent lower traffic conditions. Other rural highway stations are positioned along important non-urban corridors, providing coverage of intercity and regional travel routes. Overall, the distribution of ATR stations provides reasonable geographic representation across functional classes and supports statewide analysis of temporal traffic variation.

Each ATR record includes the station identification number, geographic location, functional classification, lane configuration, traffic direction, date and time stamp, and hourly traffic volumes for 24 hours per day. For this study, hourly traffic data from the 2023 calendar year were compiled for all eligible ATR stations.

3.2 Short-Term Count Sampling

To evaluate the performance of alternative TAFs under realistic field conditions, a short-term count sampling procedure was developed using complete annual ATR datasets. Because most roadway segments do not have continuous monitoring, AADT is typically estimated from limited-duration counts. The sampling framework was designed to replicate this operational practice in a controlled and repeatable manner.

For each ATR station, hourly traffic data from the full calendar year were treated as the ground-truth dataset. From this complete record, short-term count segments were systematically extracted to represent temporary field counts. Three commonly used count durations were evaluated:

- 24-hour duration (one full day)
- 48-hour duration (two consecutive days)
- 72-hour duration (three consecutive days)

For each random ATR station (in a specific year), multiple short-term samples were generated across different months and days of the week to capture seasonal and weekly variability. Each sampled segment was treated as if it were an actual short-term coverage count collected in the field.

Note that in the following chapter, the sampled short-term traffic totals will be used to estimate AADT using candidate TAFs developed from the rest of ATR stations (except the ATR used for short-count data sample generation) within the same functional grouping. This cross-station application prevents circular estimation and reflects how adjustment factors are applied in practice, and allows consistent quantification of estimation bias, variability, and overall accuracy for each TAF under different count durations and functional classes.

3.3 Traffic Pattern Analysis

Understanding temporal variation in traffic volume is necessary for evaluating TAF structures. Prior to factor development, exploratory analysis was conducted to examine daily and weekly traffic patterns at representative ATR locations. Figure 3.2 presents hourly traffic volumes for ATR #41 during May 2023 as an illustrative example.

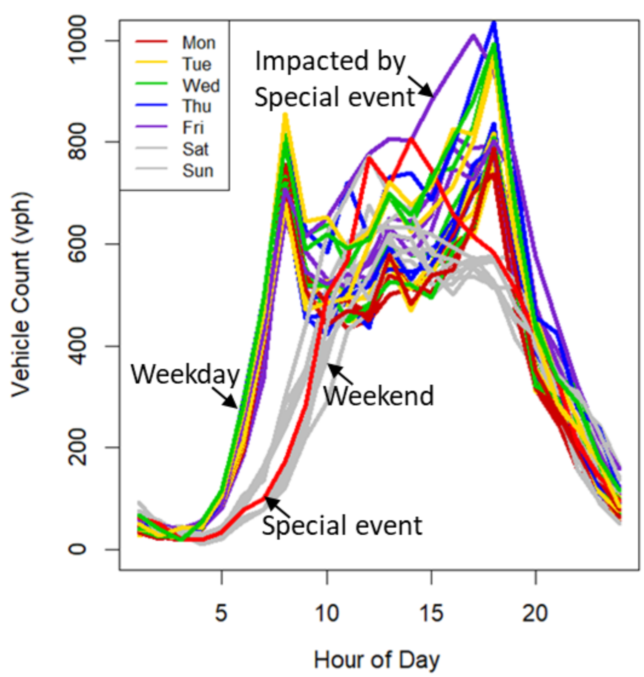


Figure 3.2 Hourly traffic patterns over a month at ATR #41 (May 2023).

As shown in Figure 3.2, weekday traffic (Monday through Friday) exhibits clear and consistent morning and evening peak periods. The morning peak typically occurs between 7:00–8:00 AM, and the evening peak occurs between 5:00–6:00 PM. These peaks reflect commuter-related travel behavior and demonstrate relatively stable daytime patterns across weekdays.

In contrast, weekend traffic (Saturday and Sunday) shows flatter daytime patterns with reduced peak intensity and later peak timing. Weekend volumes are generally lower during the morning commute period and more evenly distributed throughout the day. This distinction between weekday and weekend patterns is consistent across the majority of ATR sites examined.

The clear structural difference between weekday and weekend traffic suggests that separating weekday and weekend observations may improve factor stability. Many studies in the literature used 5-day weekday-based adjustment factors to reduce variability introduced by weekend travel behavior. However, exclusively using a 5-day structure presents several limitations. First of all, AADT is defined as the average daily traffic over all 365 days of the year. Excluding weekends during factor development may bias annual estimates unless a separate and accurate weekend adjustment is applied. Moreover, weekend traffic is not negligible. For certain functional classes, especially recreational or rural routes, weekend volumes may differ substantially from weekday volumes and may contribute significantly to annual totals.

For these reasons, this study adopts two types of TAF structures, separately, for evaluation:

- 5-day (weekday-based)
- 7-day (full-week)

The 5-day structure tests whether removing weekend variability improves estimation accuracy, while the 7-day structure preserves consistency with the definition of AADT and captures full weekly behavior. Comparing both approaches allows a statistically grounded determination of whether weekday-only aggregation provides measurable improvement over full-week aggregation for each functional class.

3.4 Data Cleaning and Quality Control

When abnormal observations remain in the dataset, the estimated factors may be inflated or deflated relative to typical traffic conditions, which may lead to biased AADT estimates and increased dispersion in the error metrics. Thus, before analysis, data were subjected to structured data screening procedures to confirm completeness, consistency, and reliability. The objective of this process was to retain stable and representative traffic observations for TAF evaluation while removing records affected by equipment malfunction or data transmission issues.

Days without a complete 24-hour record were identified. When a full day of data was missing (possibly due to equipment malfunction or other documented issues), the missing daily volume was imputed using the corresponding average daily value from the same calendar day (or average of same days) from the previous years. Through the data completeness review, each station-year was evaluated for overall data availability to confirm that no full-day traffic counts were missing from the ATR record.

In addition to completeness checks, statistical screening was applied to identify anomalous daily volumes. Specifically, interquartile range (IQR)-based filtering was used to identify unusually high or low daily volumes that deviated substantially from typical traffic patterns. The IQR method is a non-parametric statistical technique used to detect extreme values in a dataset. Unlike methods based on standard deviation, the IQR approach does not assume normality and is therefore robust to skewed traffic data distributions, which are common in short-term traffic observations. Figure 3.3 illustrates the IQR-based outlier detection concept. The box represents the interquartile range (Q1 to Q3), the central vertical line indicates the median, and the whiskers extend to the minimum and maximum non-outlier values.

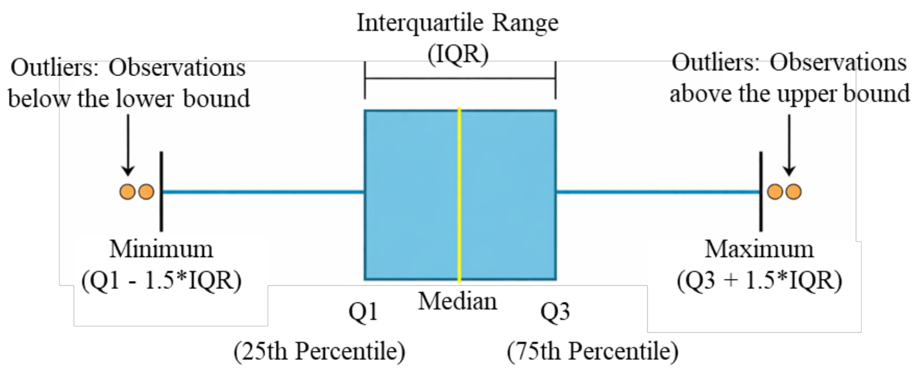


Figure 3.3 IQR method for outlier detection.

Observations are classified as outliers if they fall outside the whiskers defined by the following bounds:

$$\text{Lower Bound} = \text{Q1} - 1.5 \times (Q_3 - Q_1)$$

$$\text{Upper Bound} = \text{Q1} + 1.5 \times (Q_3 - Q_1)$$

In the equations, Q1 represents the 25th percentile of the observed daily traffic counts in the study year, and Q3 represents the 75th percentile of the observed daily traffic counts in the study year. Outliers in this study were examined to determine whether they affected the reliability of the TAF evaluation results. Accordingly, TAF performance was compared under two conditions: with outliers included and with outliers removed.

Chapter 4 Analytical Framework for Candidate Temporary Adjustment Factor

This chapter presents the analytical framework used to determine candidate TAFs for estimating AADT from short-term traffic counts. The goal is to evaluate whether the current monthly factor used by NDOT provides the highest estimation accuracy, or whether alternative temporal groupings can reduce estimation error. The initial concern was that a coarser TAF (e.g., monthly) may fail to capture short-term fluctuations caused by weather conditions or special events. In contrast, a finer TAF, such as day of year, may better capture daily variation in traffic patterns. However, this may also lead to increased variability in the adjustment factors due to smaller sample sizes within each grouping.

For each functional class included in the scope of this project (FHWA functional classes 2 through 6), candidate TAFs were calculated and then applied to sampled short-term counts extracted from the same ATR stations to estimate AADT. These estimated AADT values were compared with the reference AADT calculated from complete annual ATR data, which serves as the "ground truth". Estimation accuracy was assessed using defined statistical error measures and formal hypothesis testing procedures. These evaluation results were used as the basis for TAF determination and selection.

The remainder of this chapter is organized as follows. The next section presents the construction of all possible TAFs, and the preliminary screening process used to identify candidate factors. This is followed by the mathematical formulation used to compute each TAF. The chapter then describes the short-term count sampling procedure, the error metrics used to compare factor performance, and the statistical testing framework used to evaluate the null hypothesis. Finally, the results identifying the optimal TAFs by functional class are presented, followed by recommendations for NDOT implementation.

4.1 Prepare candidate TAFs

To systematically evaluate these alternatives, this study begins by constructing all meaningful combinations of four temporal dimensions: Day of week (D), Week of year (W), Month of year (M), and Year (Y).

These four dimensions were selected because they represent the primary time scales that influence traffic variation in Nebraska. The year dimension accounts for long-term traffic growth or decline, and in practice, AADT and the associated TAFs are typically calculated separately for each year. The month dimension reflects seasonal patterns. The week dimension captures intra-month variation, including holidays and special events. The day dimension captures weekday–weekend differences and recurring travel behavior. By considering all valid single-factor and multi-factor combinations of these four dimensions, a total of eleven temporal adjustment factor structures were defined for evaluation, as listed Table 4.1.

