Estimating Road User Costs for Work Zones in Data-Limited or Time-Constrained Environments

Randy B. Machemehl, Ph.D., P.E.
Nasser Al-Rashid Centennial Professor in Transportation Engineering
rbm@mail.utexas.edu
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
301 E. Dean Keeton St., Stop C1761, Austin, TX 78712

Natalia Zuniga-Garcia, M.Sc.
Research Assistant
nzuniga@utexas.edu
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin, TX 78712
301 E. Dean Keeton St., Stop C1761, Austin, TX 78712

Nabeel A. Khwaja, M.Sc., P.E., PMP
Senior Research Engineer
khwaja@mail.utexas.edu
Center for Transportation Research
The University of Texas at Austin
3925 W Braker Ln, Austin, TX 78759

Kristopher D. Pruner, M.Sc.
Research Associate
pruner@austin.utexas.edu
Center for Transportation Research
The University of Texas at Austin
3925 W Braker Ln, Austin, TX 78759

Mengyu Fu, M.Sc.
Research Fellow
mengyufu@utexas.edu
Center for Transportation Research
The University of Texas at Austin
3925 W Braker Ln, Austin, TX 78759

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ABSTRACT

Construction work zones on public roads typically cause mobility impacts to road users. A large fraction of roadway construction projects utilizes the design-bid-build project delivery method, and time-sensitivity invariably necessitates the use of additional contracting strategies, such as completion incentives for early completion and/or disincentives for late completion. Often the bid is modified from being cost alone to cost plus time. The economic predicate on which these strategies depend is broadly termed "road user costs" (RUC) consisting of travel delay costs and vehicle operating costs. Determining RUC for a project, or a project phase can be challenging due to limited traffic data availability, incomplete plans, and limited time to conduct the analysis. This paper describes a procedure to allow estimation of RUC measures, such as the daily travel time, using peak-hour values and the fraction of the total daily value that occurs during the peak-hour. Eleven construction cases are examined using CORSIM and VISSIM producing RUC's for each hour of a typical 24-hour day and fractions of the daily travel time are computed. The arithmetic mean of peak-hour travel time as a fraction of the daily value is 8.2 percent. Relationships are developed to predict daily total travel time using the peak-hour fraction of daily traffic volume and the number of inbound lanes serving traffic, a surrogate for capacity. Due to concerns of heteroskedasticity, a robust analysis is performed using logarithmic and Box-Cox transformations.

Keywords: work zones, road user costs, daily travel time, peak-hour percentage of daily travel time, micro-simulation.

INTRODUCTION

Construction work zones on public roadways typically cause mobility impacts to road users. According to the Federal Highway Administration (FHWA), United States (U.S.) work zones on freeways account for 10 percent of overall congestion *(1)*. A large fraction of roadway construction projects utilizes the design-bid-build (DBB) method of project delivery and it is often coupled with the low-bid method of contract award. For time-sensitive projects, this invariably necessitates the use of additional contracting tools and strategies, such as project completion incentives for early completion and/or disincentives for late completion. These incentives and disincentives can be applied to the project at-large and/or to smaller portions of the project as milestones. Another related approach is to modify the bid from being cost alone to cost plus time - commonly known as "A+B" bidding. The economic predicate on which these strategies and tools depend is broadly termed "road user costs" (RUC). RUC consist of two primary drivers: (i) travel delay costs, and (ii) vehicle operating costs (VOC).

The increase in travel time from work zone conditions is the primary performance measure for calculating travel delay costs. The increase in travel time is the difference between the total travel time (system) when work zone conditions are present versus the total travel time (system) under no-work zone conditions while all other variables are held constant. These travel delay costs are the result of the increased travel time (typically in vehicle-hours, veh-hr) multiplied by an appropriate value of time (typically in dollars per veh-hr, $/veh-hr). Determining RUC for a project, or a phase of a project, can be challenging for an analyst for a number of reasons, including limited traffic data availability, incomplete plans on which to base analysis, and limited time to conduct the analysis.

Motivation

Most urban projects typically involve several construction phases and/or sub-phases to minimize impacts on the traveling public. Each phase (and/or sub-phase) may impact a small segment of the project and may last a few days or a few months or longer. This construction phasing information is an important variable in the determination of project and/or milestone RUC. Typically, the analysis cannot begin until plan development is far enough along to indicate what the traffic configuration will be at various points throughout the project. This often limits the amount of time available to the analyst to conduct the RUC review and have project (and/or milestone) incentives and/or disincentives included in the plans, specifications, and estimate (PS&E) for contract release. Once the review is underway, the analyst often encounters a lack of suitable traffic data. It could be that data is outdated, that data is limited to a twenty-four-hour volume, or that data is limited to a daily peak-hour volume, amongst other issues. In the absence of detailed volume breakdown (hourly or better), the analyst cannot directly determine the RUC across the day.

Even with suitable data, the limited amount of time may not allow the analyst to set up and run a 24-hour traffic micro-simulation model to determine RUC, as micro-simulations tend to be time-consuming. For a simple intersection with minor congestion, the run time of a 24-hour model can be around 30 minutes. Under heavier traffic volume or/and congestion when the number of vehicles to be simultaneously simulated is high, the simulation may take hours to complete. This issue becomes more severe when retiming of traffic signals is required. Aside from the actual number of simulation runs needed to find an optimal timing plan, ten simulation runs are required under the default settings of VISSIM to confirm that a timing plan is optimal. With a "during construction" model, retiming of traffic signals is typically required and congestion tends to occur. In this case, the completion of signal retiming within the micro-simulation package may take days rather than hours. Furthermore, due to randomness of the microscopic simulation model itself, even with the model properly set up and calibrated, numerous runs are typically required, rendering a 24-hour simulation an even less favorable option. On the other hand, the simulation run time for a one-hour model is typically 2 to 5 minutes, hence greatly reducing the amount of time required to obtain reasonable results.

