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PREDICTION OF INTERSTATE TRAVEL TIME RELIABILITY: PHASE II

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Final Report VTRC 23-R12

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Abstract:

Accurate prediction of travel time reliability measures would help state departments of transportation set performance targets and communicate the progress toward meeting those targets as required by the Moving Ahead for Progress in the 21st Century Act (MAP-21). In a recent Virginia Transportation Research Council study, *Methods to Analyze and Predict Interstate Travel Time Reliability*, researchers developed and tested statistical and machine learning models to analyze and predict travel time reliability on interstate highways. The generalized random forest (GRF) model showed promise in terms of data processing (no need for pre-clustering of travel times) and the relative accuracy of the results and was recommended for further evaluation by the study's technical review panel.

The current study directly adapted the previously developed GRF models to meet the requirements of MAP-21 federal target setting. In particular, the GRF approach developed using the INRIX Traffic Message Channel network for weekday peak period traffic by the prior study was successfully (1) adapted to the federally required National Performance Management Research Dataset (NPMRDS) network, and (2) expanded to cover the weekday midday and weekend daytime periods. The technical review panel was also interested in practical steps to implement the predictive models. To that end, suggested procedures for applying the new GRF models—including relevant model inputs and data preparation steps—are documented in this report.

Direct application of the GRF models trained with INRIX data (2017-2018) to predict travel time reliability measures in 2009 on the NPMRDS network highlighted the need for developing new GRF models targeted to the NPMRDS network, especially when the 90th percentile travel time was predicted. Whereas the INRIX models showed mean absolute percentage errors of 37% and 51% for freeway and interchange segments, respectively, for the PM peak hours, the new GRF models (trained with 2017-2018 NPMRDS data) had relatively smaller mean absolute percentage errors of 34% for freeway segments and 38% for interchange segments depending on how work zones were characterized and how data were aggregated. Because operational improvements are often evaluated on the basis of how they improve reliability, especially on how the 90th percentile travel time is affected, the new GRF models are relevant for planning operational investments. In addition, because many of these improvements affect interchanges, the remedy of the new GRF models is essential for evaluating weaving strategies or traveler information systems that could be implemented at these locations.

FINAL REPORT

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ABSTRACT

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INTRODUCTION

Under the Moving Ahead for Progress in the 21st Century Act (MAP-21), state departments of transportation (DOTs) are required to assess and report the travel time reliability (TTR) performance on the National Highway System. Accurate prediction of reliability measures would help DOTs set performance targets and communicate the progress toward meeting those targets. Determining credible forecasts of TTR measures is increasingly becoming a key component of the system planning and performance measurement process at many transportation agencies, including the Virginia Department of Transportation (VDOT), as they work toward establishing reliability targets and tracking progress toward meeting them. Provided sufficient historical travel time data are available to characterize fully the distributions of trip travel times, determining the TTR measures for specific origin-destination pairs is generally straightforward. However, developing credible forecasts of TTR can be a significant challenge because of the dynamic nature of traffic and the variety of factors known to contribute to unreliable travel times, such as traffic incidents, inclement weather, work zones, special events, traffic control devices, fluctuations in demand, and inadequate base capacity (Transportation Research Board, 2003). Not surprisingly, most TTR prediction models developed in the past focused on predicting a single performance measure using a few variables (e.g., traffic volume, incidents, and weather) with data collected from one corridor or a limited number of segments (Zargari et al., 2021).

Another challenge to determining credible TTR predictions is the “largeness” and complexity of relevant input data. At present, the main source of travel time data for reliability analysis is probe vehicle data. Many state transportation agencies in the United States procure and use probe vehicle data from commercial entities such as INRIX to measure highway system performance or to provide traveler information. The Federal Highway Administration, through its National Performance Measurement Research Dataset (NPMRDS) program—and in collaboration with commercial entities such as INRIX, TomTom, and HERE—has also offered free probe data to state and local transportation agencies since 2013. These probe data sources generally have wide coverage areas and measure travel times on links termed “traffic message channel” (TMC) segments. TMCs enable access to travel time distributions at generally high spatial and temporal resolutions. This is desirable, as accurate travel time cumulative distribution functions (CDFs) are essential to successful TTR applications. However, “estimating and keeping separate CDFs for hundreds of individual TMCs may not be efficient from a data management and analysis perspective” (Zhang et al., 2021a).

The purpose of a 2021 Virginia Transportation Research Council (VTRC) study, *Methods to Analyze and Predict Interstate Travel Time Reliability* (hereinafter called "the Phase I study"), was to overcome some of these challenges by developing a linear quantile mixed modeling framework and generalized random forest (GRF) models for TTR analysis and prediction on interstate highways during the peak traffic periods (Zhang et al., 2021b). The mixed modeling framework first partitioned TMCs into approximately homogenous clusters based on the similarity of their travel time CDFs and then used linear quantile mixed models (LQMMs) to quantify TTR impact factors and predict relevant TTR measures for each cluster. Using clustered data meant that "LQMMs were only necessary for a limited number of clusters rather than for hundreds of individual segments, thus making the process more efficient and manageable" (Zhang et al., 2022). Random forests, first introduced by Breiman (2001), are one of the most commonly used machine learning techniques with a reputation for good prediction accuracy. The GRF approach as implemented in the Phase I study allowed for modeling the enormous amounts of TMC data with no need for performing clustering as an interim step of the reliability analysis. The models were developed and tested using INRIX commercial data from 2017-2019. It was found that the GRF models performed better than LQMMs at predicting the federally mandated level of travel time reliability (LOTTR) measure (as well as the 80th and 50th percentiles of travel times) and performed only slightly worse at predicting the 90th percentile. Therefore, the GRF approach was preferred over LQMMs for reliability prediction. For VDOT to apply the GRF approach for successfully predicting TTR, the Phase I study provided three recommendations:

1. VTRC should develop detailed step-by-step data preparation and modeling guidance for relevant VDOT divisions and the Office of Intermodal Planning and Investment (OIPI).

2. VTRC should conduct additional research to meet the requirements of MAP-21 federal target setting, including expansion of the GRF models to use the NPMRDS, extension to weekday midday and weekend periods, and expansion of the GRF approach to cover the non-interstate National Highway System.

3. VDOT's Traffic Engineering Division and Operations Division should explore new data sources that could augment or improve existing data sources that were identified as having limitations, such as weather data and work zone information.

This implementation study addressed Recommendation 1 and the parts of Recommendation 2 pertaining to the interstate system.

PURPOSE AND SCOPE

The purpose of this implementation study was to achieve the following objectives:

- Adapt and apply the GRF approach developed for peak periods using the INRIX TMC network in the Phase I study to the NPMRDS network and confirm, if as expected, the value in developing new models customized for the NPMRDS network.

- Expand the GRF approach to cover the weekday midday and weekend daytime periods using NPMRDS while simultaneously exploring the best way to incorporate two specific sets of data into the GRF approach: operational data (presence of Safety Service Patrol [SSP] and parallel managed lanes) and data reflecting shoulder and lane closures due to work zones.

- Develop detailed step-by-step data preparation and modeling guidance for relevant VDOT divisions and OIPI so that they can use the GRF approach developed in both this study and the Phase I study for predicting TTR.

The scope of the study was limited to interstate highways in Virginia.

BACKGROUND

Overview of Phase I Study

The methodology and major results from the Phase I study formed the framework for this implementation study. This section provides a summary of relevant portions of the Phase I study to provide background and context for the information discussed in the current study.

The VTRC report *Methods to Analyze and Predict Interstate Travel Time Reliability*, by Zhang et al. (2021b), described a study designed to develop a method to analyze and predict TTR on interstate highways. Using data collected in Virginia from 2017-2019, the study developed models to estimate the 50th, 80th, and 90th percentiles of travel times at the TMC level to quantify the effects of TTR impact factors and predict select reliability measures.

First, LQMMs were built using both data maintained by VDOT and crowdsourced event data. To enhance efficiency and make the process more manageable, segments were partitioned into approximately homogeneous clusters based on the similarity of their travel time CDFs. A single LQMM model was then fit to the data in each cluster. Model results using the crowdsourced data were unstable and difficult to interpret because of data quality issues such as unbalanced spatial density, duplicate reporting, and inconsistent event classification because of individual observer bias. The results using VDOT-maintained data were more reliable and interpretable. Those models showed that frequencies of non-recurrent events, such as incidents and weather, were correlated with higher travel time percentiles. The LQMM was compared with the trend line approach, a common prediction method used in practice, and the results showed that LQMMs significantly improved the accuracy of predictions over the trend line approach based on mean absolute percent error.

Second, GRF models were tested as an alternative prediction method. GRF models improved the prediction accuracy over LQMMs for the 50th and 80th percentiles, but the accuracy was slightly worse than LQMMs for the 90th percentile. In addition, the GRF models could also reflect the impact of variables that were removed from LQMMs because of insignificance, such as the presence of SSPs. Further, it was not necessary to cluster TMC segments into homogeneous groups with similar shapes of travel time distributions when using random forests, thus helping to reduce the work required to format data prior to modeling.

Third, before-after studies were conducted to illustrate the application of LQMMs and GRF models. Both models accurately captured actual changes in reliability created by improvement projects. GRF models were more sensitive to the reliability changes caused by non-recurrent events, such as incidents or work zones.

The study recommended that VDOT use the GRF model for predicting TTR on interstate highways. A brief description of the GRF method is provided here to provide the context for its application in this implementation study. A more detailed description is provided in Athey et al. (2019) and the Phase I study report (Zhang et al., 2021b).

Random Forest Models

Random forests, first introduced by Breiman (2001), are one of the most commonly used machine learning techniques with a reputation for good prediction accuracy and the capacity to handle large numbers of predictor variables even in the presence of complex interactions. The essential idea of random forests is to generate an ensemble of trees through bootstrap (or subsample) aggregation whereby each tree is grown on a different random subset of the training data. Individual trees are grown by recursively splitting the feature space into regions containing observations with similar values of the response variable. Each split seeks to maximize the improvement to model fit, e.g., by choosing the variable and threshold value that minimizes the sum of squared residuals. A random selection process that restricts the variables available at each step of the algorithm provides additional randomness in the trees. The prediction of the conditional mean is obtained by averaging the response across the ensemble of trees.

Generalized Random Forests

GRF is a method for nonparametric estimation that applies to an array of statistical estimation tasks including non-parametric quantile regression, conditional average partial effect estimation, and heterogeneous treatment effect estimation. It shares several attributes with the standard random forest algorithm including subsampling, recursive partitioning, and random split selection. However, whereas the standard random forest algorithm obtains the final estimate by averaging estimates from each member of an ensemble, the GRF estimate is based on a weighted average. Individual tree weights are derived as a type of adaptive nearest neighbor estimator by “averaging neighborhoods implicitly produced by different trees” (Athey et al., 2019). The node splitting rules are designed to seek trees that when combined into a forest induce weights that lead to “good” estimates able to capture heterogeneity in the target parameter. GRF for quantile estimation (Athey et al., 2019) uses the moment conditions in the form of Equation 1 to identify the best split that maximizes the heterogeneity of quantiles of interest among the child nodes.

$$\psi_{\theta}(Y_i) = q1(\{Y_i > \theta\}) - (1-q)1(\{Y_i \leq \theta\}) \qquad \text{[Eq. 1]}$$

where q is the estimated quantile, θ is the estimation a tX_i, and Y_i is the observation atX_i.

Application of GRF to Travel Time Reliability Prediction

Data used for the analysis were for the morning and afternoon peak traffic periods (6 to 10 AM; 4 to 8 PM) for the years 2017-2019. Probe travel times were obtained from INRIX. The probe travel times were based on TMC segments. The model input variables were as follows:

- Segment length (mile)
- Number of through lanes (count)
- Frozen precipitation (inches)
- Rain precipitation (inches)
- Number of fatal and severe injury crashes (count)
- Number of visible injury crashes (count)
- Number of nonvisible injury crashes (count)
- Number of property damage only crashes (count)
- Number of work zone shoulder closures (count)
- Number of work zone lane closures (count)
- Number of breakdown incidents (count)
- Number of hazard incidents (count)
- Area type (1 if rural, 0 otherwise)
- Volume to capacity ratio (ratio)
- Presence of parallel HOV/Express lanes (1 if present, 0 otherwise)
- Heavy vehicle percentage (percent)
- Availability of SSP (1 if available, 0 otherwise).

The assembled data were used to develop GRF models to predict the 50th, 80th, and 90th percentiles of travel times separately for freeway segments and interchange segments. The models were constructed using different values of model parameter *mtry*—the number, on average, of candidate variables available for node splitting of random forests. It was found that prediction accuracy increased with increasing values of *mtry* and models with *mtry* equal to the total number of variables performed best. The results tended to be more accurate for freeway segments than for interchange segments, and the prediction accuracy decreased as the travel time percentile being predicted increased.

Overall, the GRF performed better than the alternative method evaluated in the Phase I study, i.e., LQMMs, and was preferred over LQMMs for reliability prediction.

METHODS

This implementation study included four major tasks:

- Task 1: Collect and prepare data.

- Task 2: Evaluate the performance of the "INRIX-trained" GRF models with NPMRDS.

- Task 3: Develop and evaluate new GRF models using NPMRDS.

- Task 4: Develop a data preparation and modeling guide.