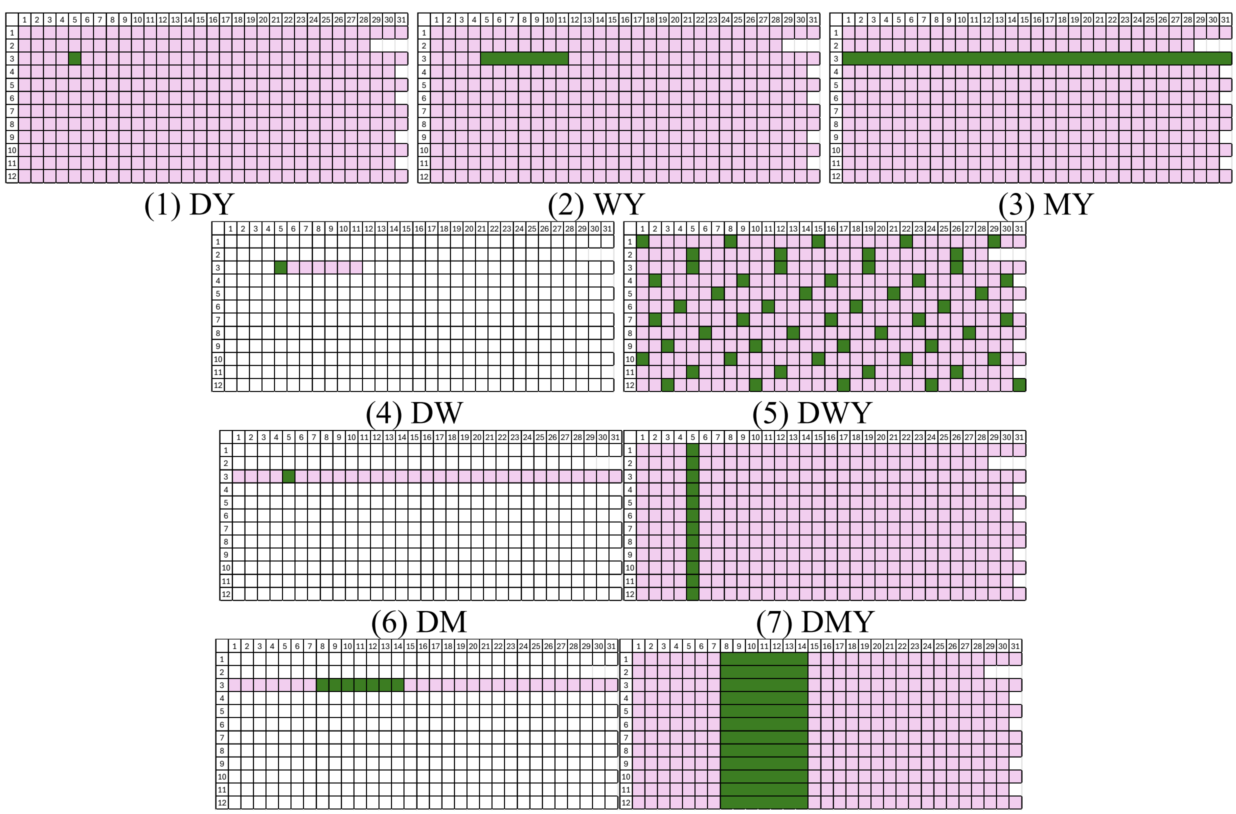
Table 4.1 List of all potential TAF candidates

No	D	W	M	Y	Mark	Factor Name
1					DY	Day of the Year
2					WY	Week of the Year
3					MY	Month of the Year
4					DW	Day of the Week
5					DWY	Day of all Weeks of the Year
6					DM	Day of the Month
7					DMY	Day of all Months of the Year
8					WM	Week of the Month
9					WMY	Week of all Months of the Year
10					DWM	Day of all Weeks of the Month
11					DWMY	Day of all Weeks of all Months of the Year

The eleven factor definitions are as follows. TAF 1 (DY – Day of the Year) groups traffic counts by calendar day number (1 through 365 or 366). Each day has its own adjustment factor. This structure captures very fine daily variation across the year. TAF 2 (WY – Week of the Year) groups traffic counts by week number (1 through 52 or 53). All days within the same week share the same factor. This structure captures short-term seasonal variation at the weekly level. TAF 3 (MY – Month of the Year) groups traffic counts by calendar month (January through December). This is the traditional month-based factor currently used by NDOT. TAF 4 (DW – Day of the Week) groups traffic counts by weekday (Monday through Sunday), regardless of month or season. This structure captures recurring weekday–weekend patterns. TAF 5 (DWY – Day of all Weeks of the Year) groups traffic by weekday within the entire year. In practice, this produces seven factors, one for each weekday, using all weeks combined. This structure preserves weekday effects while maintaining large sample sizes. TAF 6 (DM – Day of the Month) groups traffic by day number within a month (1 through 28, 30, or 31), regardless of which month it occurs in. TAF 7 (DMY – Day of all Months of the Year) groups traffic by calendar day number across the entire year. This differs from DY in that grouping is by day-of-month pattern rather than by sequential day-of-year index. TAF 8 (WM – Week of the Month) groups traffic by week position within a month, regardless of which month. TAF 9 (WMY – Week of all Months of the Year) groups traffic by week position across all months. TAF 10 (DWM – Day of all Weeks of the Month) groups traffic by weekday within each week of a month. TAF 11 (DWMY – Day of all Weeks of all Months of the Year) is the most disaggregated structure, grouping traffic by weekday within week position across all months.

To explain each TAF listed above, Figure 4.1 presents schematic representations of how traffic data are aggregated when computing each TAF. Each subfigure corresponds to one numbered TAF listed in Table 4.1. The illustrations show how numerator observations are selected relative to the total denominator observations. In each grid:

- The row represents a month of the year. There are 12 months in a year.
- The column represents a day of the month. The total number of days range from 28 to 31, depending on different months.
- The **green cells** represent the numerator data used to compute a specific TAF.
- The **pink cells** represent denominator data, which correspond to the full set of observations used as the reference for normalization.

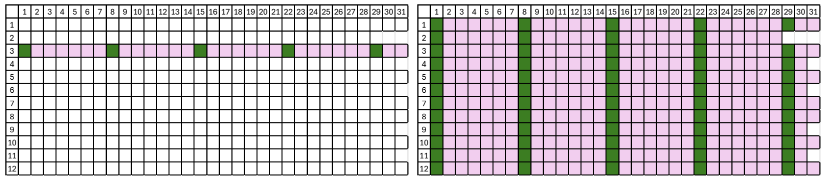


(1) DY (2) WY (3) MY

(4) DW (5) DWY

(6) DM (7) DMY

(8) WM (9) WMY



(10) DWM (11) DWMY

Figure 4.1 Conceptual Illustration of Data Aggregation for corresponding TAFs 1-11.

As can be seen, Figure 4.1 presents illustrative examples corresponding to the calculation of factors for the following specific temporal positions: (1-3) the 64th day of the year (DY), the 10th week of the year (WY), and March of the year (MY); (4-5) Monday of the 10th week (DW) and Monday across all weeks of the year (DWY); (6-7) the 5th day of March (DM) and the 5th day across all months of the year (DMY); (8-9) the 2nd week of March (WM) and the 2nd week across all months of the year (WMY); (10-11) the 1st day across all weeks of March (DWM) and the 1st day across all weeks of all months of the year (DWMY).

It is important to distinguish between TAF 4 (DW) and TAF 5 (DWY). TAF 5 (DWY) corresponds to the standard day-of-week (DOW) factor commonly used in the literature (Federal Highway Administration, 2016), which pools all Mondays, Tuesdays, etc., across the entire year and therefore produces 7 values. In contrast, TAF 4 (DW) allows weekday effects to vary by week of the year (that is, day-within-week within each week), resulting in approximately 365 values.

Based on the aggregation patterns illustrated in Figure 4.1, TAFs 9 through 11 were preliminarily excluded from detailed evaluation. This is because they introduce multiple nested temporal dimensions simultaneously, thus resulting in a large number of narrowly defined categories with limited observations per category. These structures introduce additional implementation complexity without clear theoretical justification that they would outperform simpler groupings. In contrast, TAFs 1–8 correspond to established temporal variation patterns and maintain sufficient data support for reliable factor estimation. Given that NDOT requires a method that is statistically sound, stable, and practical for routine use, excessive stratification is not desirable.

On the other hand, after screening the single-dimension TAFs, three additional compound factors were constructed by interacting weekday effects (i.e., DWY in this research, as mentioned before, this is typically referred to as "DOW" in most other studies) with broader seasonal TAFs (i.e., TAF 2 – WY, TAF 3 – MY, and TAF 8 – WM). Specifically, the three compound TAFs are defined as follows.

- TAF 9': DWY × WY
- TAF 10': DWY × MY
- TAF 11': DWY × WM

Note the revised numbering (TAF 9′–11′) replaces the previously defined single-dimension TAFs 9–11, which were excluded from further consideration in the earlier screening process. The purpose of these compound TAFs is to introduce controlled stratification by allowing weekday effects to vary across seasonal groupings, while avoiding excessive fragmentation of the data. In other words, rather than assuming that weekday patterns remain constant throughout the year, the compound structures test whether systematic interactions between weekday behavior and seasonal cycles (weekly, monthly, or within-month) provide additional explanatory power and improve AADT estimation accuracy without compromising statistical stability.

4.2 Development of Analytical Framework

In total, eleven candidate TAF structures were evaluated in this study: eight single-dimensional factors and three compound factors, as listed in Table 4.2. The total number of values of each TAF type in Table 4.2 reflects how many values are included in each TAF type within one calendar year. The number is determined by the level of temporal resolution and whether observations are aggregated across time. For high-resolution structures such as DY (Day of the Year), DW (day-within-week by week-of-year), and DM (day-of-month within a specific month), each calendar position is treated independently. Therefore, these TAFs produce 365 values (assume non-leap year). In contrast, aggregated observations across days generate fewer values. For example, WY (Week of the Year) produces 52 values, MY (Month of the Year) produces 12 values, and DMY (Day of all Months of the Year) produces 31 values. For compound TAFs, the number of values is governed by the primary aggregated dimension (week or month). Although weekday effects are incorporated, the total number of seasonal categories remains 52 (for week-based TAF) or 12 (for month-based TAF).

Table 4.2 Final TAF candidates in the research

TAF	D	W	M	Y	Mark	Number of Values	Nominator in Equation	Denominator in Equation
1					DY	365	AADT	V_d
2					WY	52	AADT	V_w
3					MY	12	AADT	V_m
4					DW	365	AADT	$V_{d_w,w}$
5					DWY	7	AADT	V_{d_w}
6					DM	365	MADT	$V_{d_m,m}$
7					DMY	31	AADT	V_{d_m}
8					WM	52	MADT	$V_{w_m,m}$
9					WY * DWY	52	(2) x (5)	
10					MY * DWY	12	(3) x (5)	
11					WM * DWY	52	(8) x (5)	

The general calculation equation for a TAF can be expressed in Equation 4.1, where the nominator and denominator expressions can be found in Table 4.2.

$$\text{TAF} = \frac{\text{Nominator}}{\text{Denominator}} \qquad (4.1)$$

The calculation of the nominator and denominator involves the following index definitions.

- Day index: $d = 1, 2, \ldots,$ total $D \in \{365, 366^*\}$
- Week index: $w = 1,2,\ldots,$ total $W \in \{52, 53^*\}$
- Month index: $m = 1,2,\ldots,$ total $M = 12$
- Day-of-week index: $d_w = 1,2,\ldots,$ total $D_w \in \{5^*, 7\}$

- Day-of-month index: $d_m = 1,2,\ldots$, total $D_m \in \{28, 29, 30, 31\}$
- Week-of-month index: $w_m = 1,2,\ldots$, total $W_m \in \{4, 5^*\}$

Two types of reference averages are used in the nominator of the TAF equations: Annual Average Daily Traffic (AADT) and Monthly Average Daily Traffic (MADT). These reference values serve as normalization baselines for the corresponding TAFs. AADT is defined as the mean daily traffic volume over all days in the year, which can be expressed using Equation 4.2. AADT represents the overall annual traffic level and serves as the reference value for TAF structures that normalize daily, weekly, or monthly variations to the annual mean.

$$AADT = \frac{1}{D}\sum_{d=1}^{D} V_d \quad (4.2)$$

MADT is defined as the mean daily traffic volume within a specific month, which can be expressed using Equation 4.3. MADT represents the seasonal traffic level for a given month and serves as the reference value for TAF structures that normalize daily variation within a month.

$$MADT = \frac{1}{D_m}\sum_{d_m=1}^{D_m} V_{d_m,m} \quad (4.3)$$

Given the nominator represents the broader aggregation level (annual or monthly), the denominator corresponds to a more detailed temporal subgroup within that aggregation level. The specific denominator formulations for each TAF type are presented below.