With limited time and data, sometimes limited analysis is the only option. One approach is then to model/simulate the impacts using only the peak-hour traffic data. This would likely over-represent the travel time during the one-hour period, given that peak traffic would be used for each roadway approach simultaneously, whereas different directions of roadways could peak at different times of the day. If a relationship could be established between the total travel time for a peak-hour and the total travel time for the day, then future projects with time/data limitations could make use of this relationship and estimate the full day travel time from an analysis based on the peak-hour volume. This paper presents an attempt to establish such a relationship.

Objective and Methodology

The principal objective of this research is to establish relationships between peak-hour RUC measures with respect to the total daily values. Clearly, the distribution of hourly total travel times across hours of the day should be similar to the distribution of hourly traffic volumes, however, the percentage of accumulated daily travel time that occurs during the peak-hour was not known to be the same as the traffic volume percentage.

The case study comprises two projects in the Dallas area. The first one corresponds to a conversion of an urban freeway section, S.M. Wright Freeway, to a parkway style facility. The second one corresponds to improvements near the intersection of State Highway (SH) 114 and US 377. Hourly traffic volume patterns for 24 hours of a typical week day, as well as, current and proposed geometry and traffic control specifications were obtained. Two different microsimulation packages were used. The first one, CORSIM micro-simulation was employed to estimate peak-hour travel times and delay values for four critical intersections along the freeway conversion project, while the VISSIM micro-simulator was used at SH 114/US 377 intersection. Both of these simulators are widely used micro-simulation software tools, and their simultaneous use enabled approximate comparison of the tools.

Outline

The remaining sections of this paper are organized as follows: the "Background" section is next, followed by the explanation of the "Methodology," "Results and Discussion," and the final section "Summary and Conclusions," summarizes main findings and future work.

BACKGROUND

Increased RUC caused by traffic diversion and reduced capacity during construction are recognized as significant components of total cost. Micro-simulation is a popular tool for estimating user delays associated with urban construction particularly since in most cases, the construction schedule must include handling existing traffic demands during construction. Existing and future geometry, traffic control and traffic demands can be specified in a micro-simulation environment and reasonable estimates of traffic flow, speeds, delays and travel times can be produced for any specified condition. However, although estimates of *daily* impacts are usually needed, traffic volumes are rather variable across the 24 hours of a typical day and most measures of effectiveness (MOE) are determined by the traffic demands. Figure 1 is a typical example of how traffic demand varies across the 24 hours of a typical day.

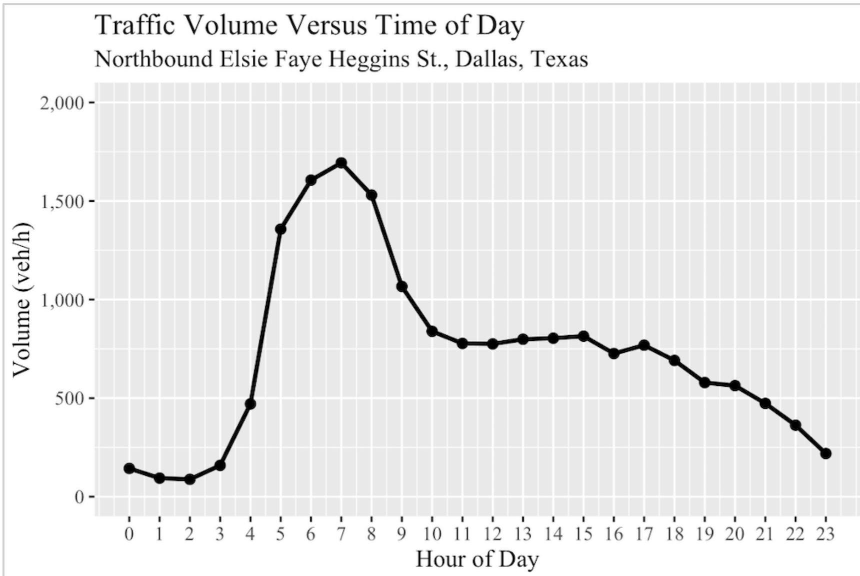


FIGURE 1 Hourly traffic volume versus hours of the day.

Daily MOE estimates can be produced by running a micro-simulation for the 24 unique hours of a day and summing to produce daily totals of travel time, delay and other values. In the fast-paced world of construction scheduling/contracting, running 24 simulations plus replicate runs and summing results to produce daily totals is a luxury that is often not possible.