Task 1: Collect and Prepare Data

This task involved collecting and preparing the data needed to expand the GRF approach developed in the Phase I study to use NPMRDS and to cover all four MAP-21 analysis periods. Those periods are defined as:

- AM: 6 AM to 10 AM on weekdays
- Midday: 10 AM to 4 PM on weekdays
- PM: 4 PM to 8 PM on weekdays
- Weekend: 6 AM to 8 PM on weekends.

Three years of data (2017-2019) were used. Major data elements and sources included the following:

- NPMRDS travel times and TMC segment metadata

- Traffic volumes, roadway geometry, incidents, work zones, managed lanes, and SSP data from internal VDOT databases

- Weather data from the Local Climatological Data provided by the National Centers for Environmental Information.

In addition to the model variables used in the Phase I study, this study collected additional information to explore new variable forms for work zones, parallel managed lanes, and SSPs that might better reflect their temporal and spatial features. Table 1 lists the variables considered in this study. In the Phase I study, work zone variables included the numbers of shoulder closures and lane closures (work zone variable option C in Table 1). To consider the impact of work zone duration, the fractions of time when there was a shoulder closure / lane closure due to a work zone (work zone variable option P in Table 1) were calculated. As the work zone shoulder and lane closures events are not directly available from VDOT's work zone database, the number of lanes affected by work zones (closed or narrowed) and the total number of lanes, which are readily available from VDOT's work zone database, were used to calculate new work zone variables (work zone variable options L and LP in Table 1).

The data conflation procedure developed in the Phase I study was used to assemble data from multiple sources. The NPMRDS TMC segment was used as the spatial unit of analysis. Datasets with a temporal dimension (such as travel time, traffic volumes, and incidents) were first aggregated at an hourly level. Three types of data aggregations were used to create datasets for analysis:

1. Type 0: Data were aggregated at an hourly level.

2. Type 1: Data were aggregated at a "whole-period" level for each of the four analysis periods. For example, the data would be aggregated from 6 AM to 10 AM on each weekday for the AM peak period. As with the Phase I study, the SSP and parallel managed lanes indicator variables were set to 1 if SSP and parallel managed lanes were present in any hour of the analysis period (option 1 for managed lanes and SSP in Table 1).

3. Type 2: Data were aggregated at a whole-period level such as type 1 aggregation, but the fraction of time when SSP/ parallel managed lanes were in operation during the whole period was calculated (option 2 for managed lanes and SSP in Table 1).

Table 1. Variables Considered for GRF Models

Variable Category	Variable		Variable Name
Geometric features	Segment length (miles)		miles
	Number of through lanes (count)		throu_lane
Managed lanes	Option 1	Presence of parallel managed lanes (presence=1, otherwise=0)	Par_lane
	Option 2	Fraction of time when parallel managed lanes are present (decimal)	Par_lane_r
Area type	Area type (urban=0, rural=1)		rural
Weather	Frozen precipitation (inches)		frozen_precip
	Rain precipitation (inches)		rain_precip
Incident	Frequency of fatal and severe injury crashes (count)		Severe_Injury
	Frequency of visible injury crashes (count)		Visible_Injury
	Frequency of nonvisible injury crashes (count)		Nonvisible_Injury
	Frequency of property damage only crashes (count)		PDO
	Frequency of breakdown incidents (disabled vehicles) (count)		breakdown
	Frequency of hazard incidents (fire related) (count)		hazard
Work zone	Option C	Number of shoulder closure work zones (count)	shoulder_closure
		Number of lane closure work zones (count)	lane_closure
	Option P	Fraction of time when there was a shoulder closure due to work zone (decimal)	shoulder_closure_r
		Fraction of time when there was a lane closure due to work zone (decimal)	lane_closure_r
	Option L	Number of lanes affected (count)	lane_affected
	Option LP	Fraction of lanes affected (decimal)	lane_affected_r
Traffic demand	Volume-to-capacity ratio (decimal)		vc_ratio
	Percentage of heavy vehicles (decimal)		heavy_percent
Safety Service Patrol (SSP)	Option 1	Presence of SSP (present=1, otherwise=0)	ssp
	Option 2	Fraction of time when SSP is present (decimal)	ssp_r

Task 2: Evaluate the Performance of the INRIX-Trained GRF Models With NPMRDS

This task applied the GRF models developed for weekday peak traffic periods (6 AM to 10 AM and 4 PM to 8 PM) based on the INRIX TMC segments in the Phase I study to NPMRDS segments and evaluated their performance. The models trained in the Phase I study were directly used to predict the 50th, 80th, and 90th percentiles of travel times using NPMRDS segments. The main purpose of this task was to assess the transferability of the Phase I GRF models to NPMRDS segments. The prediction accuracy was evaluated using performance measures including mean absolute error (MAE), mean absolute percentage error (MAPE), mean squared error (MSE), and bias (the average difference between predictions and observations).

Task 3: Develop and Evaluate New GRF Models Using NPMRDS

This task developed a new set of GRF models for all MAP-21 analysis periods using NPMRDS travel time data. As in the Phase I study, separate models were created for freeway mainline segments and interchange segments. For each of the four analysis periods, GRF models were trained using data aggregated at the hourly level and the whole-period level to identify the best modeling approach. This is in contrast to the Phase I models, which were trained solely at the whole-period level. In addition, a single model for all analysis periods together, with period specified as an indicator variable, was explored.

The GRF models were evaluated using MAE, MAPE, MSE, and bias. An average score using these four measures was calculated for each model and each predicted travel time percentile to rank the models, and then the best-performing models were selected.

Task 4: Develop Data Preparation and Modeling Guide

This task developed a step-by-step guidance document for VDOT divisions and OIPI so that they could use the GRF models for predicting TTR on interstates. This document includes specific information on data sources used, data formatting, and data conflation methods. This task also prepared the code scripts to apply the proposed GRF models.

RESULTS AND DISCUSSION

Data Collection and Preparation

Three datasets were created for developing and analyzing GRF models for this study. One was the dataset aggregated at the hourly level; the summary statistics are given in Table 2. The other two were datasets aggregated at the whole-period level using the type 1 and type 2 aggregation approaches described in the "Methods" section. In each of the three datasets, four sets of work zone variables (options C, P, L, and LP) were included.

Performance of Phase I GRF Models With NPMRDS Data

The Phase I study trained GRF models using data for 2017 and 2018 to predict the percentile of travel times on INRIX TMC segments for weekday peak traffic periods (6 AM to 10 AM, 4 PM to 8 PM). The models trained in the Phase I study were directly used to predict the 50th, 80th, and 90th percentiles of travel times for INRIX TMC and NPMRDS segments in 2019. The work zone variables used here are the number of work zone lane closures and the number of work zone shoulder closures (work zone option C).

Table 2. Summary of Variables Aggregated at the Hourly Level

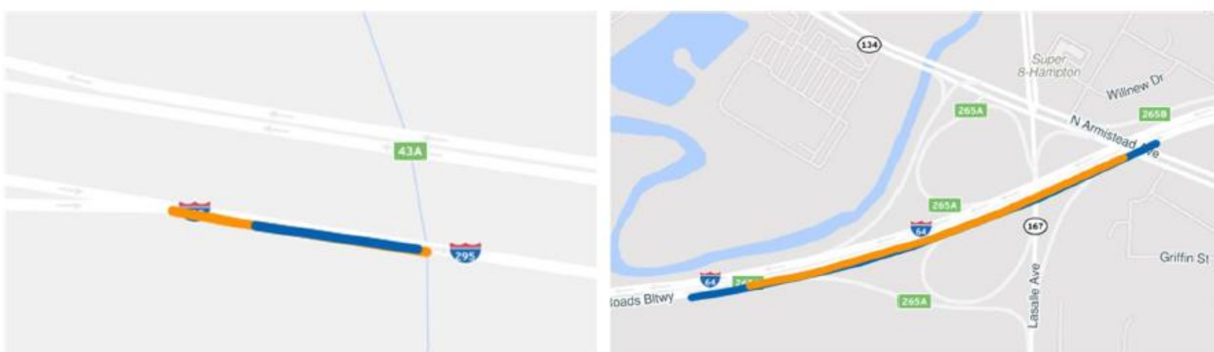
Variable	Freeway Segments				Interchange Segments			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
Segment length (miles)	2.219	2.003	0.100	9.034	0.488	0.249	0.100	2.074
Number of through lanes (count)	2.571	0.770	1.000	5.000	2.566	0.757	1.000	5.000
Frozen precipitation (inches)	0.000	0.005	0.000	5.090	0.000	0.005	0.000	5.090
Rain precipitation (inches)	0.004	0.040	0.000	8.470	0.004	0.040	0.000	8.470
Frequency of fatal and severe injury crashes (count)	0.000	0.010	0.000	3.000	0.000	0.006	0.000	1.000
Frequency of visible injury crashes (count)	0.000	0.022	0.000	4.000	0.000	0.016	0.000	3.000
Frequency of nonvisible injury crashes (count)	0.000	0.008	0.000	2.000	0.000	0.006	0.000	2.000
Frequency of property damage only crashes (count)	0.002	0.044	0.000	5.000	0.001	0.031	0.000	4.000
Number of shoulder closure work zones (count, option C)	0.058	0.235	0.000	1.000	0.044	0.205	0.000	1.000
Fraction of time when there was work zone shoulder closure (decimal, option P)	0.058	0.231	0.000	1.000	0.044	0.202	0.000	1.000
Number of lane closure work zones (count, option C)	0.020	0.142	0.000	1.000	0.016	0.126	0.000	1.000
Fraction of time when there was work zone lane closure (decimal, option P)	0.020	0.138	0.000	1.000	0.016	0.123	0.000	1.000
Number of lanes affected (count, option L)	0.161	0.725	0.000	13.000	0.127	0.657	0.000	13.000
Fraction of lanes affected (decimal, option LP)	0.019	0.083	0.000	1.000	0.014	0.075	0.000	1.000
Frequency of vehicle breakdown incidents (count)	0.008	0.091	0.000	5.000	0.002	0.046	0.000	3.000
Frequency of hazard incidents (fire related) (count)	0.000	0.012	0.000	2.000	0.000	0.007	0.000	2.000
Area type (urban=0, rural=1)	0.373	0.484	0.000	1.000	0.355	0.478	0.000	1.000
Volume-to-capacity ratio (decimal)	0.430	0.226	0.013	2.714	0.439	0.230	0.014	2.859
Presence of parallel managed lanes (present=1, otherwise=0)	0.070	0.255	0.000	1.000	0.072	0.258	0.000	1.000
Percentage of heavy vehicles (decimal)	0.128	0.049	0.001	0.546	0.127	0.046	0.004	0.534
Presence of Safety Service Patrol (present=1, otherwise=0)	0.619	0.486	0.000	1.000	0.625	0.484	0.000	1.000

Table 3 shows the prediction performance of the Phase I GRF models using input data assembled for INRIX TMC segments in the Phase I study and the input data for NPMRDS segments aggregated at the whole-period level (type 1) for peak traffic periods. As shown in Table 3, the model trained in Phase I performed better for INRIX TMC segments than for NPMRDS segments. This was not surprising as the two datasets had differences in roadway segmentation and travel time data. Although both networks have data coverage on all interstates, the roadways may be separated into TMCs differently on the NPMRDS and INRIX TMC networks. Figure 1 shows examples of TMC segments on these two networks in 2017.

Table 3. Performance of Phase I Models for Peak Traffic Periods

Segment Type	Freeway Segments		Interchange Segments	
	INRIX TMC	**NPMRDS TMC**	**INRIX TMC**	**NPMRDS TMC**
50th Percentile Travel Time				
MAE	6.15	10.48	2.31	35.13
MSE	140.83	737.16	33.61	6668.70
MAPE	6.73	9.06	7.65	20.81
Bias	-0.48	-8.22	-0.78	-33.22
80th Percentile Travel Time				
MAE	14.22	16.73	7.48	39.07
MSE	886.5	1187.77	345.89	6987.77
MAPE	14.68	19.07	17.34	32.99
Bias	-0.11	1.64	-1.95	-27.18
90th Percentile Travel Time				
MAE	22.14	30.54	11.73	45.32
MSE	1555.32	2158.01	496.10	7162.83
MAPE	25.21	38.24	33.83	56.99
Bias	7.17	16.85	2.59	-16.32

MAE = mean absolute error; MSE = mean squared error; MAPE = mean absolute percentage error.



(a) (b)

Figure 1. Example of NPMRDS (Blue Lines) and INRIX (Orange Lines) Segments: (a) NPMRDS segment shorter than overlapping INRIX segment; (b) NPMRDS segment longer than overlapping INRIX segment.

In Figure 1a, the INRIX TMC segment (orange line) is longer than the NPMRDS segment (blue line) and it includes the merging area; in Figure 1b, the NPMRDS segment is longer. The NPMRDS network included fewer segments than the INRIX TMC network for interstates in Virginia in the studied years. The travel times for NPMRDS and INRIX networks were generated from the same probe data sources, but the NPMRDS dataset did not use imputed data. In general, a model would be expected to perform better on the population for which it was trained than on a different population.

The GRF models trained in the Phase I study for peak traffic periods were also used to predict the 50th, 80th, and 90th travel time percentiles for other periods for the NPMRDS segments. The MAPEs of the predictions are shown in Figure 2. Generally, the MAPE was lower for the AM period, indicating relatively higher accuracy.