(1) Daily traffic volume (DY, basic unit in this study) for day d: V_d

(2) Average daily traffic for week w (WY): $V_w = \frac{1}{D_w}\sum_{d_w=1}^{D_w} V_{d_w,w}$

(3) Average daily traffic for month m (MY, also known as MADT): $V_m = \frac{1}{D_m}\sum_{d_m=1}^{D_m} V_{d_m,m}$

(4) Daily traffic volume for day-of-week d_w for week w (DW): $V_{d_w,w}$

(5) Average daily traffic for day-of-week d_w across the year (DWY): $V_{d_w} = \frac{1}{W_{d_w}}\sum_{w \in W} V_{d_w,w}$

(6) Daily traffic volume for day-of-month d_m for month m (DM): $V_{d_m,m}$

(7) Average daily traffic for day-of-month d_m across the year (DMY): $V_{d_m} = \frac{1}{M_{d_m}} \sum_{m \in M} V_{d_m,m}$

(8) Average daily traffic for week-of-month w_m for month m (WM): $V_{w_m,m} = \frac{1}{D_{w_m}} \sum_{w_m=1}^{W_m} V_{d_w w}$

The following sections describe the computational procedure and statistical testing framework used to determine which structure provides the most accurate AADT estimates for each functional class.

Figure 4.2 illustrates the complete computational structure used to evaluate each TAF. For every individual factor value within a given TAF type, the estimation procedure is repeated across several analytical dimensions. Each TAF value is assessed under two day-grouping schemes (5-day and 7-day) and three short-term sampling durations (24-hour, 48-hour, and 72-hour). In addition, the short-term sampling adopts a leave-one-ATR-out approach within each roadway functional class (Group C includes 9 ATRs, Group R includes 30 ATRs, and Group O includes 13 ATRs). For a given functional class, one ATR is selected to generate sampled short-term counts, while the remaining ATRs are used to derive and evaluate the corresponding TAFs. This process is repeated so that every ATR in the class serves once as the short-term site. Together, it yields 2 x 3 x (9 + 30 + 13) = 312 evaluation runs within the computational space for each factor value.

The total number of computations for a given TAF type therefore depends on the number of values the TAF contains. For example, the TAF for DY contains 365 values. Each of these values is assessed under 18 evaluation runs. Consequently, the total number of DY evaluations equals 365 x 312, which results in 77,745 evaluation runs. Summing this quantity across all eleven candidate TAFs results in a total of 425,880 evaluation runs performed in this exhaustive factor assessment.

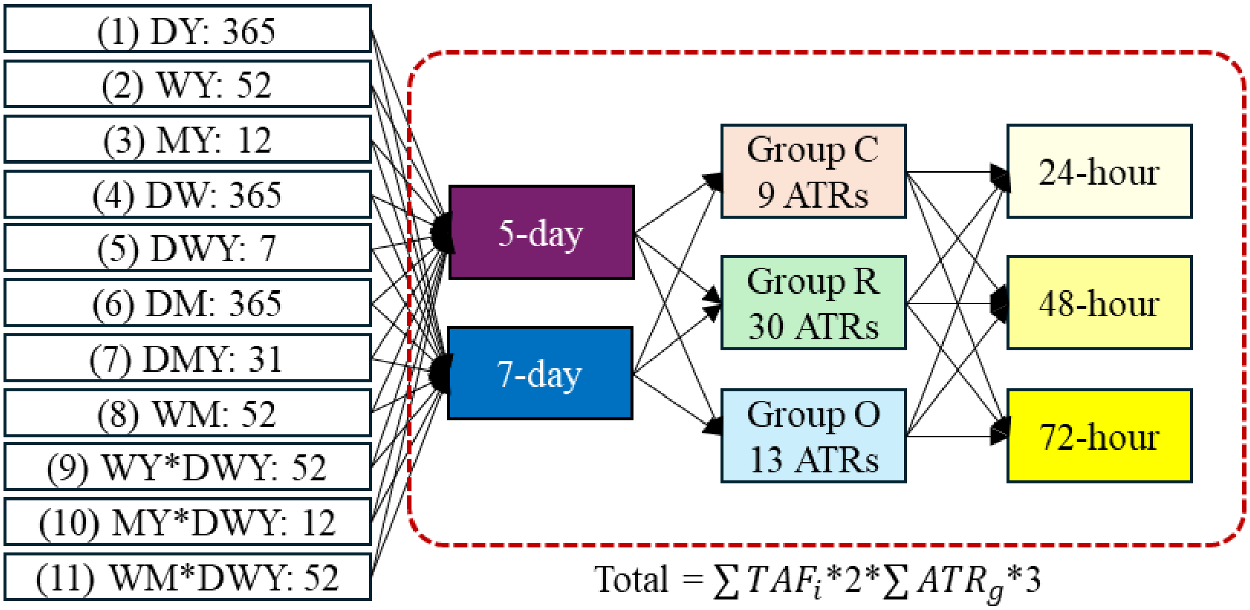


Figure 4.2 Structure of the TAF evaluation runs.

The magnitude of this computational workload necessitates automated programming. Accordingly, the entire evaluation process was implemented in Python to efficiently execute the repeated calculations and manage the large number of estimation runs.

This study evaluates alternative TAF structures using a systematic and reproducible analytical framework. The framework integrates data preprocessing, TAF construction, cross-validation sampling, estimation procedures, and performance evaluation. Figure 4.3 presents the core analytical logic of the TAF evaluation framework.

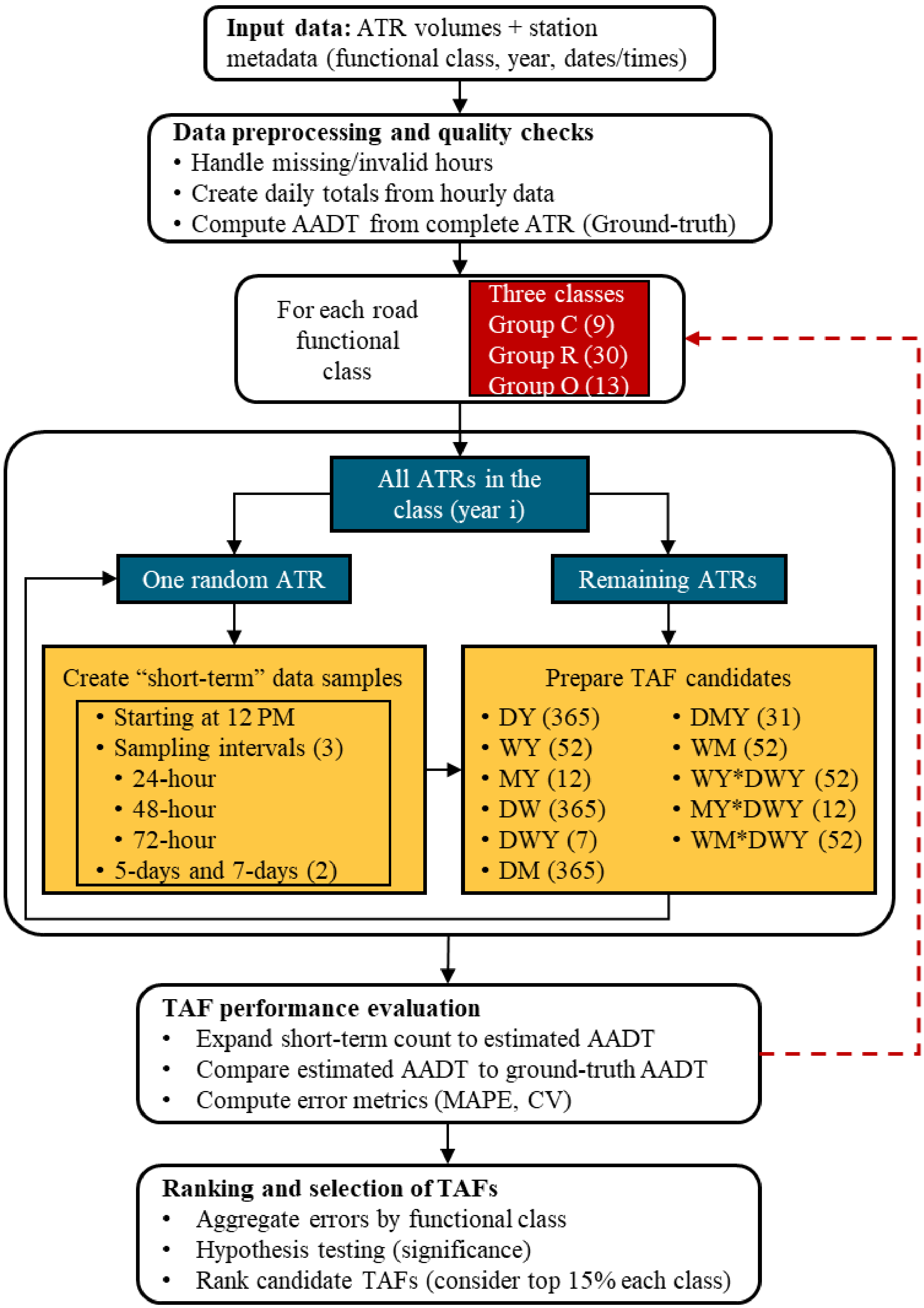


Figure 4.3 Flowchart of the analytical framework.

For a given year and functional class, all ATRs in that class are first identified. One ATR is then selected to act as the simulated short-term count site. From this ATR, short-term datasets are constructed according to the predefined sampling rules. These samples represent the observed data that would be available from a field short-term count. At the same time, the remaining ATRs within the same functional class are used exclusively to compute candidate TAFs. This separation between the short-term ATR and the remaining ATRs is a critical step in the framework. It prevents the factor development process from using information from the site being evaluated, thereby avoiding circular estimation and ensuring an unbiased performance assessment.

Once the TAFs are derived from the remaining ATRs, they are applied to the short-term samples from the selected ATR to estimate AADT. The estimated AADT is then compared with the ground-truth AADT calculated from the full-year data of that ATR. This process is repeated so that each ATR in the class serves once as the short-term site and the entire procedure is iterated across all ATRs within the class. This leave-one-out structure is the key methodological component of the analytical framework, as it enables systematic and independent evaluation of each TAF candidate.

To identify robust and consistently well-performing alternatives, the top 15 percent of TAFs, those exhibiting the lowest mean estimation error, were retained for further examination. The selected TAFs were then carried forward to the final validation phase, where they were applied to short-term count stations to evaluate their practical implementation performance and confirm their stability under realistic field conditions.

4.3 Performance Metrics for TAF Evaluation

To evaluate and compare the performance of candidate TAFs, estimation accuracy was assessed by comparing the estimated AADT obtained from simulated short-term counts with the reference AADT derived from full-year ATR data. The performance metrics were selected to quantify both bias and variability in estimation error.