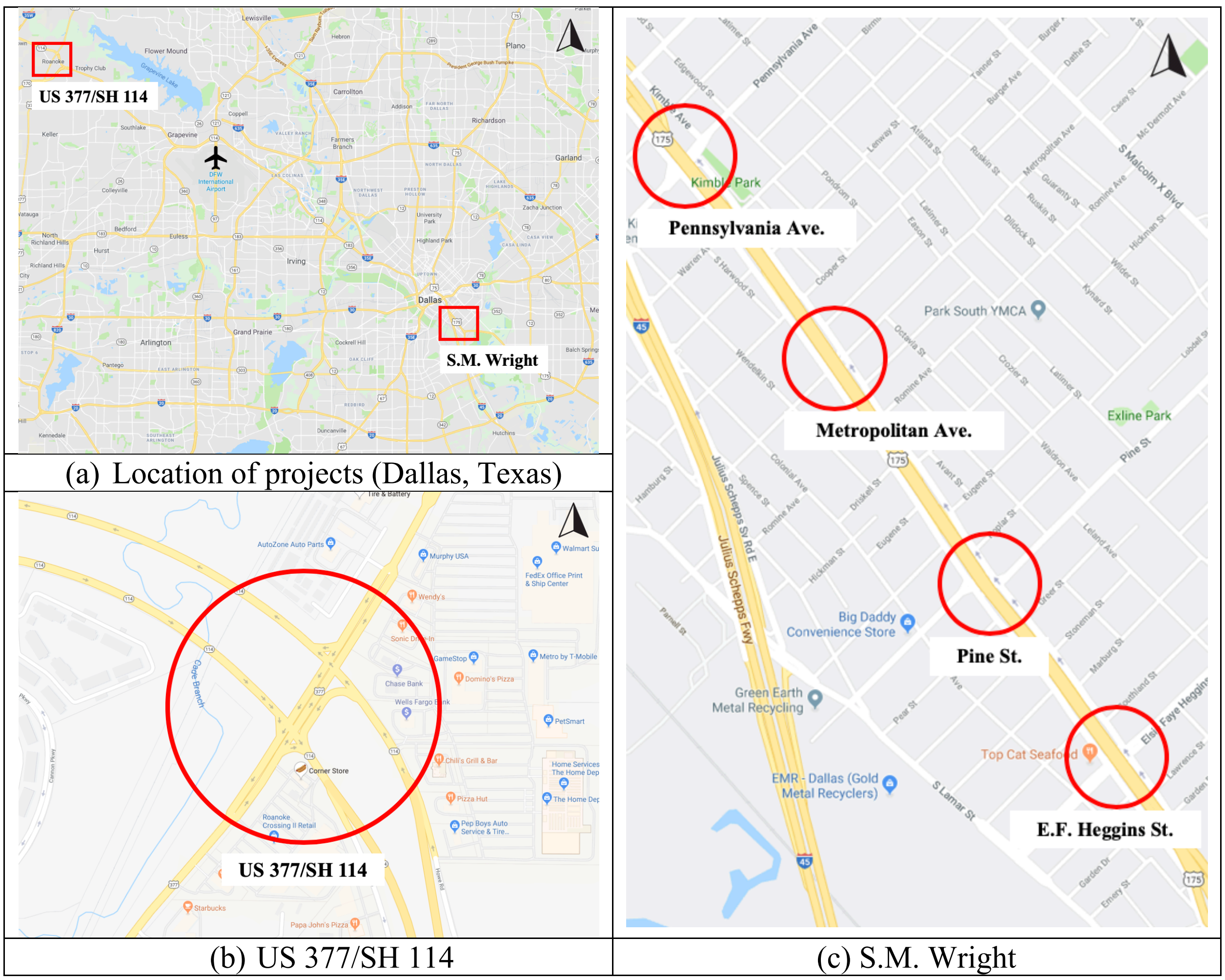
The fraction of *daily traffic volume* in the *peak-hour* has been examined by many authors. For example, almost 60 years ago, Carll and Homburger *(2)* examined the characteristics of hourly traffic volume distributions across hours of the day at locations in the Bay Area during the early 1960's *(2)*. The American Association of State Highway and Transportation Officials (AASHTO) Geometric Design Policy *(3)* suggests "Two-way DHVs (i.e., the 30 HV, or its equivalent) may be determined by applying a representative percentage (usually 8 to 12 percent in urban areas) to the ADT." A frequently used interpretation of this statement is that the peak-hour volume is usually 8 to 12 percent of the daily total volume. In fact, the peak-hour volume shown in Figure 1 is 9.7 percent of the daily total. Therefore, based upon the AASHTO suggestion, one could estimate the daily total traffic volume if one knows the peak-hour volume by simply dividing the peak-hour volume by the percentage that AASHTO says is 8 to 12 percent and in the Figure 1 example, this would be approximately 10 percent. Traffic volumes tend to exhibit significant timewise changes among days of the week, months and seasons. Bernard *(4)* explored the daily, weekly and seasonal trends in traffic volume of Atlanta freeways and recommended that time series analyses is an important part of traffic volume analyses *(4)*.

Although other researchers have explored hourly travel time and delay variation in work zones *(5-6)*, the majority of the research has been focused on evaluating reliability *(5-7)* and there is very little current evidence of a relationship between peak-hour percentages and daily total travel time. This paper attempts to fill literature gaps in this area by providing an initial evaluation and a methodological framework to develop such relationships.

CASE STUDY

The case study corresponds to two major projects located in Dallas, Texas. One of these projects is the conversion of an urban freeway section (S.M. Wright Freeway) to a parkway style facility involving several intersections. This conversion is practical due to the recent construction of a new freeway alignment connecting to the parallel interstate highway. The other project consists of improvements near the intersection of SH 114 and US 377 in a more suburban/exurban location. This project will extend the freeway portion of SH 114 by creating a grade-separated crossing for SH 114 over US 377, thus improving traffic operations in a rapidly-developing region. Figure 2 describes the location of the projects and the intersections analyzed in this study.

The two projects consist a total of five intersections, with four intersections located in the S.M. Wright Freeway area and one intersection located in the SH 114/US 377 area. For the first project, each intersection was modeled with typical construction conditions and the post-construction final configuration. In the SH 114/US 377 project, two construction cases were evaluated along with the pre-construction one, making up the total of eleven cases. Table 1 describes the configuration of each of the construction cases used for the micro-simulation analysis, including the number of inbound and outbound lanes, and the number of left/right turn bays. For more details refer to Zuniga-Garcia et al. *(8)*.



(a) Location of projects (Dallas, Texas)

(b) US 377/SH 114

(c) S.M. Wright

FIGURE 2 Location of study area (source: modified from Google Maps).

TABLE 1 Description of construction cases.