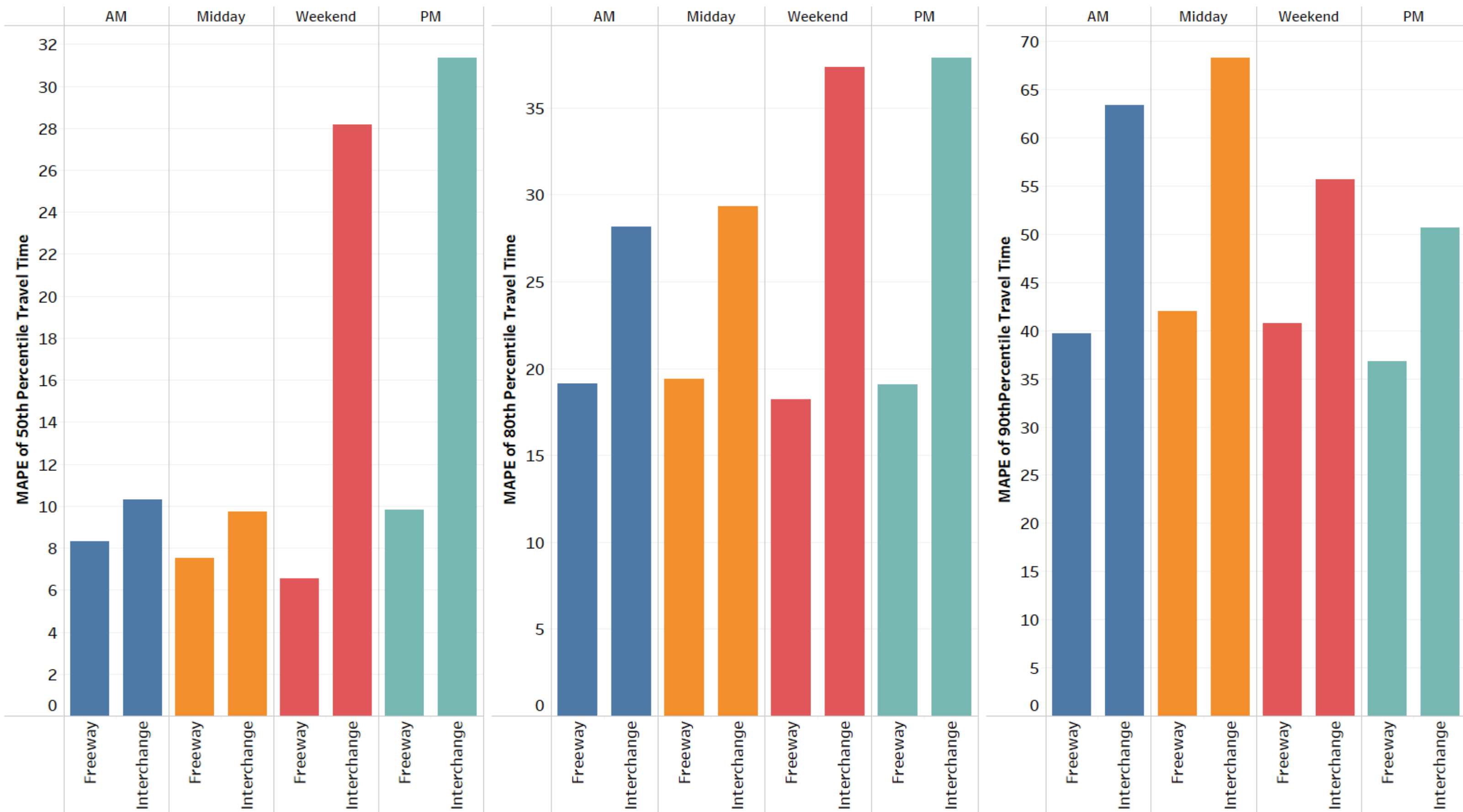


Figure 2. Mean Absolute Percent Error (MAPE) of Phase I Models' Predictions for NPMRDS Segments

The MAPEs for freeway segments were lower than for interchange segments. For freeway segments, the differences in MAPE were within 10% of one another across all analysis periods. For interchange segments, the MAPEs of the 50th and 80th percentile travel times were much higher for the weekend and PM periods than for other periods. For the 90th percentile travel time on interchange segments, the MAPEs were higher for the AM and midday periods. Other performance measures showed similar trends. The values of other performance measures are provided in Appendix A. As with the Phase I study, the prediction accuracy for the 50th percentile travel time was higher than for the 80th and 90th percentile travel times. The Phase I models performed reasonably well in predicting the 50th percentile travel time for freeway segments. However, for interchange segments, the prediction performance was relatively poorn even for the 50th percentile. Therefore, it was decided that there was value in developing new models using the NPMRDS network.

GRF Models for NPMRDS Data

A new set of GRF models was developed to predict TTR on the NPMRDS network using NPMRDS data to train the models. Different data aggregation and variable definition options for capturing the potential effects of work zone lane/shoulder closures on TTR were also explored.

Model Development

GRF models were developed using three datasets assembled using different aggregation approaches for the NPMRDS segments discussed earlier. The data for 2017 and 2018 were used for training, and the data for 2019 were used for testing. Based on the results of the Phase I study and preliminary analysis using the NPMRDS dataset, the GRF model parameter *mtry*, the number of variables tried for each split, was set to the total number of variables. Although there are other model tuning parameters, such as the minimum number of observations in a leaf node and the number of total trees, they contribute a minimal amount to prediction changes (Probst et al., 2019). For these parameters, the commonly used values were adopted. The minimum node size was set to 10, and the number of trees was 2,000 for all models.

Separate GRF models were created for freeway mainline segments and interchange segments. The GRF models trained included the following:

- *Period-specific models for each of the four analysis periods.* For each analysis period, GRF models were separately trained with three datasets aggregated at the hourly level (data aggregation type 0) and the whole-period level (data aggregation type 1 and type 2, respectively). With each dataset, four models were trained for each period using input data with different work zone variables (options C, P, L, and LP).

- *A single model for all analysis periods combined together, with each period specified as an indicator variable.* Similar to the models for individual periods, different single models were separately trained with datasets aggregated using the three different approaches. With each dataset, four models were trained using input data with different work zone variables.

Model Performance

The set of GRF models were tested using data for 2019. For each model, the 50th, 80th, and 90th percentile travel times were estimated, and the LOTTR was calculated as the ratio of the 80th percentile over the 50th percentile. Performance measures, including MAE, MAPE, MSE, and bias, were calculated for each model and for each predicted percentile. The values of the performance measures are provided in Appendix B. Due to the large model size and long computing time, the single model using hourly data was deemed to be inappropriate for implementation by VDOT, and the results of that model are not included in this report.

Comparison With Phase I Models

The performance of Phase I models and the period-specific models developed in the current study is compared in Figure 3. The left side of the figure shows the MAPEs of the 50th, 80th, and 90th percentile travel times on NPMRDS segments predicted using GRF models developed using INRIX data in Phase I, and the right side shows the MAPEs of predictions using period-specific models trained using NPMRDS data aggregated at the whole-period level (type 1). The work zone variables in the period-specific models are the same as the Phase I model (work zone option C), and data were aggregated at the hourly level (type 0). The NPMRDS period-specific models performed much better than the Phase I models. The prediction accuracy was significantly improved (by as much as 50% in some cases) for all three predicted travel time percentiles. This was consistent with expectations and supports the belief stated earlier that there may be value in training the GRF with data assembled for NPMRDS if TTR predictions are to be made for the NPMRDS network.

The accuracy of PM period models was relatively lower than for models for the other three periods, and the PM period is also the period that probably exhibits the most variability in travel times. Nevertheless, the results were generally better than with the Phase I models, even for the PM period. In particular, when PM models built from INRIX training data (from 2017-2018) in Phase I were applied to testing data (using 2019 NPMRDS data), the MAPE for the 50th percentile travel time was roughly 10% for freeway segments and 31% for interchange segments. The new period-specific GRF models—trained from NPMRDS data (from 2017-2018) and applied to 2019 NPMRDS data—yielded comparable performance for freeway segments and significant improvement for interchange segments. They had an average MAPE of 9% for freeway segments and 10% for interchange segments, depending on how work zones were characterized and how data were aggregated in the new models (see details in Appendix B). In addition, the new GRF models showed significant improvement when the 90th percentile travel time was considered. Whereas the INRIX models showed an average MAPE of 37% and 51% for freeway and interchange segments, respectively, for the PM peak hours, the new GRF models showed an average MAPE of 34% for freeway segments and 38% for interchange segments. Because operational improvements are often evaluated based on how they improve reliability, with reliability commonly based on how the 90th percentile travel time is affected, the new GRF models can be valuable for planning operational investments.

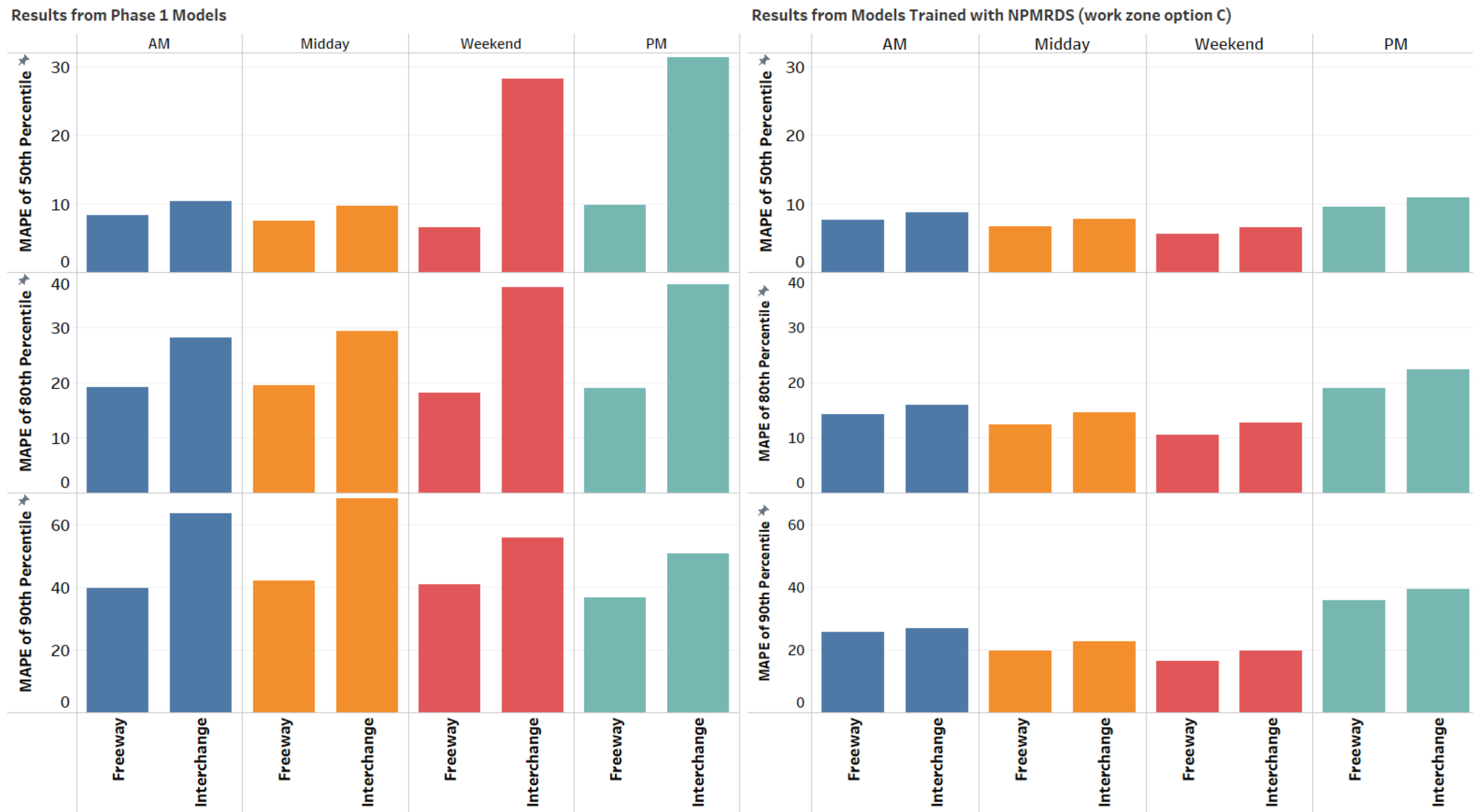


Figure 3. Mean Absolute Percent Error (MAPE) of Predictions for NPMRDS Segments

Model Selection

More than 200 models were tested. Models were evaluated based on how well they performed on the testing dataset in predicting the 50th, 80th, and 90th percentile travel times. To select the best-performing models, GRF models were ranked by MAE, MAPE, MSE, and bias for each segment type (freeway and interchange) and analysis period. A model's performance in predicting a specific travel time percentile (e.g., the 50th percentile) was determined by the average ranking based on all four performance measures. An aggregate ranking for each model was obtained by averaging across the three predicted percentiles.

The top five ranked period-specific models for each segment type and analysis period are shown in Table 4. For single models that predict the 50th, 80th, 90th percentile travel times for all analysis periods at the same time, the models were ranked for each period based on the aggregated rankings of each model. The top four ranked single models for each analysis period are listed in Table 5.