For each short-term sampling scenario, the estimation error for ATR station *s* is defined in Equation 4.3.

$$e_s = \frac{\hat{V}_{\text{AADT},s} - V_{\text{AADT},s}}{V_{\text{AADT},s}} \qquad (4.3)$$

Where $\hat{V}_{\text{AADT},s}$ is the estimated AADT using a given TAF, and $V_{\text{AADT},s}$ is computed from the complete ATR record as the ground-truth AADT reference.

- Mean Absolute Percentage Error (MAPE)

The primary performance metric used in this study is the Mean Absolute Percentage Error (MAPE). MAPE measures the average magnitude of relative error without regard to direction. It is scale-independent and allows meaningful comparison across functional classes with different traffic volumes. Because TAF performance is fundamentally about reducing proportional error in AADT estimation, MAPE provides an intuitive and interpretable metric for ranking candidate structures. Given the estimation error calculated at each ATR station, MAPE can be calculated using Equation 4.4.

$$\text{MAPE} = \frac{1}{S}\sum_{s=1}^{S} \mid e_s \mid \times 100\% \qquad (4.4)$$

Where S is the total number of evaluation ATR stations in the corresponding functional class.

- Coefficient of Variation (CV)

To evaluate the stability of estimation performance, the Coefficient of Variation (CV) of the percentage errors was also computed. CV reflects the relative dispersion of estimation errors. A lower CV indicates that the TAF produces more consistent results across stations and sampling scenarios. While MAPE evaluates average accuracy, CV evaluates reliability and robustness. The calculation of CV can be found in Equation 4.5:

$$\mathrm{CV} = \frac{\sigma_e}{\mu_e} \qquad (4.5)$$

Where σ_e is the standard deviation of the estimation errors e_s, and μ_e is the mean of the estimation errors.

Both accuracy (MAPE) and stability (CV) were considered in the final ranking and selection process. Together, these metrics provide a balanced evaluation of TAF performance, which can capture both systematic estimation accuracy and consistency across stations and sampling conditions.

Chapter 5 Factor Selection and Analysis Results

This chapter evaluates and selects the most appropriate TAFs from the eleven candidate TAF structures developed in Chapter 4. A total of 47 valid ATR stations distributed across three functional classes, i.e., Group C (8 ATRs), Group R (27 ATRs), and Group O (12 ATRs), are used to assess the TAF performance. Each candidate factor is applied under multiple analytical settings, including different day-grouping schemes (5-day and 7-day) and short-term sampling durations (24-, 48-, and 72-hour counts). The performance of each TAF is quantified by using predefined metrics (i.e., MAPE, CV). Based on these results, the candidate factors are ranked, and the optimal factors are identified. In addition, a series of sensitivity analyses are conducted to examine the robustness of the selected factors under varying seasonal conditions, potential outlier effects, and different sample sizes of ATR stations.

5.1 TAF Ranking and Selection

5.1.1 Comparative Performance of Temporal Adjustment Factors

Table 5.1 summarizes the MAPE across all eleven evaluated TAFs for each functional group. The results are averaged over the different short-term count durations to provide an overall performance comparison.

A clear performance hierarchy emerges across the three functional groups. In general, Group C exhibits the highest error levels among all groups, followed by Group R, while Group O consistently shows the lowest errors. Group O represents urban arterials (e.g., major city streets, higher-volume urban highways), indicating relatively stable and predictable traffic demand patterns throughout the year. Group R represents rural highways such as regional connectors across less populated areas, where the error levels are moderate. Group C represents low-volume rural county roads. This group consistently shows the highest MAPE values. The higher errors likely reflect greater sensitivity to the increased proportional variability in short-term counts, and may also be contributed to localized travel behavior, agricultural activity, and weather effects.

Table 5.1 MAPE (%) results across different ATR groups

Factor Type	**Group C**	**Group R**	**Group O**
1_Day of the Year_DY	20.00	9.66	7.80
2_Week of the Year_WY	16.33	8.35	7.49
3_Month of the Year_MY	16.35	8.52	7.48
4_Day of the Week_DW	22.89	14.57	12.67
5_Day of All Weeks of the Year_DWY	18.17	10.56	8.33
6_Day of the Month_DM	23.65	14.99	12.15
7_Day of All Weeks of the Month_DMY	21.37	14.18	12.53
8_Week of the Month_WM	20.63	11.67	10.48
9_WY*DWY	16.40	9.05	9.28
10_MY*DWY	16.60	9.10	9.12
11_WM*DWY	18.20	10.60	8.36
NDOT Reference: MY*DWM	16.99	9.29	8.26

Among the candidate TAFs, top 15% factors with smallest MAPE (%), i.e., 2_WY, 9_WY*DWY, and 3_MY, and 1_DY for after removing outliers demonstrate the lowest errors across Group C, Group O, and Group R. In most cases, their performance is superior to the NDOT reference factor (MY*DWM). Overall, the results support a consistent ranking of these three structures as the top-performing TAFs across the three functional groups.

5.1.2 Effect of 5-day and 7-day Configuration

Table 5.2 presents the average MAPE percentages for the 11 candidate TAFs under the 5-day and 7-day period schemes to compare how the choice of weekday-only (5-day) versus full-week (7-day) grouping influences estimation accuracy.

Table 5.2 MAPE (%) results for TAFs in 5-day and 7-day configurations

Factor Type	5-day	7-day
1_Day of the Year_DY	9.05	9.05
2_Week of the Year_WY	9.17	11.35
3_Month of the Year_MY	10.24	12.47
4_Day of the Week_DW	14.36	10.67
5_Day of All Weeks of the Year_DWY	11.81	11.81
6_Day of the Month_DM	14.00	11.07
7_Day of All Weeks of the Month_DMY	14.70	11.55
8_Week of the Month_WM	13.41	13.86
9_WY*DWY	10.60	9.41
10_MY*DWY	11.37	10.41
11_WM*DWY	11.40	11.63

Overall, there is no single aggregation scheme (5-day or 7-day) that consistently outperforms the other across all TAF structures. The relative performance depends on the interaction between the temporal structure of the factor and the weekday configuration applied in the evaluation. For example, structures that explicitly incorporate weekday variation, such as DW or interaction terms involving DWY, tend to benefit from the 7-day configuration because it preserves full weekday–weekend distinctions. In contrast, broader annual or weekly structures may perform similarly under both configurations and even slightly better under the 5-day scheme. Therefore, the choice between 5-day and 7-day groupings should be considered in conjunction with the specific TAF structure rather than treated as a universal preference.

Across both configurations, three TAFs, Day of the Year (DY), Week of the Year (WY), and the compound WY × DWY consistently rank among the lowest-error factors. DY demonstrates stable performance under both 5-day and 7-day schemes, while WY and WY × DWY remain competitive across configurations. Their consistently low MAPE values indicate that annual and week-based aggregation structures provide a favorable balance between sensitivity to temporal variation and statistical stability. It may be arguable that the NDOT reference structure (MY × DWM, 5-day configuration) performs reasonably well. Although it is slightly inferior to the top three candidates in most comparisons, its error levels remain within a competitive range relative to the broader set of evaluated factors. This suggests that the current NDOT practice is method sound, while the identified optimal TAFs represent incremental improvements rather than fundamental departures from established practice.

5.1.3 Influence of Count Duration on Estimation Accuracy

Figure 5.1 compares the average MAPE values across the 11 candidate TAF structures for three short-term count durations (i.e., 24-hour, 48-hour, and 72-hour), aggregated across all functional groups (Groups R, C, O) and evaluated under both 5-day and 7-day aggregation periods.

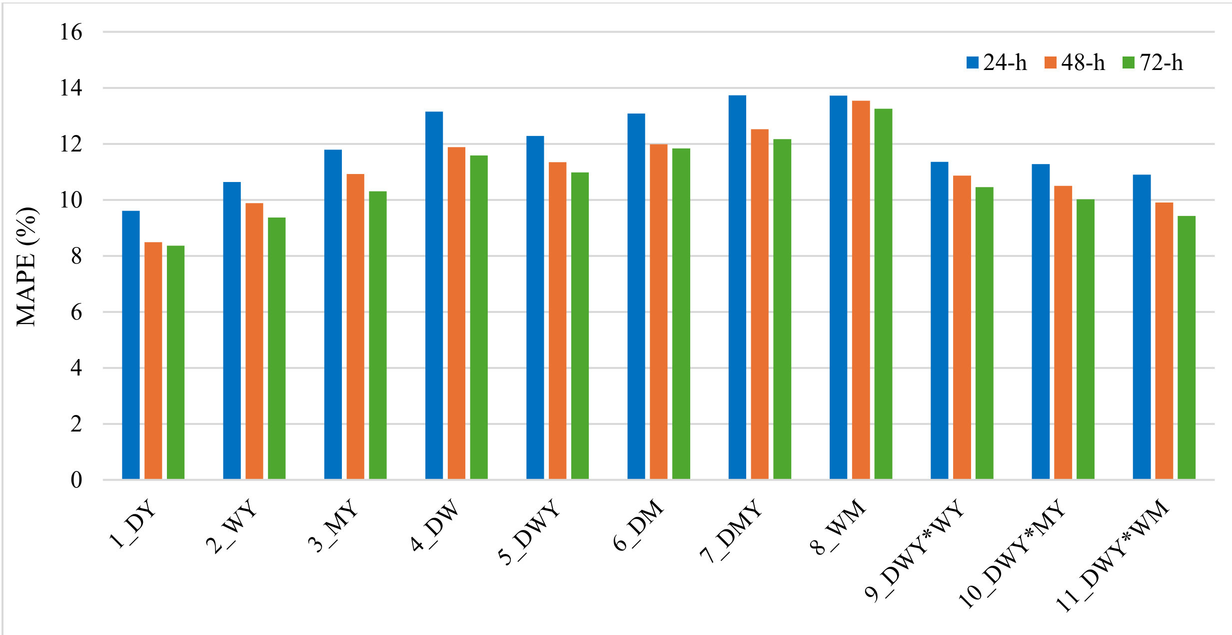


Figure 5.1 Error (MAPE %) for 24-hour, 48-hour, and 72-hour durations across TAF.

A consistent pattern is observed: for all TAF, estimation error, MAPE in percent, decreases as the short-term count duration increases from 24 hours to 48 hours and further to 72 hours. In other words, longer monitoring periods produce lower MAPE values and therefore more accurate AADT estimates.

The finding is consistent with established guidance in traffic monitoring practice. The FHWA Traffic Monitoring Guide notes that longer short-term count durations reduce sampling variability and improve the reliability of AADT estimation because they better capture day-to-day traffic variation (Federal Highway Administration, 2016). The guide emphasizes that multi-day counts provide more stable adjustment factors compared to single-day observations.

In summary, the selection of the recommended TAFs was based on two complementary performance metrics: MAPE and CV, and together, these metrics evaluate both accuracy and robustness. Based on these results, the selection criteria prioritize factors that (1) consistently achieve low MAPE across durations and groups, (2) maintain low and stable CV values, and (3) consider different functional groups (5-day or 7-day data) and count durations (24-h 48-h, 72-h). Under these criteria, DY, WY5, and DWY×WY7 are identified as the three optimal TAFs. The results of the TAF selections are shown in Table 5.3.