Int.	Case ID	Dir.	In-bound lanes	Out-bound lanes	Left turn bay	Right turn bay	Int.	Case ID	Dir.	In-bound lanes	Out-bound lanes	Left turn bay	Right turn bay
Elsie Faye Heggins	**1.** During const.	EB	1	1	-	-	Pine	**7.** During const.	EB	1	1	-	-
		WB	1	1	-	-			WB	1	1	-	-
		NB	2	2	-	-			NB	2	2	-	-
		SB	2	2	-	-			SB	2	2	-	-
	2. Post-const.	EB	3	3	1	-		**8.** Post-const.	EB	2	2	-	-
		WB	3	3	1	-			WB	2	2	-	-
		NB	3	3	1	1			NB	3	3	1	-
		SB	3	3	1	1			SB	3	3	1	-
Metropolitan	**3.** During const.	EB	1	1	1	-	US 377/SH 114	**9.** During const. (Case I)	EB	2	2	-	-
		WB	1	1	1	-			WB	2	2	-	-
		NB	2	2	1	-			NB	1	1	-	-
		SB	2	2	1	-			SB	1	1	-	-
	4. Post-const.	EB	1	1	1	-		**10.** During const. (Case II)	EB	2	2	-	-
		WB	1	1	1	-			WB	2	2	-	-
		NB	3	3	1	-			NB	2	2	-	-
		SB	3	3	1	-			SB	2	2	-	-
Pennsylvania	**5.** During const.	EB	1	1	-	-		**11.** Pre-const.	EB	2	2	1	1
		WB	1	1	-	-			WE	2	2	1	1
		NB	2	2	-	-			NB	2	2	1	1
		SB	2	2	-	-			SB	2	2	1	1
	6. Post-const.	EB	2	2	1	-							
		WB	2	2	1	-							
		NB	3	3	1	-							
		SB	3	3	1	-							

Since comparative estimates of daily travel time were desired for the eleven cases, daily traffic volume distributions like Figure 1 were developed. The hourly volume distribution was obtained from 24-hours volume counts, openly available at the North Central Texas Council of Governments (NCTCOG) website[1]. The hourly volume distribution was used to approximate the distribution of the traffic during the construction and pre/post-construction phases using the projected traffic volumes for the projects. Figure 3 presents a summary of the inbound volume distribution, in units of vehicles-per-hour, for each one of the five intersections evaluated.

[1] Accessed through: https://www.nctcog.org/trans/data/info/traffic-count-information-systems/traffic-counts

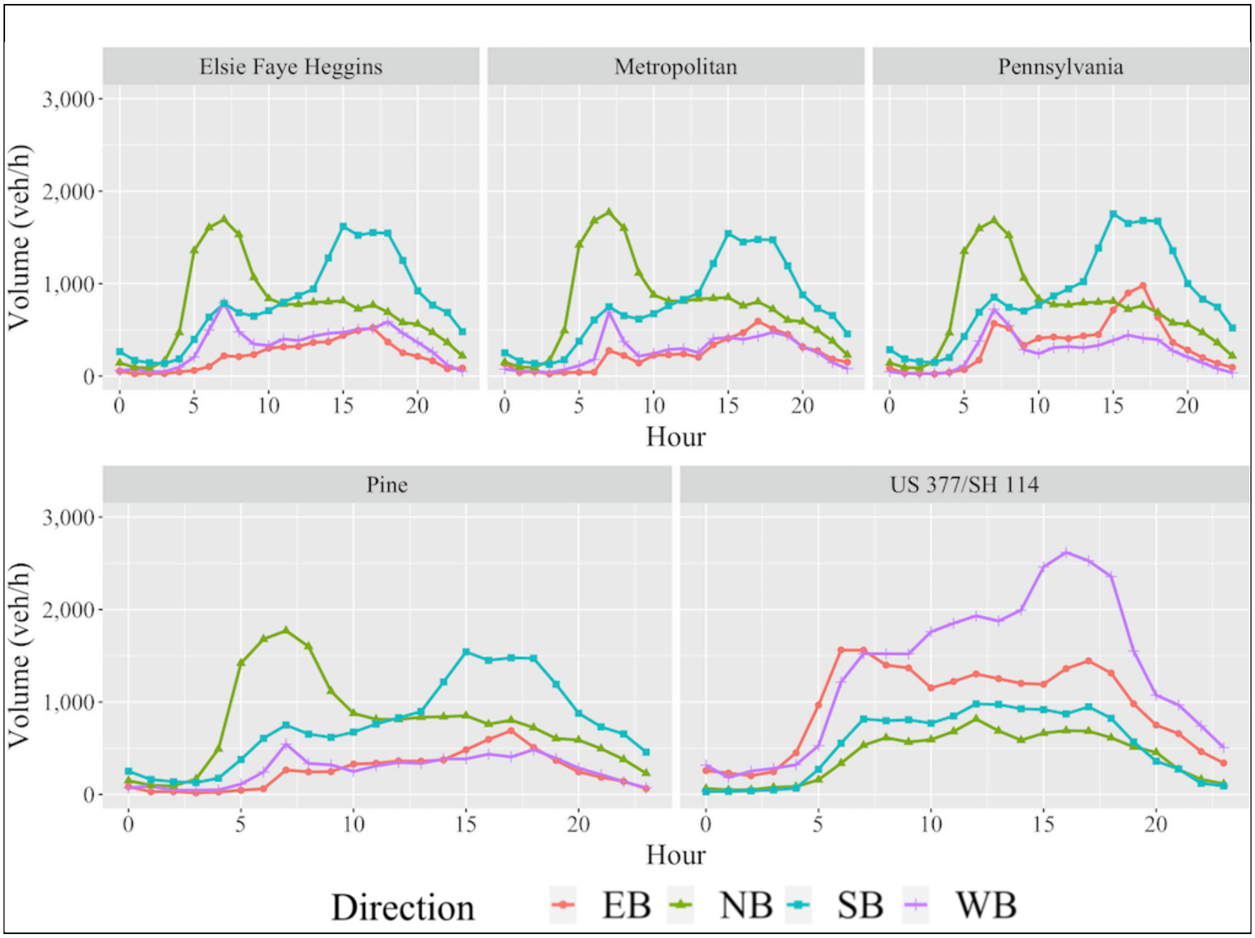


FIGURE 3 Hourly inbound traffic volume distributions in the study areas.