Table 4. Top 5 Period-Specific Models for Each Analysis Period

	Freeway Segments			Interchange Segments		
Predicted Period	**Ranking**	**Work Zone Variable Option**	**Data Aggregation Type**	**Rank**	**Work Zone Variable Option**	**Data Aggregation Type**
AM	1	C	0	1	P	0
	2	LP	0	2	LP	0
	3	L	2	3	C	2
	4	P	0	4	C	0
	5	C	2	5	P	2
Midday	1	C	1	1	C	2
	2	P	0	2	P	1
	3	C	0	3	LP	0
	4	C	2	4	C	1
	5	LP	0	5	P	0
Weekend	1	P	0	1	C	0
	2	LP	0	2	P	1
	3	L	0	3	P	0
	4	C	1	4	L	0
	5	L	1	5	LP	1
PM	1	C	0	1	P	2
	2	L	0	2	P	0
	3	LP	0	3	L	1
	4	LP	1	4	P	1
	5	P	0	5	C	0

Work zone variable option: C = count of work zone lane/shoulder closures; L= number of lanes affected; LP = fraction of lanes affected; P = fraction of time when there was a lane/shoulder closure due to the work zone. *Data aggregation type:* 0 = data were aggregated at the hourly level; 1 = data were aggregated at the whole-period level for each of the four analysis periods with the Safety Service Patrol (SSP) and parallel managed lanes indicator variables set to 1 if SSP and parallel managed lanes were present in any hour of the analysis period; 2 = data were aggregated at the whole-period level as with type 1 aggregation but the fraction of time when SSP / parallel managed lanes were in operation was calculated.

Table 5. Top 4 Single GRF Models for Each Analysis Period

Predicted Period	Freeway Segments			Interchange Segments		
	Ranking	**Work Zone Variable Option**	**Data Aggregation Type**	**Rank**	**Work Zone Variable Option**	**Data Aggregation Type**
AM	1	LP	2	1	L	1
	2	L	2	2	P	2
	3	C	2	3	P	1
	4	P	2	4	C	1
Midday	1	LP	2	1	L	1
	2	P	2	2	C	2
	3	L	2	3	LP	2
	4	C	1	4	LP	1
Weekend	1	L	2	1	L	1
	2	LP	2	2	C	2
	3	C	2	3	LP	2
	4	P	2	4	P	2
PM	1	LP	2	1	L	2
	2	L	2	2	C	2
	3	P	2	3	LP	2
	4	C	2	4	P	2

Work zone variable option: C = count of work zone lane/shoulder closures; L= number of lanes affected; LP = fraction of lanes affected; P = fraction of time when there was a lane/shoulder closure due to the work zone. *Data aggregation type:* 0 = data were aggregated at the hourly level; 1 = data were aggregated at the whole-period level for each of the four analysis periods with the Safety Service Patrol (SSP) and parallel managed lanes indicator variables set to 1 if SSP and parallel managed lanes were present in any hour of the analysis period; 2 = data were aggregated at the whole-period level as with type 1 aggregation but the fraction of time when SSP / parallel managed lanes were in operation was calculated.

From Table 4, the period-specific models trained using the hourly datasets (data aggregation type 0) with the work zone variables defined by fraction of lanes affected (option LP) or fraction of time when there was a work zone lane/shoulder closure (option P) had relatively higher rankings for all analysis periods. The differences in prediction accuracy between the period-specific models trained using work zone variable options LP and P were not considerable. As shown in Figure 4, the differences in MAPE for models trained with work zone variables option LP and P were around 1% for all analysis periods and all three predicted travel time percentiles. Differences in other performance measures (see Appendix B) showed similar trends.

From Table 5, for all analysis periods, the single GRF models trained with the dataset created using type 2 aggregation (whole-period level aggregation; SSP and managed lanes variables are set equal to the fraction of time present in the analysis period) ranked relatively higher than models trained with datasets of other aggregation types. Similar to the period-specific models, single models using work zone variables defined by fraction of lanes affected (option LP) or fraction of time when there was work zone lane/shoulder closure (option P) ranked relatively higher than models using other work zone variables, and the prediction performance was similar for the single models trained with work zone variable options LP and P.

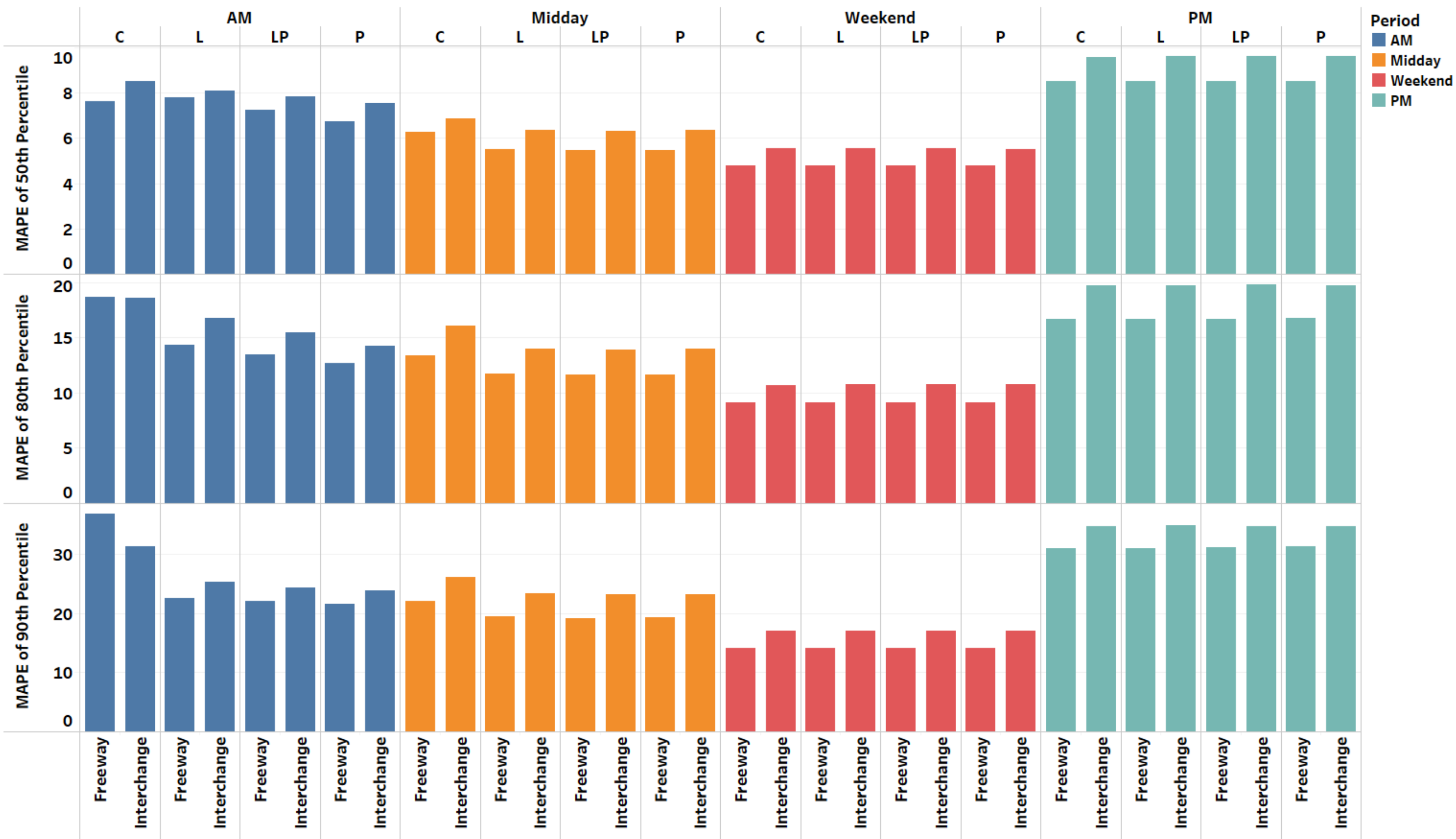


Figure 4. Mean Absolute Percent Error (MAPE) of Predictions From Period-Specific Models Using Different Work Zone Variables. Work zone variable options: C= count of lane/shoulder closure events, L= number of lanes affected, LP = fraction of lanes affected, P = fraction of time when there was lane/shoulder closure due to a work zone.

Overall, GRF models with the work zone variable defined by the fraction of lanes affected (option LP) or the fraction of time the lane or shoulder is closed (option P) occurred more frequently in the top five and may be more desirable. Using the fraction of lanes affected variable may be especially appealing as it is readily obtained from VDOT's work zone database (by dividing the number of lanes affected by the total number of lanes) and less data preparation effort is required compared to using the fraction of time the lane/shoulder is closed.

With regard to the data aggregation approach, the period-specific models frequently performed better when an hourly level aggregation was used with the indicator variables of SSP and parallel managed lanes set equal to 1 if present at any time within the hour (data aggregation type 0). For the single models, aggregating data over the constituent analysis periods with the SSP and parallel managed lanes variables set equal to the fraction of time present in the analysis period (data aggregation type 2) tended to give better performance.

Figures 5 and 6 show the MAPEs for predictions of the 50th, 80th, and 90th percentile travel times using the period-specific models trained with hourly data and the single models trained with data aggregated at the whole-period level (data aggregation type 2). For both figures, the work zone variable is modeled by the fraction of lanes affected (type LP).