Table 5.3 Summary of the TAF selection

	MAPE			**CV**		
Factor Type	**24-h**	**48-h**	**72-h**	**24-h**	**48-h**	**72-h**
Group R						
Day of the Year (DY)	6.51	5.62	5.61	1.13	1.11	1.13
Week of the Year, 5-day (WY5)	6.68	6.03	5.55	1.09	1.13	1.11
Day of all Weeks of Year* Week of the Year, 7-day (DWYxWY7)	7.19	6.39	5.84	1.16	1.16	1.13
Group O						
Day of the Year (DY)	6.34	5.76	5.75	1.03	1.01	1.01
Week of the Year, 5-day (WY5)	6.60	6.06	5.80	0.98	1.01	1.00
Day of all Weeks of Year* Week of the Year, 7-day (DWYxWY7)	6.76	6.08	5.83	1.03	1.04	1.01
Group C						
Day of the Year (DY)	15.97	14.08	13.74	1.09	1.10	1.07
Week of the Year, 5-day (WY5)	15.59	14.04	13.31	1.03	1.07	1.01

	MAPE			CV		
Factor Type	**24-h**	**48-h**	**72-h**	**24-h**	**48-h**	**72-h**
Day of all Weeks of Year* Week of the Year, 7-day (DWYxWY7)	15.81	14.23	13.40	1.11	1.11	1.11

The three candidate factors, i.e., DY, WY5, and DWY×WY7, demonstrate similarly strong performance overall, with only minor differences depending on functional group and count duration. The final selection is based on a comprehensive evaluation that considers both MAPE and CV across all groups and sampling durations.

When jointly examining estimation accuracy and stability, and aggregating results across the three functional classes, WY5 exhibits the most balanced performance. It consistently maintains low MAPE values while also demonstrating stable CV levels, making it slightly more favorable in overall comparison.

5.2 Sensitivity Analysis

5.2.1 Seasonal Performance Analysis

Figure 5.2 presents the seasonal evaluation of the candidate TAFs across winter, spring, summer, and fall conditions. The analysis is conducted separately for the three functional classes and for the different short-term count durations. Seasonal comparison allows assessment of whether the relative ranking and performance stability of the TAF structures remain consistent under varying traffic demand patterns throughout the year. Several important findings emerge from the seasonal evaluation.

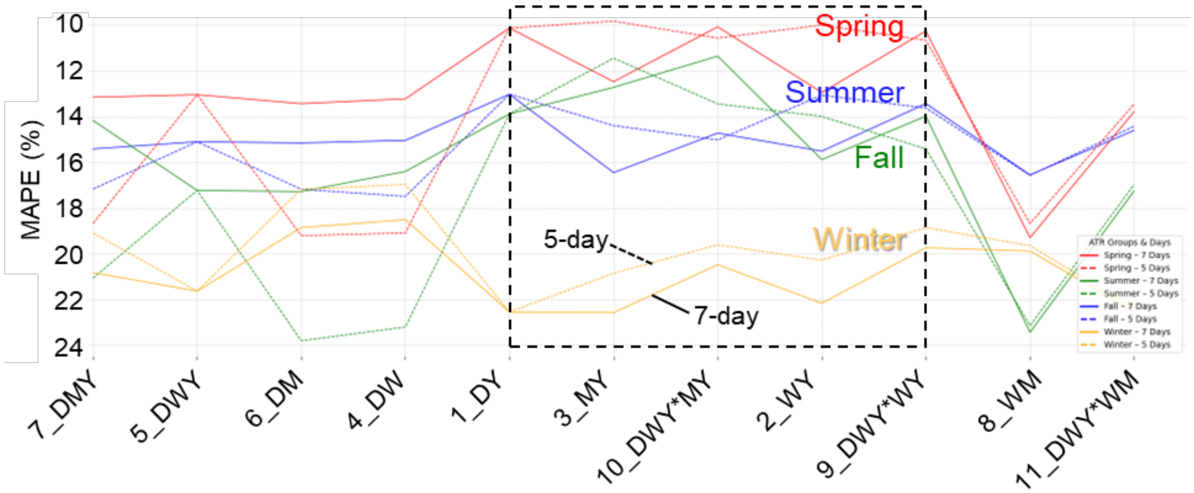


Figure 5.2 TAF performance in different seasons

First, winter consistently exhibits the highest estimation errors, particularly for Group C and Group R facilities. These roadway classes are more sensitive to weather-related disruptions such as snow, reduced visibility, and temporary demand shifts. Winter traffic patterns often include irregular travel behavior, trip cancellations, freight delays, and route diversions. Such variability increases day-to-day fluctuation, which in turn reduces the stability of short-term count expansion factors.

Second, daily-based TAF structures demonstrate greater seasonal volatility, especially during winter months. Because daily TAFs rely on finer temporal resolution, they are more sensitive to abnormal single-day conditions. When atypical weather events or traffic disruptions occur, daily factors reflect those deviations directly, resulting in larger seasonal swings in error metrics. This effect is less pronounced in other seasons but remains observable across groups.

Third, week-based structures remain comparatively stable across seasons, particularly under the 48-hour configuration. Aggregation at the weekly level smooths short-term irregularities while still capturing systematic weekly travel patterns. This balance between sensitivity and stability contributes to more consistent performance throughout the year.

Fourth, as can be seen in Table 5.4 - Table 5.6, seasonal differences are clearly reflected in the MAPE results. Winter exhibits the highest estimation errors across nearly all TAF structures. This pattern likely reflects increased traffic variability during winter months due to weather conditions, travel disruptions, and irregular demand patterns. The variation across seasons makes it difficult to identify a single TAF that consistently outperforms others under all seasonal conditions. Some factors perform well in one season but less favorably in another. This indicates seasonal dynamics influence the relative ranking of candidate structures.

Among the evaluated factors, Day of the Year (DY) tends to achieve the lowest MAPE values across seasons. This may be attributed to its finer temporal resolution, which allows it to capture daily-level variation more precisely. However, this detailed temporal factor structure also introduces greater dispersion in performance, as reflected by comparatively higher CV values. This trade-off may compromise the selection of DY as the overall best factor. Although it produces the lowest MAPE in many cases, factor selection in this study considers both accuracy and stability. For the DY factor, there is no difference between the 5-day and 7-day schemes since the structure is defined at the individual calendar-day level across the full year. It does not explicitly distinguish between weekday-only and full-week configurations, and therefore the aggregation scheme does not alter the factor definition or its computed values.

Finally, as can be seen in Table 5.4 - Table 5.6, urban arterials (Group O) exhibit the smallest seasonal fluctuation among the three functional classes. This suggests that urban traffic demand is relatively consistent across seasons, likely due to stable commuting and commercial activity patterns. In contrast, rural and collector facilities are more influenced by seasonal travel behavior, agricultural activity, and weather conditions.

Table 5.4 MAPE across seasons and time durations (Group C)

Factor Type	Fall		Spring		Summer		Winter	
	5-day	7-day	5-day	7-day	5-day	7-day	5-day	7-day
1_DY	14.15	14.15	11.10	11.10	14.85	14.85	21.35	21.35
2_WY	13.92	16.77	10.76	13.62	14.80	16.45	21.35	23.32
3_MY	15.17	17.51	10.65	13.17	12.16	13.22	21.58	23.41
4_ DW	18.34	16.00	20.02	14.07	24.06	17.31	17.87	19.56
5_DWY	15.89	15.89	13.85	13.85	17.39	17.39	22.63	22.63
6_DM	17.88	15.88	20.14	14.46	24.10	17.91	18.28	20.08
7_DMY	17.68	15.75	19.65	14.03	21.63	15.31	20.23	21.89
8_WM	17.70	17.87	19.02	19.61	23.30	23.60	20.22	20.39
9_WY*DWY	14.20	14.42	11.40	11.17	16.23	14.76	19.92	20.87
10_MY*DWY	15.58	15.54	11.29	10.96	14.88	13.06	20.30	21.24
11_WM*DWY	15.44	15.50	14.19	14.52	17.56	17.68	22.77	22.75

Table 5.5 MAPE across seasons and time durations (Group O)

Factor Type	Fall		Spring		Summer		Winter	
	5-day	7-day	5-day	7-day	5-day	7-day	5-day	7-day
1_DY	5.88	5.88	5.86	5.86	4.83	4.83	8.05	8.05
2_WY	6.06	7.48	5.49	8.60	4.99	8.11	9.28	11.58
3_MY	7.35	10.94	5.85	8.67	5.55	8.71	10.07	12.67
4_ DW	10.63	5.72	13.18	6.93	12.11	5.78	8.48	9.26
5_DWY	7.28	7.28	6.98	6.98	6.32	6.32	11.31	11.31
6_DM	8.41	6.45	13.10	7.12	10.96	5.56	8.50	9.92
7_DMY	9.81	6.69	13.27	6.97	11.33	6.23	10.27	10.91
8_WM	7.71	7.42	11.90	12.17	9.92	10.61	9.90	9.90
9_WY*DWY	9.38	5.82	8.04	6.00	7.63	5.15	11.52	9.80
10_MY*DWY	9.40	7.69	7.97	6.09	7.91	5.59	11.59	10.48
11_WM*DWY	6.46	6.40	6.91	7.14	6.03	6.28	11.25	11.26

Table 5.6 MAPE across seasons and time durations (Group R)

Factor Type	Fall		Spring		Summer		Winter	
	5-day	7-day	5-day	7-day	5-day	7-day	5-day	7-day
1_DY	6.85	6.85	4.69	4.69	5.18	5.18	8.64	8.64
2_WY	7.44	9.24	5.36	9.75	5.41	9.44	11.28	12.78
3_MY	8.83	11.34	5.56	6.44	6.05	6.63	12.32	14.73
4_ DW	10.48	7.81	13.99	8.76	13.48	8.47	9.27	12.07
5_DWY	9.20	9.20	8.47	8.47	8.03	8.03	14.99	14.99
6_DM	9.63	8.49	13.58	8.80	12.76	7.84	10.52	13.21
7_DMY	11.02	9.08	13.77	8.89	12.99	8.47	12.41	14.62
8_WM	8.53	9.61	11.60	11.65	10.84	10.91	13.07	12.92
9_WY*DWY	8.68	7.92	7.30	5.08	7.21	5.59	11.94	12.14
10_MY*DWY	9.62	9.62	5.40	5.40	5.78	5.78	13.25	13.25
11_WM*DWY	8.48	8.47	8.24	8.44	7.64	7.62	15.04	14.95

5.2.2 Outlier Effects

Table 5.7 presents the TAF evaluation results using ATR data containing outliers (e.g., missing values and extreme observations) in the original (*.101) format, as well as the cleaned dataset prepared by the research team (including missing data imputation based on prior years and outlier removal; see Subsection 3.4). The red-highlighted entries indicate the top 15% of TAFs (i.e., those with the lowest error values) within each category, reported separately for datasets with and without outliers and for both 5-day and 7-day configurations.

Table 5.7 MAPE (%) of the TAFs with and without outliers

Factor Type (error%)	With Outlier (Raw Count)		Without Outlier (Cleared Count)	
	5-day	7-day	5-day	7-day
1_Day of the Year_DY	12.49	12.49	9.59	9.59
2_Week of the Year_WY	10.72	12.59	9.60	11.66
3_Month of the Year_MY	10.78	12.94	10.77	12.92
4_Day of the Week_DW	16.71	13.42	15.05	11.28
5_Day of All Weeks of the Year_DWY	12.36	12.36	12.34	12.34
6_Day of the Month_DM	16.93	13.83	14.52	11.62
7_Day of All Weeks of the Month_DWM	16.03	12.84	15.39	12.10
8_Week of the Month_WM	14.26	14.28	13.45	13.95
9_ DWY* WY	11.58	10.83	10.65	9.91
10_ DWY* MY	11.61*	11.13	11.58	11.05
11_ DWY* WM	12.39	12.44	11.88	12.04

In general, results without outliers exhibit lower error percentages and therefore better performance compared to results based on raw ATR counts containing outliers. This is not surprising because extreme values and missing observations introduce additional variability into the daily traffic totals, which directly affects both the numerator and denominator of the TAF calculations.