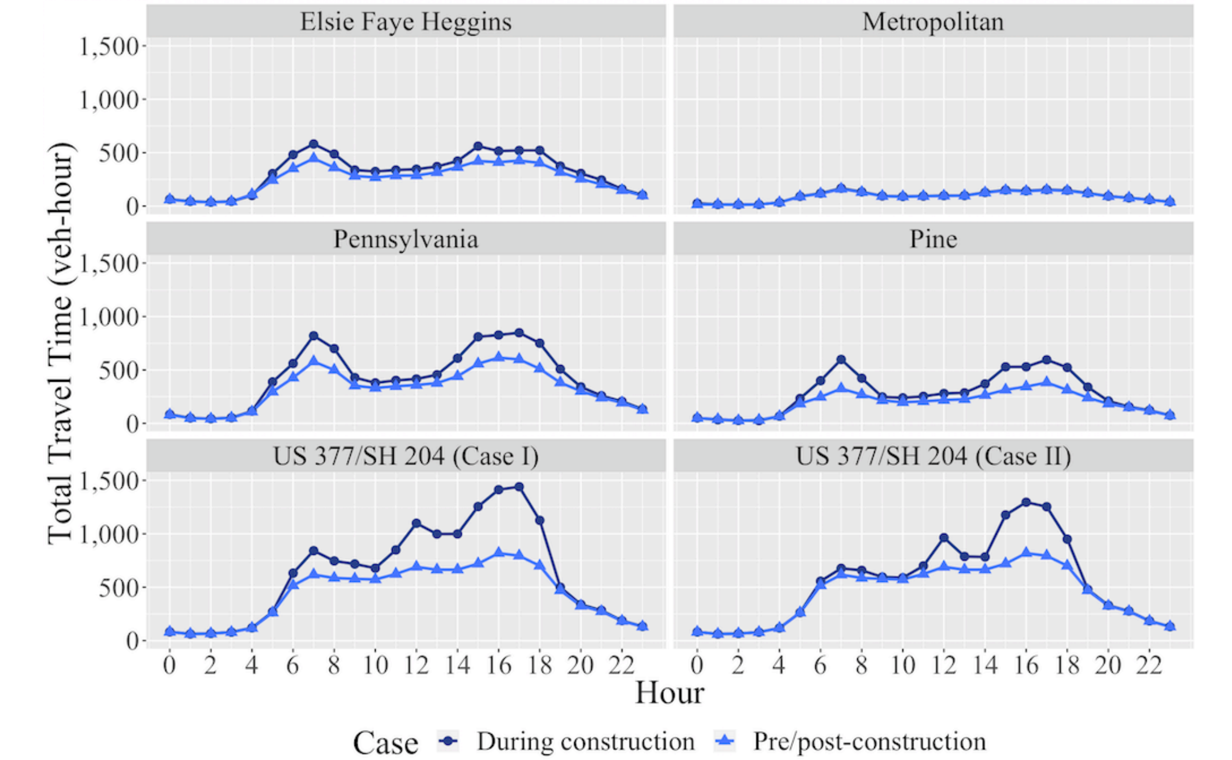
METHODOLOGY

This section describes the methodology used to run the micro-simulations, the modeling method and assumptions.