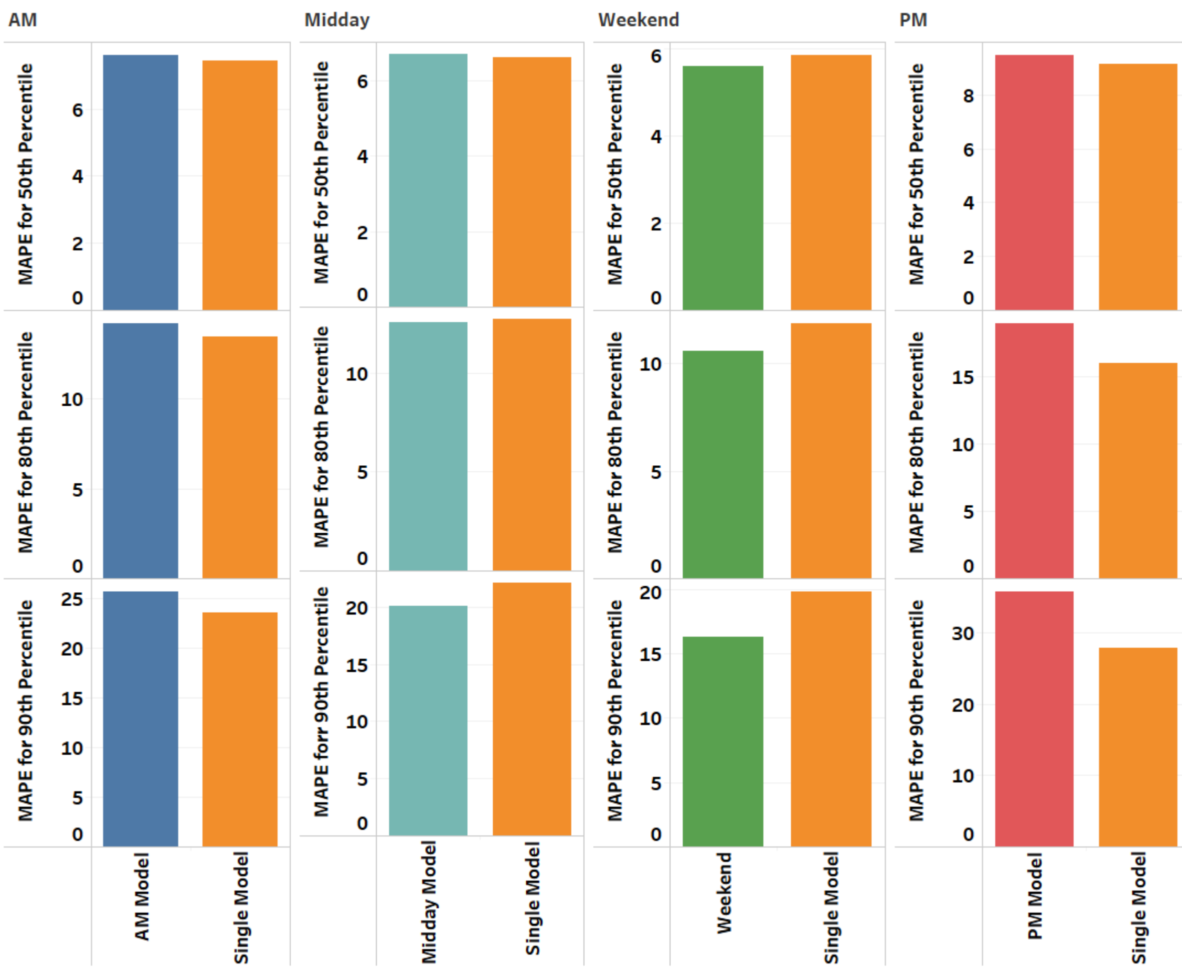


Figure 5. Mean Absolute Percent Error (MAPE) of Models for Freeway Segments

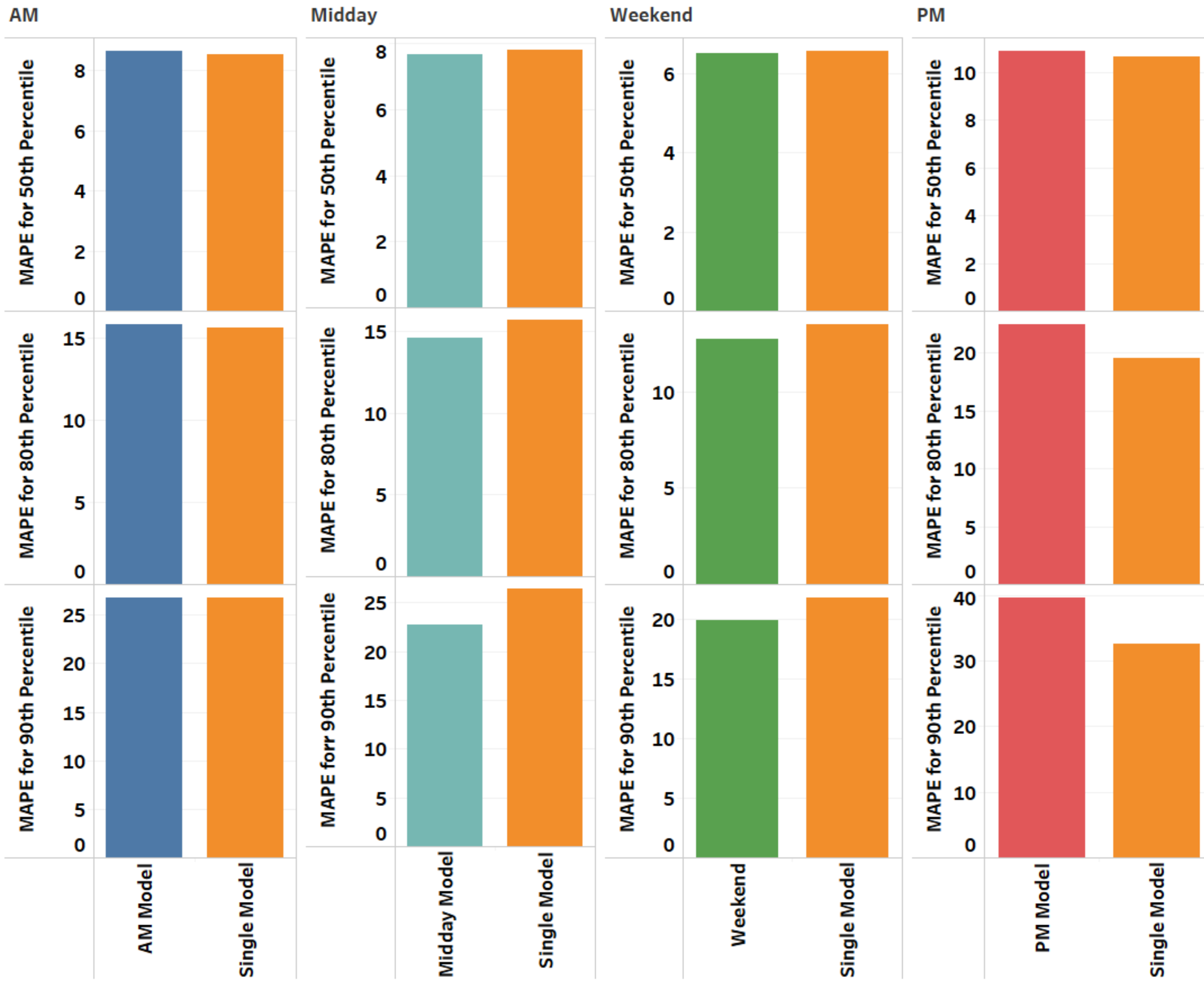


Figure 6. Mean Absolute Percent Error (MAPE) of Models for Interchange Segments

From Figures 5 and 6 it can be seen that the differences between the MAPEs of predictions from the period-specific models and the single models were within 5% in most cases, with the maximum being 7%. The MAE, MSE, and bias (see Appendix B) also indicated a similar prediction performance for the two forms of models. The distributions of errors of the two forms of models, as shown in Figures 7 through 10, were also similar. The difference in median errors of the predictions for corresponding travel time percentiles were within 1 second. These results suggest that using either (1) four period-specific models or (2) a single model with period level data aggregation results in reasonable predictions of travel time percentiles.

Because the difference in prediction accuracy is generally low, the choice of one model form over the other may be based on implementation considerations rather than accuracy. For example, the size of each individual period-specific model is smaller than for the combined model, but taken together, the period-specific models may be larger than the single model. The total computing time for the single model is also shorter than for the four periodic-specific models. In addition, because data are aggregated at the hourly level, the overall data input size is larger for the period-specific models than for the single model.

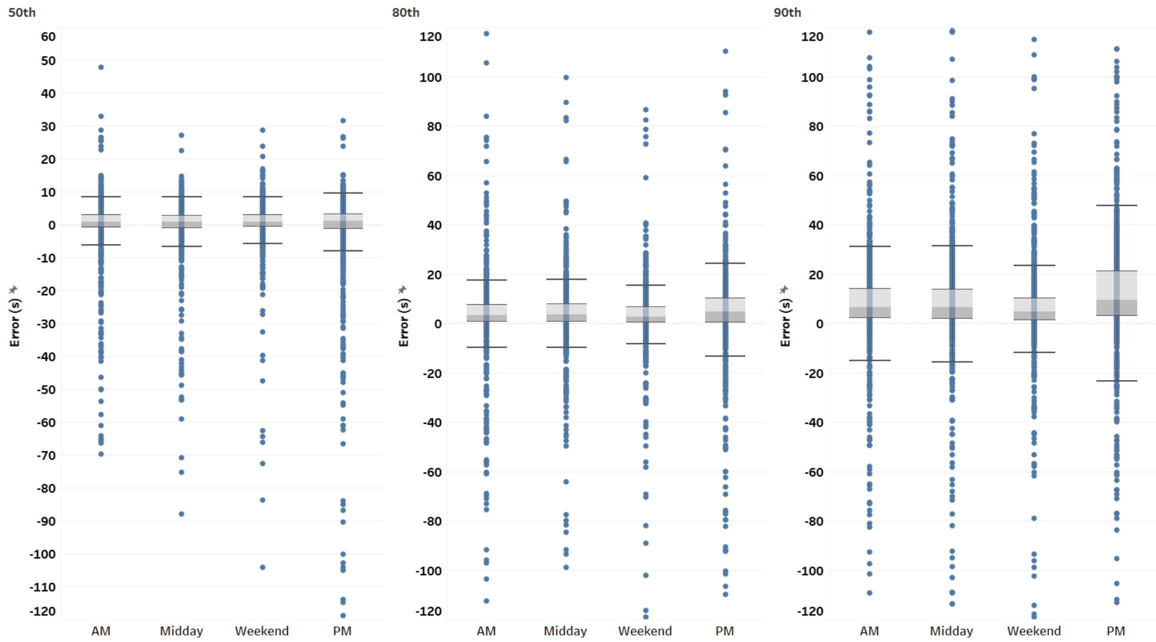


Figure 7. Box Plots of Prediction Errors of Period-Specific Models for Freeway Segments. Note that, for clarity, the y-axes were limited between -120 and 60 for the 50th percentile travel time and between -120 and 120 for the 80th and 90th percentile travel times since the distributions had longer tails.

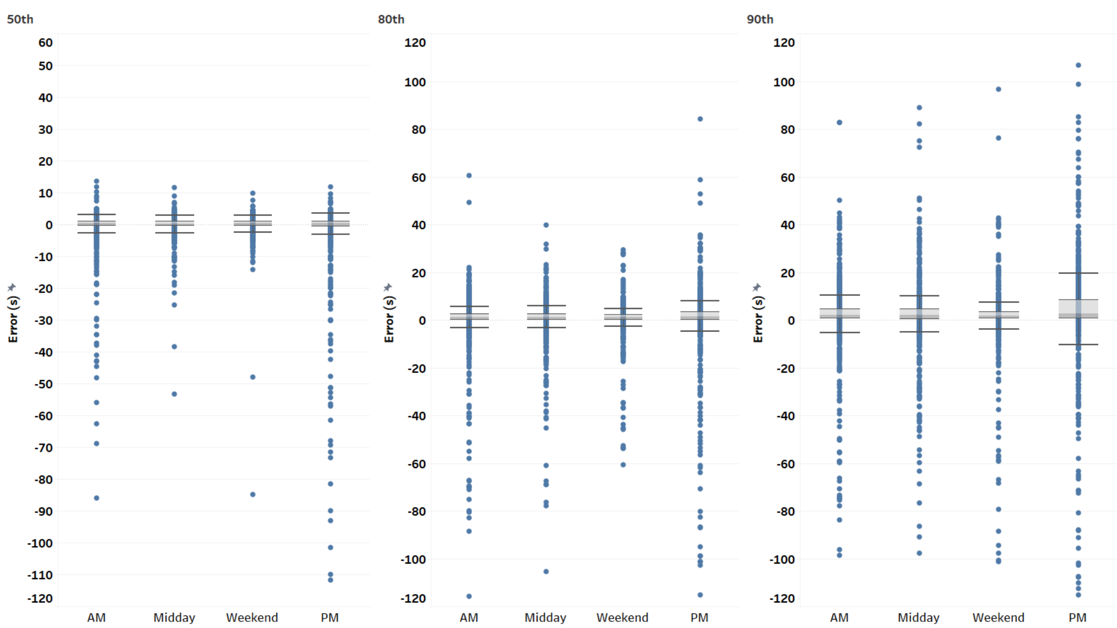


Figure 8. Box Plots of Prediction Errors of Period-Specific Models for Interchange Segments. Note that, for clarity, the y-axes were limited between -120 and 60 for the 50th percentile travel time and between -120 and 120 for the 80th and 90th percentile travel times since the distributions had longer tails.

It is worth noting that the difference in computing times and overall model size of the two forms of models were not significant for the dataset used in this study. One advantage of the periodic-specific models is that they avoid the additional data aggregation step required for the combined model. They may also be more amenable to future changes because of the use of hourly aggregation. The period-specific models were also preferred from an implementation perspective by several TRP members. Therefore, the period-specific models trained with hourly data with work zone variables defined by the fraction of lanes affected were finalized and archived for VDOT and OIPI analysts to use to predict TTR metrics.

Based on the evaluation results using the testing dataset, the period-specific GRF models are expected to produce credible TTR predictions. However, it is important that the inputs used when predictions are made do not deviate significantly from the range of inputs used for model development. When there are significant changes in the NPMRDS and/or changes in conditions that may not be reflected by the model variables, the proposed GRF models may need to be retrained with new information. One way to assess the need to retrain the models is to compare model predictions for a future year to actual values when future year data are available; an update is recommended if the realized values differ significantly from the predicted values in terms of error metrics such as MAE, MSE, MAPE, and bias.

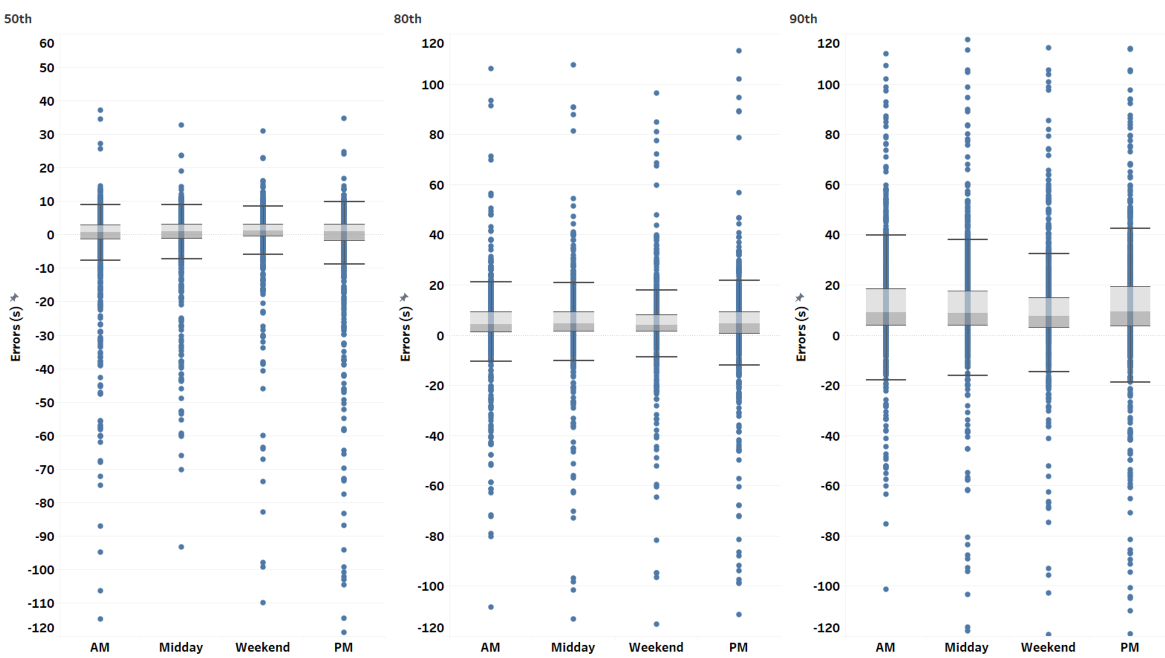


Figure 9. Box Plots of Prediction Errors of the Single Model for Freeway Segments. Note that, for clarity, the y-axes were limited between -120 and 60 for the 50th percentile travel time and between -120 and 120 for the 80th and 90th percentile travel times since the distributions had longer tails.