Across all evaluation TAFs, the three selected ones, i.e., WY5, DWY × WY7, and DY, demonstrate lower error values in respective categories than the current NDOT reference factor. When outliers remain in the ATR dataset, the weekly-based factors (i.e., WY5 and DWY × WY7) generally exhibit superior performance. When outliers are removed and the dataset is cleaned, the daily-based structure (i.e., DY) shows improved relative performance.

5.3 Validation Using Short-Term Stations

To further evaluate the practical performance of the selected high-performing TAFs, an independent validation was conducted using 13 short-term stations in Group R that are geographically proximate to corresponding ATR locations. Unlike the leave-one-out cross-validation applied in the ATR-based evaluation, this step applies the recommended factors to actual short-term count conditions and compares the estimated AADT against the corresponding ATR-derived ground truth. Figure 5.3 presents the MAPE distribution across these stations for the selected factor types.

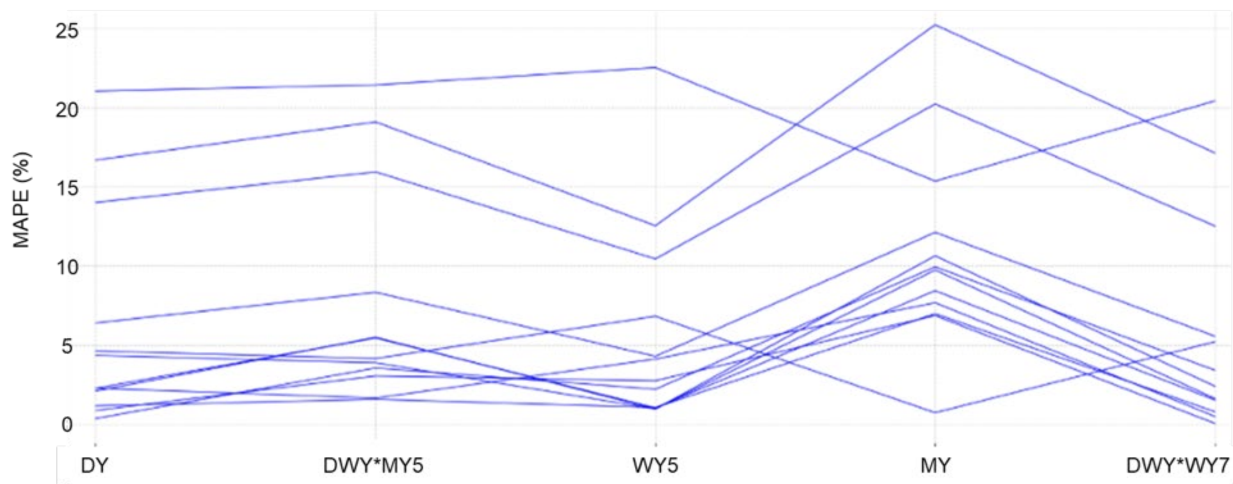


Figure 5.3 Percentage error for each factor types across 13 short-term stations in Group R

The results show that the Week of the Year × Day of All Weeks of the Year (7-day), i.e., DWY×WY7, exhibits the lowest MAPE. In contrast, the monthly factor alone demonstrates the poorest performance among the compared structures.

Compared to monthly-based TAF, the week-based interaction configuration appears less sensitive to localized anomalies or short-term irregularities. This supports the interpretation that combining weekly aggregation with weekday differentiation provides an effective balance between capturing systematic temporal patterns and maintaining statistical stability.

The independent validation using short-term stations therefore confirms the practical applicability of the selected high-performing factors. The consistency observed across stations strengthens confidence that the recommended TAFs can be implemented in routine practice without introducing excessive variability at individual locations.

5.4 Synthesis of Results

The comprehensive evaluation across functional groups, count durations, seasonal conditions, and independent short-term validation supports several consistent conclusions.

First, 72-hour short-term counts consistently outperform 48-hour counts, and 48-hour counts outperform 24-hour counts, in terms of estimation accuracy. Increasing the duration reduces sampling variability and improves representativeness of the observed traffic pattern. Although 72-hour counts yield further incremental improvements, the 48-hour configuration may be providing a practical balance between accuracy and data collection efficiency.

Second, week-based aggregation structures (i.e., WY5, or WY7*DWY) provide a favorable balance between sensitivity and stability. Compared to highly disaggregated daily-level structures, week-based factors smooth short-term irregularities while preserving systematic weekly variation. This balance results in lower dispersion and more consistent performance across roadway functional classes. The WY7*DWY configuration demonstrates the most consistent overall performance across groups, durations, and seasons. It maintains competitive MAPE values while controlling dispersion, and it performs reliably in both cross-validation and independent short-term station testing.

Finally, seasonal variability is most pronounced during winter; however, it does not substantially alter the relative ranking of the top-performing factors. The recommended TAFs remain competitive across seasonal conditions. Together, these findings provide a clear quantitative basis for selecting the three recommended TAFs, i.e., DWY*WY7, WY5, DY, and are presented in the following chapter.

Chapter 6 Spreadsheet Tool Development

As the project deliverable, an implementation tool was developed in Microsoft Excel with VBA to automate TAF processing and support routine AADT estimation. This chapter describes the tool development and provides guidance for applying the tool in practice. The tool is designed around two primary functions. First, it computes and reports TAF values using ATR data for a user-selected roadway functional class. Second, it estimates AADT from field-collected short-term count data and the corresponding day-weighted factor values.

6.1 Temporal Adjustment Factor Generation Module

The first function of the tool is to automate the generation of temporal adjustment factors using ATR data. The NDOT_Factor_Tool worksheet serves as the primary user interface of the function. The layout is intentionally divided into two functional regions. The left side contains all user inputs and control buttons, while the right side displays the computed TAF results.

Figure 6.1(a) shows the left panel of the NDOT_Factor_Tool worksheet. Instructions are provided to indicate the five steps in sequence to generate the TAF values. At the top of the interface, the “Select Data Path” section allows users to specify the directory containing ATR data files. The path can be updated by clicking the corresponding button, which opens a folder selection dialog. For example, the data in this demonstration is stored in C:\Project\NDOT\FY25(048)\ATR_Data\2023\, under this path in the folder named 2023, 12 folders indicating 12 months of the data, and each month’s folder containing all the ATR data file, where the format is assumed to be *.101, as shown in Figure 6.1(b).

The tool includes a selection dropdown list for roadway functional class groups (Group R, Group O, and Group C), which define the ATR grouping used in the analysis. Note that the classification of each ATR station into R, O, or C is determined by NDOT and is fixed within the dataset. When a group is selected, all factor calculations are based only on ATR stations belonging to that group. The temporal factor selection provides four options. Three of these are the recommended TAF structures identified in Chapters 4 and 5: Week of the Year (WY5), Week of the Year × Day of Week (DWYx WY7), and Day of the Year (DY). In addition, one monthly factor option is included to represent NDOT's previous practice, which serves as a reference for comparison with the recommended TAF.

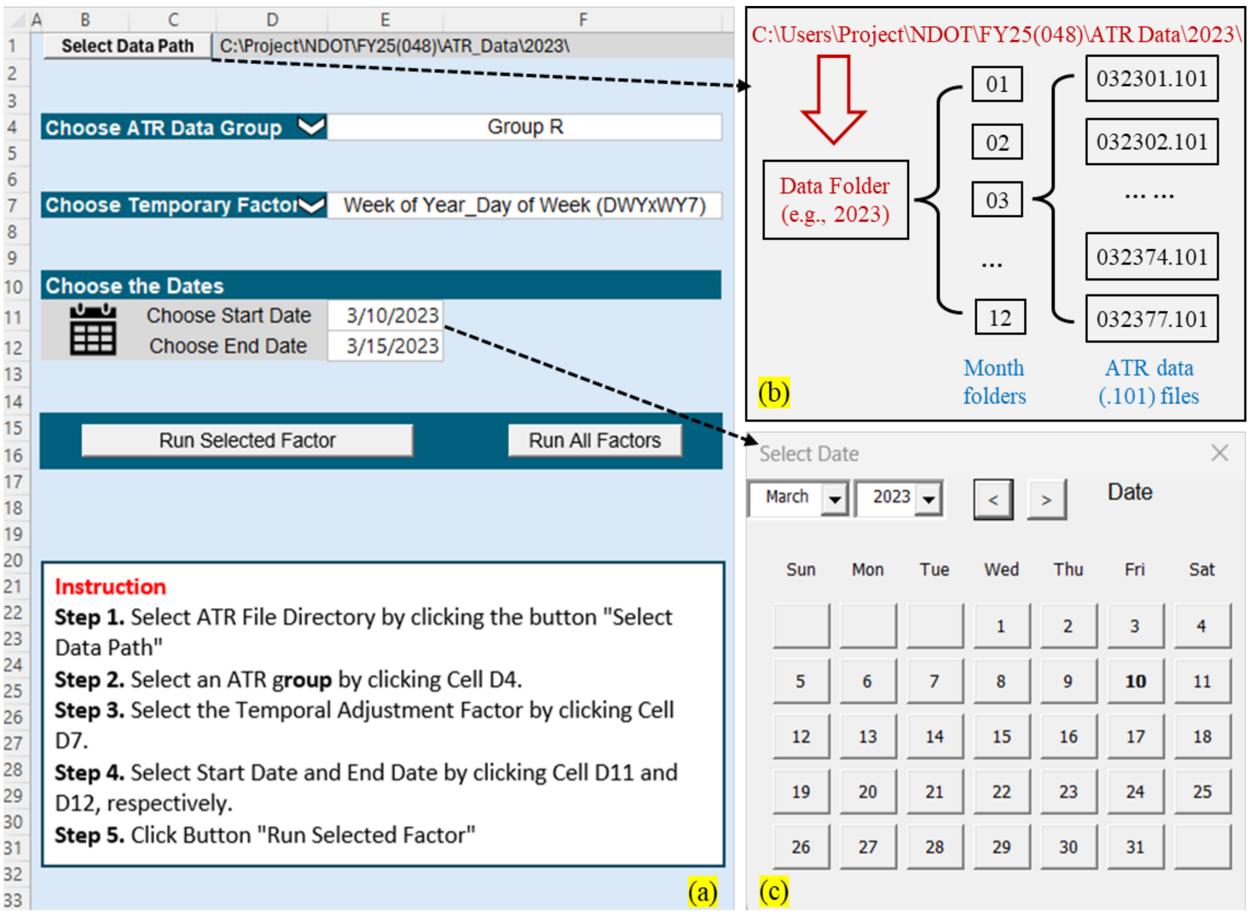


Figure 6.1 Left panel in NDOT_Factor_Tool worksheet

The Start Date and End Date fields allow users to define the period of interest for reviewing factor values. When a user clicks the date cell, a calendar interface appears, as shown in shown in Figure 6.1(c). The calendar supports selection of individual days and facilitates navigation by month and year. Users may specify any continuous range, such as a single day, several consecutive days, one week, one month, or an entire year, depending on their analysis needs.