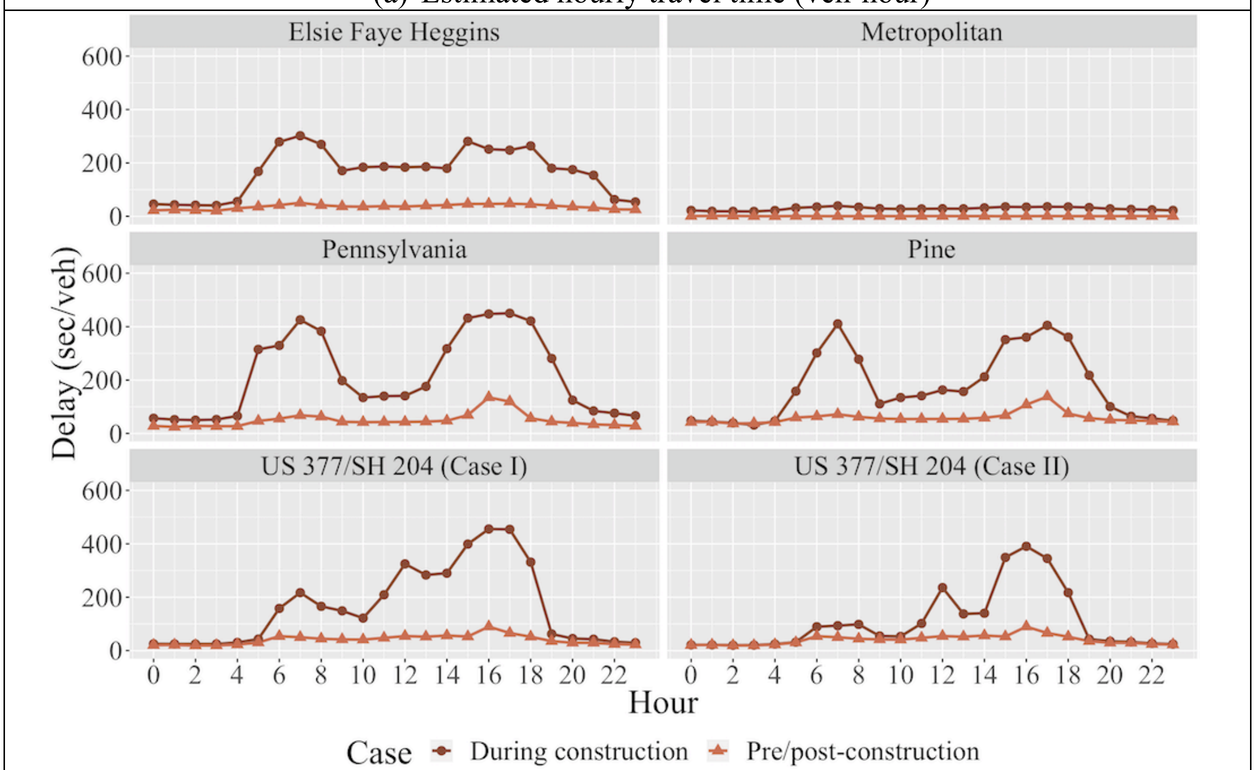
Micro-Simulation

Two micro-simulation software packages were used in this study. CORSIM was used for the projects along S.M. Wright while VISSIM was used for US 377/SH 114. The models consisted of one-hour simulations using volumes and configurations discussed in the previous section. The micro-simulators were run for each of the 24-hourly traffic demand conditions, and with three replicate runs for each case, this became 72 simulations for each of the eleven cases or a total of 792 simulations.

The simulation output consists of performance measures such as the total travel time, delay, and speed. The results from the three replicates are reported as the mean values and its corresponding standard deviations. For this study, the predicted variable analyzed is the total travel time (in vehicle-hours). This measure is estimated for each intersection and corresponds to the total simulated network statistic. Figure 4a presents the output for the 24-hour simulations in each of the intersections; each subplot shows the comparison of the construction case with the pre/post-construction scenario. Figure 4b presents results for delay per vehicle (in sec/veh).



(a) Estimated hourly travel time (veh-hour)



(b) Estimated hourly delay per vehicle (sec/veh)

FIGURE 4 Results from micro-simulations.

Modeling

This study aims to provide predictive relationships for the road user cost in data-limited and/or time-constrained environments. Through the micro-simulations, we obtained 24-hourly values of travel time for each case, and the ultimate goal is development of a model to predict 24-hour sums using peak hour values. Linear regression is a widely-used modeling method that assumes a linear relationship with predictor variables as shown in Equation 1.

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \epsilon_i \qquad \text{Equation (1)}$$

Where, i corresponds to the number of observations, y is the response variable, x*'s* are the predictors, p the number of predictors, ϵ are the unobserved random errors, and $\beta's$ are the unknown parameters. Multiple available software packages can be used to find the unknown parameters, generally using the linear least squares (LLS) method. Variants of the LLS include the ordinary (unweighted) LLS (or OLS), which is the most common method.

OLS results are usually validated using a two-tailed hypothesis test to determine if the independent variables (x_p) included in the models have a statistically significant influence on the response variable (y). In this case, the null hypothesis (H_0), shown in Equation 2, assumes that the coefficient (β_p) is equal to 0, meaning that the corresponding independent variable did not have an impact on y. For the hypothesis testing, we analyzed the t-static and p-value for each coefficient. These two indicators determine whether to reject the null hypothesis. The t-statistic is a ratio of the departure of an estimated parameter from its notional value and its standard error. The p-value (or observed significance level) represents the probability, assuming that the null hypothesis is true, of obtaining the value of the t-statistic essentially due to chance alone.

$$H_0: \beta_p = 0 \qquad \text{Equation (2)}$$

The OLS method assumes the errors (ϵ_i) as independent and identically distributed (iid) random variables, with equal variance (homoscedasticity). When the equal-variance assumption is not met, known as heteroskedasticity, it is possible to obtain incorrect estimations for the model. In this research, an additional assessment was performed due to concerns for heteroskedasticity. There are multiple tests to detect heteroskedasticity. We used the Breush-Pagan's test *(9)* to determine whether the constant variance assumption holds after estimating the OLS. The null hypothesis is homoscedasticity, as shown in Equation 3. The Breush-Pagan's test is asymptotically distributed as χ^2_{p-1} under the null hypothesis.

$$H_0: Var(\epsilon|\boldsymbol{X}) = \sigma^2 \qquad \text{Equation (3)}$$

Corrections for the presence of heteroskedasticity include the transformation to logarithmic data, or the use of the Box-Cox transformation *(10)*, shown in Equation 4. The Box-Cox transformation is used to transform non-normal dependent variables into a normal shape and shows good performance in correcting heteroskedasticity in linear relationships *(10)*.