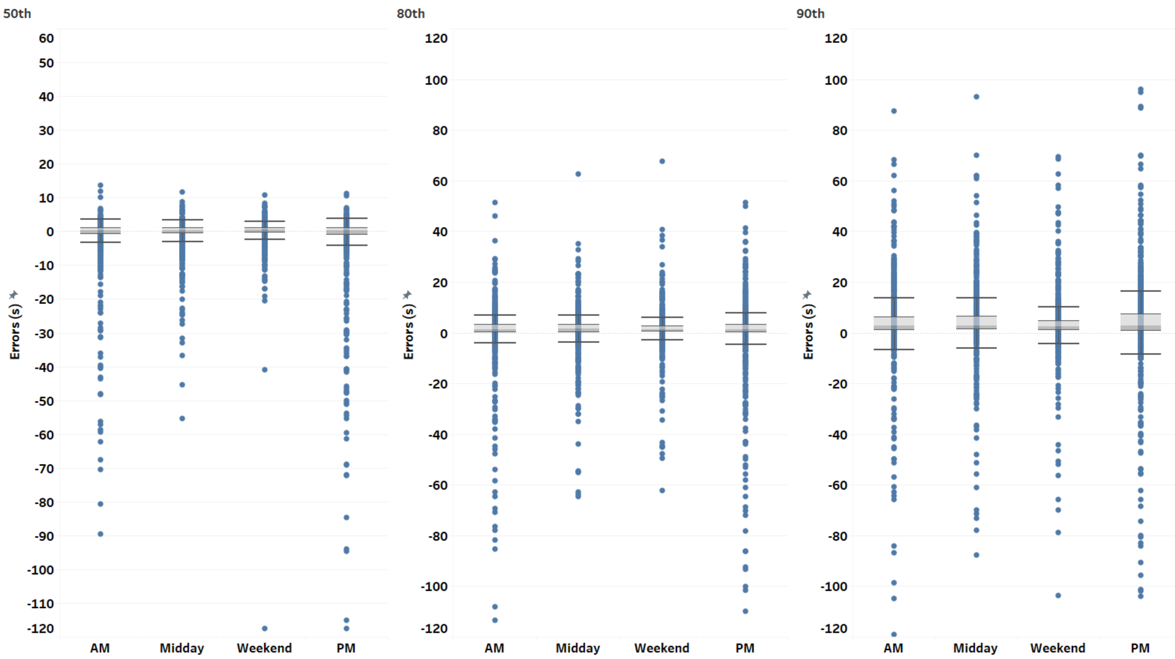


Figure 10. Box Plots of Prediction Errors of the Single Model for Interchange Segments. Note that, for clarity, the y-axes were limited between -120 and 60 for the 50th percentile travel time and between -120 and 120 for the 80th and 90th percentile travel times since the distributions had longer tails.

Data Preparation and Modeling Guide

A step-by-step data preparation and modeling guide was prepared for VDOT and OIPI analysts for the use of the period-specific GRF models to predict TTR on interstates. The guide is included as Appendix C. Code scripts to apply the GRF models for prediction are available to VDOT and OIPI users. The instruction and technical specifications of computational resources needed to run the codes were enclosed in the code scripts.

CONCLUSIONS

- *GRF models developed using the NPMRDS network performed better than the Phase I (INRIX) models for predicting TTR on the NPMRDS network.* The performance of GRF models trained with data for the INRIX TMC network for peak traffic periods in the Phase I study was generally poor for predicting TTR on the NPMRDS network, especially for the 80th and 90th percentile travel times. The GRF models trained with data assembled for the NPMRDS network significantly improved prediction performance (by as much as 50% in some cases).

- *For GRF models trained with the NPMRDS network, using either the fraction of lanes affected (option LP) or the fraction of time the lane/shoulder is closed (option P) as work zone variables resulted in better prediction performance. The fraction of lanes affected is preferred, as it is readily obtained from VDOT's work zone database.* Four different options to represent work zone variables were tested to identify the variables that could better capture the potential effects of work zones on TTR. For both the period-specific models and the single models, the models where the work zone variable was defined by the fraction of lanes affected (option LP) or the fraction of time the lane or shoulder was closed (option P) generally ranked higher among all models based on an aggregated ranking calculated for each model.

- *The period-specific models developed using hourly data with the work zone variable defined by the fraction of lanes affected were selected for implementation*. Based on performance measures, including MAE, MAPE, MSE, and bias, the prediction performance is similar (e.g., within 5% for MAPE in most cases) for the period-specific models trained using hourly data with SSP and managed lane indicator variables set to 1 if present in any time in the hour and the single model trained using data aggregated at the whole-period level with SSP and managed lane variables defined by the fraction of time SSP/managed lanes are present. The period-specific models were preferred for implementation considering the prediction accuracy, the computing resources needed, the amount of data preparation efforts required, and the flexibility to adapt to future data changes.

RECOMMENDATIONS

1. *VDOT's Traffic Operations Division, VDOT's Transportation Mobility and Planning Division, and the Office of Intermodal Planning and Investment (OIPI) should use the GRF models developed in this study to predict travel time reliability on the NPMRDS network*. The data preparation and modeling guidance should be followed to prepare model input data and make predictions.

IMPLEMENTATION AND BENEFITS

Implementation

VTRC provided the step-by-step guidance document, trained GRF models, and the code scripts to run the models to VDOT divisions and the OIPI. The users will check model accuracy when future year data are available and retrain the GFR models, following the instructions in the code scripts, if the desired accuracy, in terms of error metrics such as MAE, MSE, MAPE, and bias, is not met.

Benefits

This implementation study provides VDOT and the OIPI with a set of machine learning models to predict TTR on statewide interstate highways. The GRF models developed for all MAP-21 analysis periods could be used to help VDOT set more reasonable TTR targets and better track the progress toward meeting the targets. The data preparation and modeling guide along with the code scripts developed in this study will help VDOT and OIPI analysts use the GRF models to predict TTR for various applications such as setting federal performance targets, prioritizing project sites for reliability improvement, and conducting before-after studies. Further, the datasets and codes for data preparation and analysis could be used for future research and implementation projects.

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APPENDIX A

PREDICTION PERFORMANCE FOR NPMRDS NETWORK USING GRF MODELS TRAINED WITH INRIX DATA IN THE PHASE I STUDY

Table A1. Prediction Performance for NPMRDS Network Using GRF Models Trained With INRIX Data in the Phase I Study

Predicted Period	Mean Absolute Error			Bias			Mean Absolute Percentage Error			Mean Squared Error		
	50th	**80th**	**90th**	**50th**	**80th**	**90th**	**50th**	**80th**	**90th**	**50th**	**80th**	**90th**
Freeway Segments												
AM	9.27	15.57	29.48	-6.99	3.41	19.48	8.31	19.10	39.70	509.59	872.55	1858.40
Midday	7.91	14.93	31.63	-5.61	5.38	21.68	7.54	19.41	42.01	280.57	623.86	1883.32
Weekend	6.67	13.45	27.14	-3.96	3.60	17.13	6.56	18.21	40.73	237.96	586.30	1504.62
PM	11.69	17.90	31.61	-9.46	-0.12	14.24	9.82	19.05	36.78	964.72	1502.99	2457.61
Interchange Segments												
AM	3.73	8.79	17.85	-1.55	3.85	13.52	10.29	28.13	63.36	113.36	256.64	615.91
Midday	2.78	8.14	18.48	-0.44	5.74	16.15	9.72	29.33	68.26	34.61	148.26	560.46
Weekend	61.29	65.55	70.10	-59.35	-54.62	-42.10	28.15	37.35	55.73	12107.59	12709.46	12857.81
PM	66.53	69.35	72.80	-64.89	-58.21	-46.16	31.33	37.86	50.63	13224.04	13718.91	13709.75

APPENDIX B

PREDICTION PERFORMANCE OF PERIOD-SPECIFIC GRF MODELS

Table B1. Prediction Performance of Period-Specific GRF Models for Freeway Segments

Predicted Period	Work Zone Option	Data Aggregation Type	Mean Absolute Error			Bias			Mean Absolute Percentage Error			Mean Squared Error		
			50th	80th	90th	50th	80th	90th	50th	80th	90th	50th	80th	90th
AM	C	0	7.04	13.77	20.90	-1.00	2.16	8.54	6.74	12.65	21.41	290.20	1035.33	1690.54
AM	C	1	7.65	13.57	22.56	-1.64	5.57	15.36	7.61	14.26	25.69	358.92	743.77	1430.92
AM	C	2	7.66	13.38	22.30	-1.50	5.62	15.27	7.65	14.16	25.42	355.04	720.45	1376.39
AM	L	1	7.70	13.58	22.64	-1.66	5.58	15.47	7.64	14.32	25.81	361.04	738.43	1426.27
AM	L	2	7.65	13.37	22.38	-1.51	5.64	15.35	7.63	14.17	25.65	354.44	712.93	1366.84
AM	LP	0	7.02	13.76	21.01	-1.01	2.23	8.70	6.73	12.63	21.47	288.63	1028.16	1693.38
AM	LP	1	7.68	13.53	22.71	-1.66	5.67	15.58	7.62	14.21	25.55	359.67	727.48	1459.35
AM	LP	2	7.62	13.37	22.45	-1.47	5.74	15.48	7.61	14.22	25.74	352.48	699.90	1371.31
AM	P	0	7.04	13.80	20.98	-0.97	2.20	8.58	6.74	12.70	21.60	288.66	1045.22	1698.36
AM	P	1	7.69	13.63	22.69	-1.62	5.66	15.51	7.63	14.28	25.66	359.77	742.00	1434.56
AM	P	2	7.73	13.81	22.95	-1.40	6.04	15.93	7.72	14.62	25.88	357.71	741.87	1429.47
Midday	C	0	5.27	11.86	20.41	0.31	2.85	6.13	5.49	11.67	19.33	98.66	570.11	1939.62
Midday	C	1	6.00	12.04	19.86	-0.55	4.74	10.22	6.69	12.40	19.70	130.40	567.42	1311.31
Midday	C	2	6.00	12.05	19.95	-0.52	4.84	10.43	6.69	12.47	19.93	131.38	561.45	1292.44
Midday	L	0	5.29	11.93	20.64	0.32	2.92	6.34	5.50	11.70	19.49	100.45	578.99	1977.19
Midday	L	1	6.02	12.12	20.16	-0.57	4.82	10.49	6.71	12.48	19.82	133.38	565.74	1338.31
Midday	L	2	5.98	12.15	20.12	-0.49	4.92	10.57	6.69	12.55	20.01	130.21	564.97	1306.17
Midday	LP	0	5.28	11.97	20.58	0.34	2.97	6.34	5.47	11.67	19.21	99.41	581.15	1975.71
Midday	LP	1	5.98	12.13	20.12	-0.51	4.87	10.50	6.68	12.52	19.99	130.29	571.84	1332.82
Midday	LP	2	6.01	12.12	20.10	-0.55	4.87	10.54	6.69	12.55	20.12	131.92	562.67	1313.82
Midday	P	0	5.28	11.87	20.46	0.30	2.85	6.21	5.48	11.62	19.27	98.74	575.09	1955.42
Midday	P	1	6.02	12.09	20.02	-0.55	4.82	10.44	6.71	12.42	19.79	131.94	567.41	1315.19
Midday	P	2	6.02	12.07	20.05	-0.55	4.81	10.51	6.69	12.49	19.97	132.34	560.72	1298.27
Weekend	C	0	4.97	10.66	17.68	1.59	3.04	4.24	4.79	9.14	14.17	87.07	620.93	1511.62
Weekend	C	1	5.81	11.60	18.08	0.76	4.75	9.59	5.57	10.56	16.28	146.59	473.96	963.65
Weekend	C	2	5.78	11.61	18.13	0.84	4.81	9.73	5.57	10.59	16.35	141.23	480.97	962.17
Weekend	L	0	4.95	10.58	17.65	1.57	2.95	4.15	4.77	9.10	14.17	86.86	616.25	1505.88
Weekend	L	1	5.81	11.64	18.07	0.75	4.75	9.55	5.56	10.56	16.24	146.10	479.62	963.94
Weekend	L	2	5.77	11.65	18.14	0.85	4.84	9.72	5.59	10.65	16.43	141.16	479.82	966.72
Weekend	LP	0	4.95	10.57	17.60	1.58	2.92	4.11	4.79	9.11	14.20	86.94	612.94	1492.71
Weekend	LP	1	5.81	11.59	18.13	0.77	4.73	9.64	5.57	10.59	16.39	146.46	476.01	964.65
Weekend	LP	2	5.81	11.58	18.07	0.77	4.77	9.60	5.60	10.59	16.32	144.33	477.46	960.71
Weekend	P	0	4.96	10.55	17.56	1.57	2.91	4.05	4.79	9.11	14.12	87.37	612.19	1503.52