Below the input fields, two execution buttons are provided. The "Run Selected Factor" button executes the computation only for the factor chosen in the dropdown. Results for this execution are directly shown in the worksheet on the right panel. On the right panel, the factor values are organized by month (columns) and day (rows). Selected range of the values within the start and end dates are highlighted in yellow. As an example, Figure 6.2 provides the results display.

I	J	K	L	M	N	O	P	Q	R	S	T	U
	January	February	March	April	May	June	July	August	September	October	November	December
1	1.70	1.14	1.03	1.16	0.94	0.88	1.00	0.88	0.81	1.19	0.98	0.89
2	1.34	1.12	1.02	1.29	0.91	0.81	1.25	0.87	1.06	0.94	0.96	1.15
3	1.31	1.03	0.94	1.02	0.90	1.06	0.98	0.86	1.23	0.91	0.89	1.32
4	1.29	1.35	1.22	0.99	0.88	1.15	0.95	0.79	0.97	0.90	1.16	1.06
5	1.27	1.39	1.44	0.98	0.81	0.91	0.94	1.03	0.94	0.89	1.24	1.03
6	1.17	1.10	1.14	0.96	1.06	0.88	0.93	1.16	0.93	0.82	0.98	1.02
7	1.53	1.07	1.11	0.89	1.18	0.87	0.85	0.92	0.92	1.06	0.96	1.00
8	1.37	1.05	1.09	1.16	0.93	0.86	1.12	0.89	0.84	1.19	0.94	0.92
9	1.08	1.04	1.07	1.22	0.90	0.79	1.15	0.88	1.10	0.94	0.93	1.19
10	1.06	0.96	0.99	0.96	0.89	1.03	0.90	0.86	1.17	0.92	0.85	1.32
11	1.04	1.25	1.29	0.94	0.88	1.13	0.88	0.80	0.92	0.90	1.11	1.05
12	1.02	1.53	1.39	0.92	0.81	0.89	0.87	1.04	0.90	0.89	1.22	1.03
13	0.94	1.21	1.10	0.91	1.05	0.87	0.85	1.18	0.88	0.82	0.95	1.01
14	1.23	1.17	1.07	0.84	1.17	0.86	0.79	0.93	0.87	1.07	0.93	0.99
15	1.68	1.16	1.06	1.09	0.92	0.84	1.03	0.91	0.80	1.16	0.92	0.91
16	1.32	1.14	1.04	1.24	0.90	0.78	1.16	0.89	1.05	0.92	0.90	1.19
17	1.29	1.05	0.96	0.98	0.88	1.02	0.91	0.88	1.17	0.89	0.83	1.28
18	1.27	1.37	1.25	0.95	0.87	1.13	0.89	0.81	0.92	0.88	1.07	1.02
19	1.25	1.54	1.32	0.94	0.80	0.89	0.88	1.06	0.90	0.87	1.38	0.99
20	1.15	1.22	1.05	0.92	1.05	0.87	0.86	1.23	0.89	0.80	1.09	0.98
21	1.51	1.19	1.02	0.85	1.12	0.85	0.79	0.97	0.87	1.04	1.06	0.96
22	1.46	1.17	1.00	1.11	0.89	0.84	1.04	0.94	0.80	1.23	1.05	0.88
23	1.16	1.15	0.99	1.21	0.86	0.77	1.16	0.93	1.05	0.97	1.03	1.15
24	1.13	1.06	0.91	0.96	0.85	1.01	0.92	0.92	1.17	0.94	0.95	1.69
25	1.11	1.38	1.18	0.93	0.84	1.12	0.89	0.84	0.92	0.93	1.24	1.35
26	1.09	1.36	1.29	0.92	0.77	0.88	0.88	1.10	0.90	0.92	1.27	1.31
27	1.01	1.08	1.02	0.90	1.01	0.86	0.86	1.19	0.88	0.84	1.01	1.29
28	1.31	1.05	0.99	0.83	1.18	0.85	0.80	0.94	0.87	1.10	0.98	1.27
29	1.50		0.98	1.09	0.93	0.83	1.04	0.91	0.80	1.29	0.97	1.17
30	1.18		0.96	1.18	0.91	0.77	1.16	0.90	1.05	1.02	0.95	1.53
31	1.15		0.89		0.90		0.91	0.88		1.00		2.15

Figure 6.2 Results in the right panel with highlighted TAF values.

The “Run All Factors” button performs batch processing for all defined factor types for all ATR groups. This function is typically used for comparative analysis or sensitivity evaluation, and a separate worksheet “All Factor Results” will be created to save the results when executing this button.

6.2 AADT Estimation from Short-Term Counts Module

This function allows users to estimate AADT by providing short-term counts (e.g., typically 1-3 days) collected from the field. This function is shown in the “AADT Estimation” worksheet. The data input and execution panel is shown in Figure 6.3. Instruction is provided so users can follow the four steps to calculate the AADT results, which are shown in Cell B13.

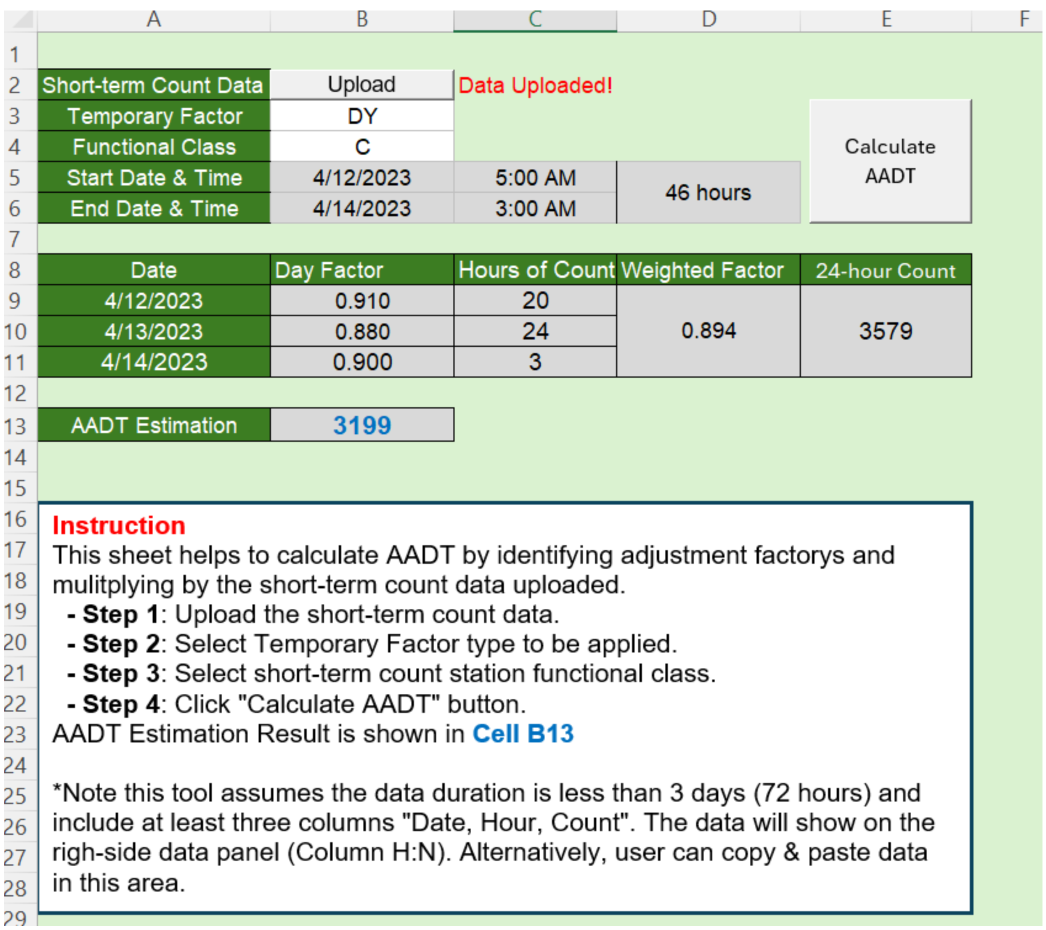


Figure 6.3 Left panel of the AADT estimation function

To upload the short-term count data, users need to click the "Upload" button to select the path of the data as a .xlsx file. When data are uploaded, a message is shown next to the button. The function essentially copies the data into the worksheet on the right panel data section. Therefore, users can directly copy their short-term count data into this area (i.e., Cells H1:N80). This provides a data format when preparing the short-term count data. Six columns are expected in the input data: Station, Lat, Lon, Date, Time, and Count. The tool assumes that the dataset contains no more than three days of data (maximum of 79 hourly records), which is consistent with typical short-term data collection practice at NDOT. If a longer data period is provided, the input area must be expanded accordingly to accommodate the additional rows.

The selection of the temporal adjustment factor (i.e., WY5, DWY×WY7, DY, and the reference DWY×MY5) and the selection of roadway functional class (i.e., Group O, Group R, and Group C) follow the same procedure described previously. Once the short-term count data are uploaded into the worksheet, the start date and time, end date and time, and the total duration in hours are automatically detected and populated based on the loaded dataset.

When the user clicks the "Calculate AADT" button, the uploaded short-term count data (which originally consisted of six columns including Date, Time, and Count) are reorganized into a structured day–hour matrix format. Specifically, the tool reads the Date and Time fields to determine the corresponding calendar day and hour of day (1–24) and then arranges the traffic counts into a two-dimensional table. In this table, each column represents a specific date, each row represents an hour of the day, and each cell contains the traffic count observed during that hour on that date. This data is shown as data input on the right panel of the worksheet (Columns P:T), as indicated in Figure 6.4.

P	Q	R	S	T
Hour	4/12/2023	4/13/2023	4/14/2023	Average
1		5		5
2		3		3
3		4		4
4		7		7
5	19	31		25
6	63	58		61
7	143	138		141
8	259	249		254
9	260	273		267
10	249	245		247
11	250	250		250
12	246	246		246
13	267	267		267
14	265	265		265
15	254	254		254
16	252	252		252
17	237			237
18	279			279
19	185			185
20	116			116
21	87			87
22	72			72
23	44			44
24	12			12

Figure 6.4 Calculation of the hourly average counts (in Columns P:T in the worksheet)

If the short-term dataset spans multiple consecutive days (which is highly likely), multiple columns will appear in the matrix. The tool then computes the hourly average across the available days for each hour. For example, the counts at 8:00–9:00 across all included days are averaged to obtain a representative volume for Hour 8. The resulting "Average" column represents the mean hourly volume profile over the data collection period. The total traffic counts in a 24-hour period (i.e., average daily traffic, ADT) is then summed across the 24 hours.

The computed ADT is converted to AADT through application of a "weighted" TAF. The weight accounts for the number of observation hours contributed by each day within the short-term count period. Because the short-term dataset may not contain a full 24 hours for every day, the adjustment factor is calculated as a weighted average of the daily TAF values, where the weights correspond to the number of included hours for each day i. The weighted temporal adjustment factor is defined as Equation 6.1, and the estimated AADT is then computed as Equation 6.2.

$$TAF_w = \frac{\sum_i (TAF_i \times Hours_i)}{\sum_i Hour\ s_i} \tag{6.1}$$

$$AADT = ADT \times TAF_w \tag{6.2}$$

Where TAF_i is the temporal adjustment factor corresponding to date i, and $Hours_i$ is the number of valid hourly observations for that date included in the short-term dataset.