$$w_i = \frac{y_i^{\lambda} - 1}{\lambda} \qquad \text{Equation (4)}$$

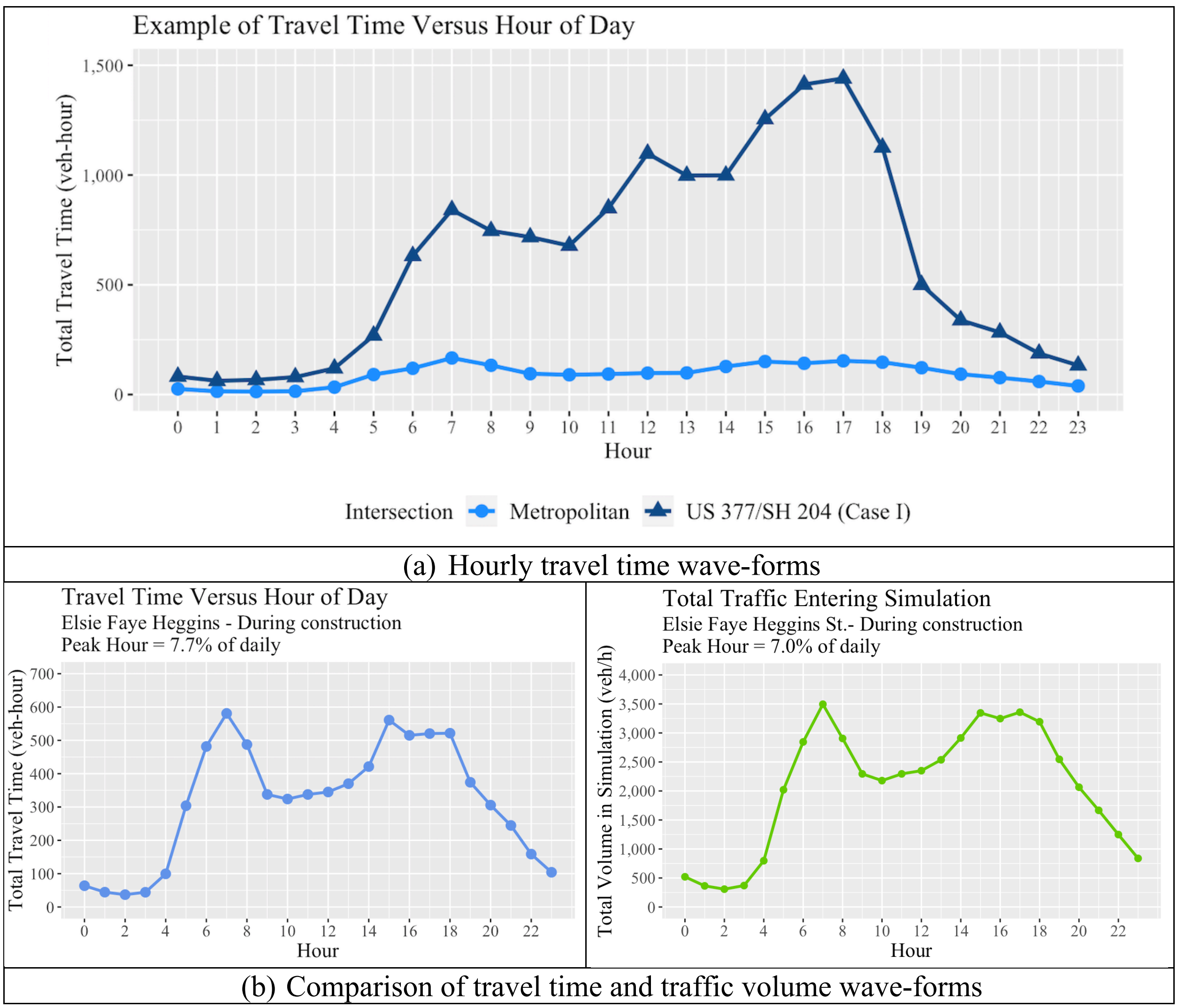
Where, $\lambda > 0$.

RESULTS AND DISCUSSION

In this section, we present the primary results and provide discussion that leads to the main findings. We first analyzed the hourly wave-form of the performance metrics and then we evaluated predictive relationships.

Wave-forms

Micro-simulation results in Figure 4 show hourly distributions of the performance variables. Specific examples of the diverse set of wave-forms of hourly travel time across hours of the day are illustrated for the Metropolitan Avenue/S.M. Wright and SH 114/US 377 intersection environments in Figure 5a. The Metropolitan intersection case depicts post construction conditions with minimal accumulated travel times across all 24 hours and the peak-hour travel time is 7.5 percent of the total daily travel time. The SH 114/US 377 case is a "during construction" scenario showing much larger accumulated travel times and the peak-hour representing 9.9 percent of the daily travel time.



(a) Hourly travel time wave-forms

(b) Comparison of travel time and traffic volume wave-forms

FIGURE 5 Example of travel time and traffic volume wave-forms.

One might be curious about how similar traffic volume and travel time wave-forms might be. Figure 5b provides such a comparison showing travel time and traffic volume versus time of day for one of the intersections along the urban freeway conversion project. The travel time chart provides travel time for the entire intersection environment, and the traffic volume chart includes all traffic entering the simulation during each hour of the 24 different simulated hours. The similarity of the two charts is not surprising since travel time is accumulated by vehicles, so more vehicles accumulate more travel time. However, this example is an exceptionally comparable case. Although the fractions of the daily travel time and volume during the peak-hour are not identical, they are similar at 7.7 percent for travel time and 7.0 percent for traffic volume. Generally, the shapes and timewise distributions of the two are quite similar as ideally, they should be. The delay wave-form, not shown in Figure 5, seems to have a wave form similar to travel time but with more contrast between construction and pre/post-construction cases, as presented in Figure 4.

A summary of results from the 11-case experiment, a pair of during and post-construction scenarios for the four intersections along the freeway conversion and an existing and two construction scenarios at SH 114/US 377 is presented as Table 2. The daily travel time column in Table 2 is the summation of the 24-hourly total system travel times (each hourly value was the mean of three replicate runs). The differences in variance of travel times across the three replicate runs was confirmed to be not statistically significant. Accumulated travel time for the hour with greatest travel time among the 24 hours of the day is shown as “Peak Hour Travel Time (hrs.)” and the fraction of the 24-hour total represented by the peak travel time hour is shown as “Peak Hour Percent of Daily Travel Time”. The ratio of standard deviation to the mean for each case, or coefficient of variation, is noted as “Coef of Variation Hourly Travel Time”. Since the coefficient of variation incorporates both a measure of central tendency, the mean, and a measure of scatter, the standard deviation, it provides a robust descriptor of the wave form representing the 24-hour travel time pattern.

TABLE 2 Summary of simulation results for the eleven cases.