Weekend	P	1	5.81	11.63	18.13	0.78	4.75	9.56	5.58	10.59	16.32	145.50	478.44	971.19
Weekend	P	2	5.80	11.58	18.08	0.80	4.76	9.64	5.59	10.60	16.31	143.83	478.65	961.73
PM	C	0	9.65	17.22	28.06	-3.21	1.02	10.85	8.51	16.69	31.06	706.21	1820.87	3140.37
PM	C	1	10.02	16.59	28.44	-3.50	5.04	16.78	9.53	19.05	35.72	739.86	1210.29	2343.43
PM	C	2	9.96	16.56	28.30	-3.41	5.06	16.75	9.52	18.93	35.30	730.93	1207.04	2308.20
PM	L	0	9.66	17.26	28.15	-3.20	1.01	10.88	8.51	16.63	31.06	706.69	1833.91	3169.70
PM	L	1	9.98	16.57	28.49	-3.47	5.01	16.83	9.49	18.89	35.58	733.79	1208.87	2353.05
PM	L	2	9.96	16.53	28.36	-3.40	5.08	16.96	9.49	18.85	35.43	730.23	1202.11	2324.32
PM	LP	0	9.68	17.21	28.13	-3.19	1.03	10.98	8.51	16.71	31.17	707.12	1822.19	3138.30
PM	LP	1	10.01	16.55	28.28	-3.49	4.98	16.58	9.51	18.77	34.98	737.51	1210.47	2322.70
PM	LP	2	9.97	16.54	28.38	-3.41	5.07	16.90	9.49	18.97	35.86	730.49	1204.07	2311.42
PM	P	0	9.65	17.23	28.14	-3.19	1.04	10.94	8.52	16.72	31.30	704.50	1825.63	3159.23
PM	P	1	9.98	16.49	28.13	-3.52	4.89	16.48	9.51	18.89	35.34	741.05	1208.30	2317.52
PM	P	2	9.94	16.54	28.30	-3.37	5.11	16.92	9.53	18.91	35.52	724.07	1199.00	2302.84

Table B2. Prediction Performance of Period-Specific GRF Models for Interchange Segments

Predicted Period	Work Zone Option	Data Aggregation Type	Mean Absolute Error			Bias			Mean Absolute Percentage Error			Mean Squared Error		
			50th	80th	90th	50th	80th	90th	50th	80th	90th	50th	80th	90th
AM	C	0	2.73	6.05	10.13	-1.03	-1.16	0.94	7.56	14.22	23.89	68.01	295.08	575.88
AM	C	1	3.31	5.85	9.47	-1.54	0.42	3.88	8.71	15.91	26.90	94.60	198.16	361.36
AM	C	2	3.28	5.78	9.37	-1.49	0.46	3.92	8.66	15.76	26.83	92.84	192.49	351.56
AM	L	1	3.32	5.82	9.41	-1.54	0.38	3.81	8.70	15.79	26.65	95.66	197.50	355.79
AM	L	2	3.27	5.79	9.41	-1.47	0.49	3.99	8.66	15.83	26.90	92.16	192.20	351.65
AM	LP	0	2.72	6.07	10.12	-1.02	-1.14	0.97	7.56	14.22	23.80	67.04	296.15	580.51
AM	LP	1	3.30	5.86	9.44	-1.52	0.44	3.85	8.69	15.88	26.76	94.01	198.63	364.34
AM	LP	2	3.28	5.81	9.40	-1.48	0.48	3.94	8.66	15.83	26.81	92.98	194.05	352.72
AM	P	0	2.72	6.05	10.11	-1.02	-1.16	0.91	7.55	14.22	23.84	67.11	295.84	580.24
AM	P	1	3.31	5.82	9.42	-1.54	0.37	3.82	8.69	15.77	26.81	94.94	196.39	356.93
AM	P	2	3.28	5.78	9.42	-1.47	0.46	3.97	8.65	15.78	26.96	91.90	191.95	351.03
Midday	C	0	1.72	4.87	9.25	-0.05	0.05	1.07	6.34	14.00	23.41	14.47	147.70	441.01
Midday	C	1	2.39	4.75	7.53	-0.67	0.69	2.67	7.70	14.63	22.61	30.60	94.48	204.37
Midday	C	2	2.39	4.75	7.52	-0.68	0.67	2.63	7.68	14.57	22.44	30.53	94.71	203.72
Midday	L	0	1.72	4.88	9.24	-0.05	0.02	1.00	6.35	13.98	23.38	14.58	149.68	439.94
Midday	L	1	2.39	4.75	7.56	-0.69	0.69	2.71	7.68	14.61	22.66	30.67	94.33	205.00
Midday	L	2	2.39	4.76	7.53	-0.69	0.67	2.63	7.73	14.63	22.57	30.70	95.28	203.69
Midday	LP	0	1.72	4.86	9.19	-0.07	0.00	0.95	6.33	13.89	23.20	14.58	148.27	438.31
Midday	LP	1	2.39	4.76	7.54	-0.69	0.68	2.67	7.69	14.63	22.63	30.86	94.90	204.63
Midday	LP	2	2.38	4.77	7.59	-0.69	0.71	2.75	7.67	14.63	22.70	30.42	94.84	205.34
Midday	P	0	1.72	4.86	9.20	-0.05	0.02	0.98	6.36	13.94	23.23	14.49	148.58	439.28
Midday	P	1	2.39	4.74	7.48	-0.69	0.65	2.57	7.69	14.57	22.42	30.83	94.67	203.02
Midday	P	2	2.39	4.77	7.56	-0.68	0.70	2.71	7.68	14.65	22.66	30.68	95.53	206.09
Weekend	C	0	1.49	3.62	6.59	0.20	0.28	0.99	5.54	10.70	17.01	19.19	154.03	342.74
Weekend	C	1	1.84	4.00	6.40	-0.08	0.91	2.68	6.50	12.68	19.63	31.50	99.18	195.92
Weekend	C	2	1.84	3.98	6.39	-0.07	0.90	2.68	6.52	12.69	19.70	31.35	97.05	192.96
Weekend	L	0	1.49	3.64	6.62	0.20	0.32	1.05	5.53	10.73	17.05	19.06	154.07	345.76
Weekend	L	1	1.84	3.97	6.40	-0.09	0.87	2.66	6.50	12.58	19.63	31.44	97.48	193.87
Weekend	L	2	1.84	3.98	6.38	-0.08	0.89	2.67	6.50	12.64	19.65	31.48	96.61	191.87
Weekend	LP	0	1.49	3.64	6.62	0.20	0.30	1.02	5.54	10.76	17.05	19.21	154.92	346.43
Weekend	LP	1	1.85	3.97	6.37	-0.08	0.87	2.64	6.54	12.61	19.59	31.45	97.12	194.06
Weekend	LP	2	1.84	4.00	6.42	-0.07	0.91	2.71	6.52	12.72	19.86	31.58	98.06	194.21
Weekend	P	0	1.49	3.64	6.60	0.20	0.32	1.04	5.53	10.74	17.04	19.15	155.16	341.68
Weekend	P	1	1.84	3.96	6.37	-0.09	0.86	2.62	6.50	12.57	19.53	31.49	96.86	191.87
Weekend	P	2	1.84	3.98	6.41	-0.07	0.90	2.71	6.52	12.67	19.79	31.43	96.14	193.48
PM	C	0	4.67	10.25	16.16	-2.80	-2.94	1.11	9.59	19.73	34.81	308.40	914.25	1449.25
PM	C	1	5.40	9.38	14.89	-3.35	-0.27	5.31	10.94	22.34	39.41	318.30	546.95	931.33
PM	C	2	5.35	9.35	14.91	-3.29	-0.12	5.53	10.87	22.40	39.95	313.53	545.07	920.18
PM	L	0	4.66	10.25	16.18	-2.79	-2.97	1.13	9.59	19.71	34.89	306.70	915.64	1455.62

PM	L	1	5.40	9.36	14.85	-3.37	-0.39	5.12	10.93	22.19	39.18	318.48	548.63	929.54
PM	L	2	5.34	9.34	14.86	-3.26	-0.10	5.57	10.90	22.38	39.79	310.34	542.02	919.00
PM	LP	0	4.67	10.27	16.14	-2.79	-2.96	1.12	9.60	19.76	34.81	307.93	916.70	1447.36
PM	LP	1	5.40	9.46	14.90	-3.36	-0.31	5.18	10.90	22.41	39.27	318.82	555.64	933.29
PM	LP	2	5.36	9.37	14.84	-3.29	-0.14	5.48	10.90	22.51	39.68	313.51	544.89	910.41
PM	P	0	4.67	10.25	16.16	-2.79	-2.98	1.04	9.60	19.68	34.70	307.67	914.88	1456.99
PM	P	1	5.41	9.38	14.79	-3.37	-0.37	5.14	10.93	22.23	39.06	318.74	551.72	926.21
PM	P	2	5.35	9.34	14.82	-3.30	-0.18	5.43	10.88	22.33	39.55	313.49	542.66	915.18

Table B3. Prediction Performance of Single GRF Models for Freeways Segments

Predicted Period	Work Zone Option	Data Aggregation Type	Mean Absolute Error			Bias			Mean Absolute Percentage Error			Mean Squared Error		
			50th	80th	90th	50th	80th	90th	50th	80th	90th	50th	80th	90th
AM	C	1	7.84	13.22	21.03	-1.64	4.56	13.24	7.54	13.53	23.64	366.68	724.39	1291.12
AM	C	2	7.72	13.10	20.90	-1.58	4.76	13.46	7.46	13.49	23.59	356.17	692.43	1268.11
AM	L	1	7.85	13.18	21.24	-1.61	4.57	13.51	7.55	13.58	23.98	366.52	715.86	1300.77
AM	L	2	7.72	13.13	20.84	-1.56	4.75	13.41	7.44	13.48	23.60	356.56	705.16	1262.99
AM	LP	1	7.82	13.17	21.14	-1.66	4.64	13.47	7.54	13.56	23.92	364.89	705.03	1286.25
AM	LP	2	7.71	13.07	20.74	-1.56	4.68	13.31	7.45	13.47	23.54	356.66	700.31	1252.88
AM	P	1	7.82	13.23	21.25	-1.69	4.63	13.52	7.55	13.64	24.13	364.63	716.78	1298.72
AM	P	2	7.71	13.12	20.84	-1.56	4.75	13.44	7.45	13.50	23.64	354.78	694.76	1259.25
Midday	C	1	6.26	12.09	20.66	-0.39	5.21	11.99	6.67	12.63	21.89	141.21	497.43	1225.06
Midday	C	2	6.22	11.96	20.51	-0.41	5.18	11.99	6.64	12.69	22.06	137.38	458.64	1136.83
Midday	L	1	6.27	12.07	20.82	-0.38	5.20	12.14	6.67	12.72	22.14	141.09	499.30	1260.71
Midday	L	2	6.20	12.02	20.37	-0.37	5.18	11.81	6.62	12.67	22.05	136.13	475.62	1131.58
Midday	LP	1	6.25	12.09	20.78	-0.41	5.30	12.15	6.66	12.71	22.07	140.33	492.94	1238.52
Midday	LP	2	6.19	11.95	20.31	-0.39	5.10	11.73	6.62	12.69	22.07	137.09	467.94	1116.88
Midday	P	1	6.25	12.08	20.90	-0.42	5.29	12.29	6.67	12.71	22.27	139.13	490.92	1253.27
Midday	P	2	6.18	11.98	20.35	-0.40	5.12	11.78	6.62	12.65	21.99	135.64	466.73	1123.13
Weekend	C	1	5.88	12.01	18.91	1.02	5.16	10.58	5.88	11.85	19.72	143.65	540.37	1036.12
Weekend	C	2	5.86	11.97	18.90	0.97	5.14	10.55	5.84	11.83	19.67	144.66	539.00	1026.98
Weekend	L	1	5.89	12.03	19.05	1.02	5.16	10.65	5.89	11.92	19.99	144.82	542.78	1054.53
Weekend	L	2	5.84	11.91	18.78	0.97	5.06	10.41	5.84	11.81	19.67	142.43	536.14	1016.14
Weekend	LP	1	5.88	12.03	19.01	1.02	5.21	10.69	5.90	11.93	19.97	143.98	537.90	1039.80
Weekend	LP	2	5.83	11.92	18.83	0.99	5.07	10.45	5.86	11.88	19.84	142.16	535.55	1013.51
Weekend	P	1	5.87	12.04	19.11	1.00	5.19	10.80	5.88	11.90	19.95	143.31	541.56	1056.21
Weekend	P	2	5.84	11.96	18.90	0.97	5.11	10.56	5.85	11.84	19.77	143.13	541.32	1026.07
PM	C	1	10.06	15.91	25.15	-3.73	2.79	11.53	9.21	16.22	28.21	745.07	1230.56	2025.26
PM	C	2	9.97	15.64	24.80	-3.74	2.70	11.41	9.14	16.02	27.83	732.14	1193.51	1985.80
PM	L	1	10.08	15.87	25.28	-3.71	2.81	11.65	9.22	16.35	28.45	746.98	1228.10	2052.52
PM	L	2	9.98	15.67	24.78	-3.71	2.72	11.31	9.13	16.00	27.81	731.80	1200.51	1974.85
PM	LP	1	10.06	15.93	25.30	-3.75	2.91	11.81	9.21	16.40	28.59	745.67	1228.29	2047.66
PM	LP	2	9.97	15.59	24.74	-3.72	2.59	11.21	9.14	15.95	27.85	733.58	1198.26	1970.94
PM	P	1	10.05	15.91	25.36	-3.77	2.90	11.87	9.22	16.38	28.56	741.02	1219.07	2049.01
PM	P	2	9.96	15.66	24.86	-3.72	2.68	11.33	9.14	15.99	27.91	731.78	1197.11	1983.29