It should be noted that this AADT estimation procedure may differ from the standard method described by FHWA (Federal Highway Administration 2018), but it is consistent with current NDOT practice. The adjustment factors applied in this tool account only for temporal variation. If additional adjustment components are required, such as axle correction factors or other classification-related factors, they must be applied separately to the estimated AADT values.

Chapter 7 Conclusions, Recommendations, and Limitations

This chapter summarizes the findings of the study and presents recommendations for practical implementation of TAFs for AADT estimation. Based on quantitative performance metrics and cross-validation results, the most robust and accurate TAFs are identified. Section 7.1 first presents the principal conclusions drawn from the analysis, then outlines recommendations for implementation. Finally, Section 7.2 discusses the limitations of the study and considerations for future refinement.

7.1 Conclusions and Recommendations

This study developed and implemented a systematic analytical framework to evaluate alternative TAFs for estimating AADT from short-term traffic counts using ATR data. The evaluation incorporated two day-grouping schemes (5-day and 7-day), three sampling durations (24-hour, 48-hour, and 72-hour), and three functional classes with corresponding number of ATR stations (Group C: 9 ATRs; Group R: 30 ATRs; Group O: 13 ATRs) with a leave-one-ATR-out cross-validation procedure. Performance was assessed using mean absolute percentage error and variability measures to ensure both accuracy and stability. Across functional classes, sampling durations, and seasonal conditions, several consistent findings emerged.

First, 48-hour counts consistently outperformed 24-hour counts in terms of estimation accuracy and stability. The additional day of observation reduces sensitivity to day-specific variability and improves representativeness of typical traffic conditions. While 72-hour samples provide marginal additional improvement, the incremental benefit relative to 48-hour sampling is comparatively small when balanced against increased data collection effort.

Second, week-based aggregation structures provide the most effective balance between sensitivity to temporal variation and statistical stability. TAFs defined at the weekly level capture meaningful seasonal fluctuations while maintaining sufficient sample sizes within each temporal category. In contrast, month-based structures smooth important within-month variation, and daily-level structures introduce excessive segmentation.

Third, the Week of the Year × Day of the Week (7-day), i.e., TAF 9 (WY × DWY), demonstrates the most consistent and lowest estimation error across functional classes and sampling durations. The Week of the Year (5-day), i.e., TAF 2 (WY), ranks second in overall performance. The Day of the Year, i.e., TAF 1 (DY), ranks third. While the DY factor offers the highest temporal resolution and can reflect fine-grained seasonal variation, its large number of factor values increases sensitivity to short-term fluctuations. As a result, it may not achieve the same level of stability as the top-ranked week-based factors as the first two factors.

In addition, this project developed a spreadsheet-based implementation tool to automate adjustment factor calculation and AADT estimation using the optimal TAFs identified in the study. The tool translates the research findings into a practical workflow and is intended to support NDOT staff in routine traffic data processing and analysis.

7.2 Limitations

While the study provides a comprehensive evaluation framework, several limitations should be acknowledged. Most importantly, the analysis is based on ATR data from specific functional classes within Nebraska. Although the evaluation covers multiple roadway types and seasonal conditions, results may differ in regions with substantially different traffic patterns, climatic conditions, or travel behavior.

The leave-one-ATR-out procedure assumes that the remaining ATRs within a functional class adequately represent the temporal characteristics of the excluded station. In areas with sparse ATR coverage, this assumption may be weaker. The evaluation is based on historical traffic conditions. Structural changes in travel behavior, land use, or extreme weather patterns could affect future factor performance and may require periodic recalibration.

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Appendix A

- **Results with and without outliers**

Table A.1 MAPE results for TAFs in different groups, with outliers

Factor Type (%)	Days in week	With Outliers (Raw data)		
		Group C	Group R	Group O
Day of the Year	5-day	20.00	9.66	7.80
Week of the Year	5-day	16.33	8.35	7.49
Month of the Year	5-day	16.35	8.52	7.48
Day of the Week	5-day	22.89	14.57	12.67
Day of All Weeks of the Year	5-day	18.17	10.56	8.33
Day of the Month	5-day	23.65	14.99	12.15
Day of All Weeks of the Month	5-day	21.37	14.18	12.53
Week of the Month	5-day	20.63	11.67	10.48
Week of the Year*DOW	5-day	16.40	9.05	9.28
Month of the Year*DOW	5-day	16.60	9.10	9.12
Week of the Month*DOW	5-day	18.20	10.60	8.36
Week of the Month*Day of All Weeks of the Month	5-day	21.39	13.92	12.13
Month of the Year*Day of All Weeks of the Month	5-day	16.99	9.29	8.26
Day of the Year	7-day	20.00	9.66	7.80
Week of the Year	7-day	18.55	9.54	9.68
Month of the Year	7-day	18.40	10.05	10.38
Day of the Week	7-day	19.72	11.90	8.65
Day of All Weeks of the Year	7-day	18.17	10.56	8.33
Day of the Month	7-day	20.29	12.36	8.83
Day of All Weeks of the Month	7-day	18.37	11.34	8.81
Week of the Month	7-day	20.70	11.65	10.49
Week of the Year*DOW	7-day	16.33	8.60	7.57
Month of the Year*DOW	7-day	16.47	9.01	7.91
Week of the Month*DOW	7-day	18.29	10.62	8.40
Week of the Month*Day of All Weeks of the Month	7-day	18.43	11.19	8.66
Month of the Year*Day of All Weeks of the Month	7-day	16.99	9.29	8.28

Table A.2 MAPE results for TAFs in different groups, without outliers

Factor Type (%)	Days in week	Without Outlier (Cleared data)		
		Group C	Group R	Group O
Day of the Year	5-day	15.95	6.50	6.33
Week of the Year	5-day	15.59	6.61	6.60
Month of the Year	5-day	16.34	8.51	7.45
Day of the Week	5-day	20.85	12.52	11.78
Day of All Weeks of the Year	5-day	18.18	10.54	8.31
Day of the Month	5-day	20.95	12.05	10.56
Day of All Weeks of the Month	5-day	20.87	13.47	11.83
Week of the Month	5-day	20.18	10.34	9.83
Week of the Year*DOW	5-day	15.68	7.62	8.64
Month of the Year*DOW	5-day	16.59	9.09	9.06
Week of the Month*DOW	5-day	18.01	9.59	8.05
Week of the Month*Day of All Weeks of the Month	5-day	21.06	13.05	11.76
Month of the Year*Day of All Weeks of the Month	5-day	16.15	7.17	7.34

- **Results for TAFs given different data durations (24-h, 48-h, 72-h)**

Table A.3 MAPE (%) results for TAFs given different data durations, Group C for 5 days a week

Factor Type	Group C (5-day)		
	24-h	48-h	72-h
1_Day of the Year_DY	15.97	14.08	13.74
2_Week of the Year_WY	15.59	14.04	13.31
3_Month of the Year_MY	16.28	14.72	13.84
4_Day of the Week_DW	20.85	19.32	18.91
5_Day of All Weeks of the Year_DWY	18.08	16.74	16.04
6_Day of the Month_DM	20.99	19.4	19.32
7_Day of All Weeks of the Month	20.88	19.2	18.6
8_Week of the Month	20.2	19.29	18.86
9_DWY*WY	15.68	14.4	13.48
10_DWY*MY	16.5	15.13	14.35
11_DWY*WM	18.02	16.71	16.27

Table A.4 MAPE (%) results for TAFs given different data durations, Group O for 5 days a week

Factor Type	Group O (5-day)		
	24-h	48-h	72-h
1_Day of the Year_DY	6.34	5.76	5.75
2_Week of the Year_WY	6.6	6.06	5.8
3_Month of the Year_MY	7.37	6.85	6.55
4_Day of the Week_DW	11.82	10.8	10.67
5_Day of All Weeks of the Year_DWY	8.26	7.58	7.44
6_Day of the Month_DM	10.7	9.99	10.13
7_Day of All Weeks of the Month	11.91	10.86	10.73
8_Week of the Month	9.95	10.04	9.86
9_DWY*WY	8.62	9	8.79
10_DWY*MY	8.99	9.24	9.1
11_DWY*WM	8.07	7.17	6.89

Table A.5 MAPE (%) results for TAFs given different data durations, Group R for 5 days a week

Factor Type	Group R (5-day)		
	24-h	48-h	72-h
1_Day of the Year_DY	6.51	5.62	5.61
2_Week of the Year_WY	6.68	6.03	5.55
3_Month of the Year_MY	8.55	7.69	7.23
4_Day of the Week_DW	12.4	10.98	10.91
5_Day of All Weeks of the Year_DWY	10.49	9.72	9.47
6_Day of the Month_DM	11.96	10.95	10.96
7_Day of All Weeks of the Month	13.4	11.95	11.73
8_Week of the Month	10.28	10.68	10.43
9_DWY*WY	7.74	8.17	7.83
10_DWY*MY	9.17	9.17	8.86
11_DWY*WM	9.56	8.87	8.29

Table A.6 MAPE (%) results for TAFs given different data durations, Group C for 7 days a week

Factor Type	Group C (7-day)		
	24-h	48-h	72-h
1_Day of the Year_DY	15.97	14.08	13.74
2_Week of the Year_WY	18.08	16.54	15.83
3_Month of the Year_MY	18.35	16.79	15.91
4_Day of the Week_DW	17.49	15.44	14.86
5_Day of All Weeks of the Year_DWY	18.08	16.74	16.04
6_Day of the Month_DM	17.88	16.03	15.63

Factor Type	Group C (7-day)		
	24-h	48-h	72-h
7_Day of All Weeks of the Month	17.65	15.89	15.13
8_Week of the Month	20.43	19.56	19.2
9_DWY*WY	17.91	16.74	16.22
10_DWY*MY	16.41	14.79	13.9
11_DWY*WM	15.81	14.23	13.4

Table A.7 MAPE (%) results for TAFs given different data durations, Group O for 7 days a week

Factor Type	Group O (7-day)		
	24-h	48-h	72-h
1_Day of the Year_DY	6.34	5.76	5.75
2_Week of the Year_WY	8.78	8.81	8.57
3_Month of the Year_MY	10.21	10.01	9.56
4_Day of the Week_DW	7.04	6.53	6.26
5_Day of All Weeks of the Year_DWY	8.26	7.58	7.44
6_Day of the Month_DM	7.38	6.84	6.76
7_Day of All Weeks of the Month	8.06	7.46	7.34
8_Week of the Month	10.29	10.31	10.06
9_DWY*WY	8.12	7.45	7.3
10_DWY*MY	7.58	6.79	6.55
11_DWY*WM	6.76	6.08	5.83

Table A.8 MAPE (%) results for TAFs given different data durations, Group R for 7 days a week

Factor Type	Group R (7-day)		
	24-h	48-h	72-h
1_Day of the Year_DY	6.51	5.62	5.61
2_Week of the Year_WY	8.07	7.79	7.17
3_Month of the Year_MY	9.98	9.46	8.73
4_Day of the Week_DW	9.29	8.24	7.87
5_Day of All Weeks of the Year_DWY	10.49	9.72	9.47
6_Day of the Month_DM	9.58	8.71	8.23
7_Day of All Weeks of the Month	10.48	9.76	9.47
8_Week of the Month	11.2	11.35	11.09
9_DWY*WY	10.09	9.44	9.11
10_DWY*MY	8.98	7.88	7.37
11_DWY*WM	7.19	6.39	5.84