Table B4. Prediction Performance of Single GRF Models for Interchange Segments

Predicted Period	Work Zone Option	Data Aggregation Type	Mean Absolute Error			Bias			Mean Absolute Percentage Error			Mean Squared Error		
			50th	80th	90th	50th	80th	90th	50th	80th	90th	50th	80th	90th
AM	C	1	3.30	5.83	9.37	-1.51	0.20	3.51	8.59	15.73	26.73	93.81	206.20	359.99
AM	C	2	3.25	5.72	9.40	-1.44	0.29	3.77	8.51	15.52	26.87	90.80	198.74	361.15
AM	L	1	3.29	5.78	9.29	-1.52	0.14	3.44	8.55	15.54	26.40	93.56	205.09	356.72
AM	L	2	3.26	5.75	9.44	-1.44	0.29	3.77	8.53	15.55	26.78	91.45	201.15	366.08
AM	LP	1	3.30	5.81	9.39	-1.52	0.16	3.51	8.61	15.71	26.88	94.01	205.92	360.23
AM	LP	2	3.26	5.74	9.41	-1.43	0.33	3.82	8.53	15.58	26.80	90.89	198.81	362.15
AM	P	1	3.29	5.80	9.35	-1.49	0.19	3.52	8.58	15.72	26.84	92.71	205.85	360.07
AM	P	2	3.25	5.73	9.33	-1.44	0.27	3.66	8.50	15.51	26.55	91.05	199.57	357.86
Midday	C	1	2.38	5.05	8.64	-0.55	1.24	4.17	7.76	15.81	26.56	28.93	100.30	246.90
Midday	C	2	2.39	5.02	8.63	-0.57	1.16	4.13	7.75	15.65	26.42	28.86	99.69	248.72
Midday	L	1	2.37	5.01	8.53	-0.56	1.16	4.04	7.73	15.62	26.12	29.18	99.90	242.37
Midday	L	2	2.39	5.04	8.66	-0.56	1.19	4.16	7.78	15.75	26.48	28.87	99.69	250.49
Midday	LP	1	2.38	5.03	8.59	-0.56	1.18	4.09	7.76	15.72	26.44	29.35	99.66	243.35
Midday	LP	2	2.40	5.03	8.63	-0.57	1.17	4.12	7.78	15.69	26.39	29.08	99.25	248.52
Midday	P	1	2.37	5.03	8.61	-0.55	1.21	4.14	7.74	15.71	26.39	28.98	100.31	246.81
Midday	P	2	2.39	5.03	8.63	-0.57	1.17	4.11	7.78	15.69	26.42	29.02	100.39	249.42
Weekend	C	1	1.86	4.28	7.16	0.06	1.42	3.66	6.61	13.71	21.98	29.85	98.01	223.21
Weekend	C	2	1.85	4.25	7.15	0.06	1.37	3.66	6.58	13.55	21.85	30.00	98.54	222.57
Weekend	L	1	1.86	4.25	7.09	0.06	1.39	3.58	6.60	13.58	21.73	30.02	97.03	220.73
Weekend	L	2	1.85	4.27	7.17	0.07	1.39	3.67	6.61	13.61	21.88	29.99	99.70	224.73
Weekend	LP	1	1.86	4.26	7.13	0.06	1.39	3.62	6.62	13.66	21.91	30.28	96.51	220.18
Weekend	LP	2	1.85	4.24	7.16	0.06	1.37	3.66	6.59	13.52	21.82	30.01	97.93	222.18
Weekend	P	1	1.86	4.27	7.16	0.06	1.42	3.66	6.62	13.69	21.94	29.47	98.69	225.30
Weekend	P	2	1.86	4.26	7.16	0.07	1.38	3.65	6.59	13.56	21.83	30.10	99.46	223.50
PM	C	1	5.42	9.04	13.57	-3.54	-1.71	2.31	10.73	20.01	33.25	320.88	566.10	892.62
PM	C	2	5.33	8.83	13.30	-3.47	-1.67	2.31	10.58	19.49	32.78	313.45	556.65	880.23
PM	L	1	5.42	8.97	13.45	-3.56	-1.82	2.12	10.69	19.73	32.81	322.69	568.52	885.90
PM	L	2	5.35	8.83	13.25	-3.48	-1.67	2.19	10.63	19.51	32.50	315.16	556.82	876.35
PM	LP	1	5.43	9.01	13.52	-3.55	-1.77	2.22	10.75	19.93	33.20	322.85	568.32	887.28
PM	LP	2	5.36	8.86	13.29	-3.49	-1.67	2.24	10.63	19.55	32.60	316.78	556.94	876.26
PM	P	1	5.38	9.01	13.58	-3.52	-1.68	2.38	10.68	19.93	33.24	318.19	565.46	898.29
PM	P	2	5.36	8.86	13.25	-3.49	-1.65	2.27	10.59	19.53	32.56	316.16	558.70	882.07

APPENDIX C

DATA PREPARATION AND MODELING GUIDE

This appendix describes data preparation and modeling guidance for using the period-specific GRF models developed in this study. The intent is to facilitate the use of these models for TTR prediction by analysts within VDOT and OIPI. The procedure involves five steps:

1. Determine spatial and temporal level of data aggregation.
2. Identify relevant data elements and data sources.
3. Obtain data for the study period.
4. Combine and conflate the data.
5. Estimate the predictive model.

Step 1: Determine Spatial and Temporal Level of Data Aggregation

Probe vehicle sources generally measure travel times on segments shorter than typical VDOT sources. The data may also be available at different temporal resolutions. This step is intended to establish a common spatial framework and temporal resolution that will be used for all subsequent modeling tasks. In addition, this task identifies the MAP-21 analysis periods (weekday AM, weekday midday, weekday PM, and weekend). The GRF models developed in this study were spatially referenced to the NPMRDS network at a temporal resolution of 1 hour. This appendix describes the scenario where a separate model is desired for each analysis period.

Step 2: Identify Relevant Data Elements and Data Sources

The data needed to predict the travel time percentiles discussed in this study include several geometric, traffic, weather, and incident variables. Most of these may be obtained from internal VDOT databases such as the Roadway Network System (RNS), Traffic Monitoring System (TMS), Highway Traffic Records Inventory System (HTRIS), and the Virginia Traffic Information Management System (VaTraffic) or via the VDOT Traffic Operations Division's Oracle database (COTEDOP) frontend. A summary of relevant data elements and potential sources is provided in Table C1. The list of potential sources in Table C1 is intended to be illustrative, not exhaustive. Other non-VDOT sources and non–Oracle-based VDOT sources are available for some of the data elements.

Step 3: Obtain Data for the Study Period

A dataset consisting of the data elements identified in Step 2 is assembled for each hour of the analysis period (weekday AM, weekday midday, weekday PM, and weekend) for the intended study duration (e.g., 1 year). The following are examples of how the different data elements may be obtained from some of the sources identified in Table C1.

Table C1. Data Elements and Sources

Data Element	Potential Source
Geometric Data	
Segment length	National Performance Management Research Data Set (NPMRDS)
Number of through lanes	COTEDOP, HTRIS, NPMRDS
Incident Data	
Crash incidents by severity	COTEDOP, RNS
Breakdown incidents	VaTraffic
Hazard incidents	VaTraffic
Traffic Data	
AADT	COTEDOP, TMS
Traffic volume profile	COTEDOP
Heavy vehicle percentage	COTEDOP
Capacity	Calculated using Highway Capacity Manual methodology
Weather	
Rain precipitation amount	National Centers for Environmental Information
Frozen precipitation amount	National Centers for Environmental Information
Other	
Number of lanes affected by work zone activity	VaTraffic
Availability of Safety Service Patrol (SSP)	VDOT Traffic Operations Division
Presence of HOV/HOT lane	COTEDOP, VDOT Traffic Operations Division
Area type (rural or urban)	COTEDOP, HTRIS
Travel time	NPMRDS

NPMRDS = National Performance Management Research Dataset; COTEDOP = VDOT Traffic Operations Division's Oracle database; HTRIS = Highway Traffic Records Inventory System; RNS = Roadway Network System; AADT = annual average daily traffic; VaTraffic = Virginia Traffic Information Management System; TMS = Traffic Monitoring System.

TMC Travel Time and Segment Length Data

Probe travel time data at the desired temporal aggregation (e.g., 1 hour) may be obtained for all relevant TMC segments (identified by unique IDs) by direct download from the Regional Integrated Transportation Information System (RITIS). Alternatively, the travel times may be derived from the TMC segment length and speed data that are also available in NPMRDS. Relevant metadata such as TMC location (indicated by the start and end GPS coordinates) may be retrieved for use in the data conflation step.

AADT and Roadway Attribute Data

The COTEDOP database is a good source of annual average daily traffic (AADT) and roadway attribute data including number of lanes and area type. These data elements may be obtained by querying the HTRIS.EYROAD tables of this Oracle database. Roadway segments in this database are demarcated by a start mile post and an end mile post, unlike TMC segments where latitude and longitude coordinates are used to demarcate the start and end points.

Traffic Volume Profiles and Heavy Vehicle Percentage

The COTEDOP database contains tables that may be used to translate the AADT data for a given roadway segment to an equivalent hourly volume for every hour of the day, every day of the week, and every month of the year.

First, the table TMS.FACTORVALUE is queried to obtain values that serve as seasonal adjustment factors for converting the AADT to equivalent average daily traffic (ADT) volumes for every day of the week and every month of the year. Second, Replicate.TMSRawData is queried to obtain the average hourly percentage distribution of traffic for every hour of a weekday and every hour of a weekend. Third, the percentage distribution is multiplied by the ADT values to obtain the hourly volume profile.

The heavy vehicle volume profile (and hence the percentage of heavy vehicles) is obtained in a similar fashion except that hourly distributions of heavy vehicles for weekdays and for weekends are queried from Replicate.TMSRawDataClassified (R. Jones, personal communication, 2021).

Work Zone and Non-Crash Incident Data

The VaTraffic database contains information on traffic incidents and roadway maintenance activities. This database may be queried for the location (route number, route prefix, route suffix, mile post) and start/end time of vehicle breakdown events (e.g., disabled vehicle on the shoulder), hazard or non-crash disruptive events such as vehicle fires, and work zone activity. Work zone location, start and end time, and number of lanes affected by work zone activity may be retrieved directly from the ORCIDEV_DBA.V_WORK_ZONES table in VaTraffic.

Crash Data

The CRASHDATA.CRASHDOCUMENT table in the COTEDOP database may be queried for the location (route number, route prefix, route suffix, and mile post), date/time, and unique ID (document number) of all crash events that occurred during the study period. The KABCO severity of the crash events may then be retrieved from the RNS_CRASH.TBL_CRASH table of the RNS database via the “documentnumber” field, which is common to both tables.

Weather Data

Local climatological data consisting of more than 20 types of weather conditions including rain, snow, drizzle, hail, and so on by location (weather station) and date/time are available for direct download from the website of the National Centers for Environmental Information. For the purposes of applying the GRF models developed in this study, the total amount of liquid precipitation at a station during a specified time interval is the sum of the drizzle, rain, and thunderstorm amounts. Likewise, the total amount of frozen precipitation for a time interval is the sum of snow, snow grains, snow pellets, ice pellets, and hail amounts during that interval.

Because weather data are available at a limited number of weather stations rather than at individual TMC locations, a reasonable approximation is to assign every TMC the same weather data as that of the nearest weather station based on its GPS coordinates. This assignment may be inaccurate as there are only approximately 57 weather stations statewide and not all of these stations provide data at an hourly or more granular level for the desired study periods. However, these are the best known data currently available. In this study, the TMCs were associated with the nearest weather station using a spatial join based on the GPS coordinates of the weather stations and the coordinates of the start/end points of the TMCs.

Step 4: Combine and Conflate the Data

The assembled data are combined and spatially conflated to the NPMRDS TMC network in this step. It is worth noting that at the start of this step, the NPMRDS and weather data elements are spatially indexed by the start and end longitude-latitude coordinate pairs of the associated TMC segments. All other data elements are spatially indexed by the start and end mile posts of the VDOT TMS network.

Data from these two versions of network segmentation may be combined by identifying start/end mile posts for the TMC segments, identifying start/end longitude-latitude coordinates for the TMS segments, or both. Three possible options for establishing such a connection include the following:

1. *TMC length and order from NPMRDS*. The metadata associated with the NPMRDS travel time data include TMC length and order. By finding the very first TMC segment of each route and setting its start mile post to zero, the start and end mile posts could be calculated consecutively using TMC length and order.

2. *VDOT linear referencing system (LRS)*. The LRS network contains longitude-latitude information and m-values (mile posts) corresponding to the vertices in the polyline along a route. The availability of both longitude-latitude and mile post information in the LRS makes it a good candidate for merging the TMC and TMS datasets.

3. *Navigation data from commercial/private sources*. Navigation data including distances and GPS location for several points along a route may be obtained from sources such as Google Maps. These may be used as in the previous example to establish a connection between the TMC and TMS networks.

Option 3 was adopted for this study. Essentially, with a line traced along a route from the start point (origin) to the end point (destination), the mile post corresponding to the start/end point of a TMC was obtained by projecting its coordinates to the line and then measuring the distance from the origin.

Step 5: Predict TTR Using the GRF Models

The period-specific GRF models developed in this study, the R codes for using these models for prediction, and sample input data are made available to VDOT users by VTRC. Follow the instructions in the R codes to load the input data prepared in previous steps and make predictions.