Case ID	Peak Hour Percent of Daily Travel Time	Peak Hour Travel Time (hrs.)	Daily Travel Time (hrs.)	Mean Hourly Travel Time (hrs.)	Std. Dev. Hourly Travel Time	Std. Error Hourly Travel Time	Coef .of Variation Hourly Travel Time
1	7.7	580.8	7,583.4	316.0	179.5	36.6	56.8
2	7.2	445.3	6,174.1	257.3	134.8	27.5	52.4
3	7.6	166.5	2,200.0	91.7	48.0	9.8	52.4
4	7.5	160.6	2,144.8	89.4	47.2	9.6	52.8
5	8.3	848.0	10,183.1	424.3	271.5	55.4	64.0
6	7.8	614.9	7,858.0	327.4	183.9	37.5	56.2
7	9.1	598.0	6,606.7	275.3	271.5	55.4	98.6
8	8.2	381.8	4,678.0	194.9	183.9	37.5	56.2
9	9.7	1,439.9	14,912.6	621.4	106.2	21.7	54.5
10	9.9	1,295.1	13,050.8	543.8	262.7	53.6	59.5
11	7.7	818.4	10,593.1	441.4	187.6	38.3	68.2
Min.	*7.2*	*160.6*	*2,144.8*	*89.4*	*47.2*	*9.6*	*52.4*
Max.	*9.9*	*1,439.9*	*14,912.6*	*621.4*	*271.5*	*55.4*	*98.6*
Mean	*8.2*	*668.1*	*7,816.8*	*325.7*	*170.6*	*34.8*	*61.0*
Std. Dev.	*0.9*	*412.3*	*4,109.0*	*171.2*	*80.8*	*16.5*	*13.4*

Not surprisingly, the range of the percentages, 7.2 to 9.9 is similar to the AASHTO suggestion for the fraction of the daily traffic that occurs during the peak hour, that is, 8 to 12 percent. The mean percentage of the daily travel time for the peak hour is about 8.2 percent and the 95 percent confidence limits are 7.6 to 8.8 percent. The percentages of the daily travel time associated with the peak hour are shown graphically in Figure 6. The chart seems to depict a rather smooth relationship between peak hour fractions and daily travel times with the peak hour fractions increasing slightly as daily travel time increases.

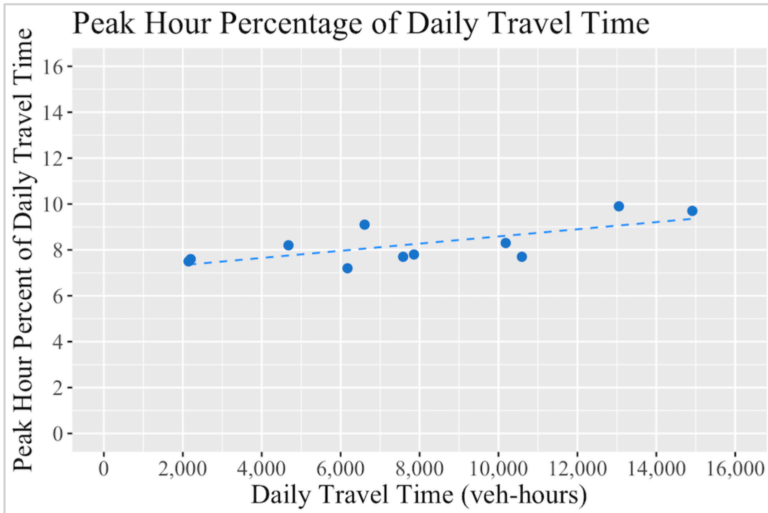


FIGURE 6 Peak-hour fractions of daily travel time.

Predictive Relationships

Recognizing the large effort required to properly perform micro-simulation of all 24-hours of a typical day, and the likely need to perform that task for several construction scenarios associated with one job, the research team developed several effort reduction procedures. If one develops a micro-simulation of travel time for only the peak-hour condition, then one could estimate the daily total travel time by dividing the peak-hour value by the fraction of the daily total represented by the peak-hour. Estimation of the daily total travel time could be based upon the mean, 8.2 percent or a range using the 95 percent confidence limits (7.6 to 8.8 percent).

Additionally, predictive relationships for the peak-hour fraction of daily travel time were developed using two predictive variables. The variables incorporate a measure of the demand and a measure of the capacity of the location. The predictors include the fraction of daily total *traffic volume* during the peak-hour and the *number of inbound lanes* serving the traffic demand. The number of lanes serves as an easily computed surrogate for capacity but does not require detailed capacity analysis of multiple geometric configuration scenarios. The basic relationship is shown in Equation 5.

$$Y_i = \beta_1 X_{Demand\ i} + \beta_2 X_{Capacity\ i} \qquad \text{Equation (5)}$$

Where,
Y_i = Percentage of daily travel time during peak hour for scenario i.
$X_{Demand\ i}$ = Percentage of daily traffic volume during peak-hour for scenario i.
$X_{Capacity\ i}$ = Number of inbound lanes serving traffic during scenario i.

Review of the residuals for the equation indicated a possibility of heteroskedasticity or non-constant variance so Breush-Pagan's test for detection of heteroskedasticity was performed in each of the cases. Additionally, two measures to correct heteroskedasticity were implemented. The first one includes transformation of the dependent variable using the natural logarithm. The second includes the Box-Cox transformation (Equation 4). Therefore, a total of three models were evaluated using R software and Microsoft Excel. Results for the models are summarized in Table 3, including the estimate and the p-value for the β_1 and β_2 parameters[2] along with the model summary and the Breush-Pagan test results.

The model estimation results show adjusted R^2 values within 0.88 and 0.89, indicating a high linear relationship between the variables. The Breush-Pagan's test indicates that only the travel time model using logarithmic transformation (second column) was not statistically significant at the 10 percent probability level, while the travel time model without variable transformation (first column) was significant at a five percent probability level. This result implies that these two cases may present problems with heteroskedasticity at those specific significant levels because it rejects the null hypothesis of equal variance (Equation 3).

In terms of the demand coefficient, representing the variables for the percentage of daily traffic volume during peak-hour, the positive coefficient is statistically significant for all the models. The coefficient suggests that traffic demand has a positive relationship with travel time as expected since more vehicles would tend to increase travel time. The capacity coefficient, defined by the number of inbound lanes, is negative, as expected. A reduced capacity will likely increase the user's travel time and delay.

TABLE 3 Estimation result for the models.

Variables	***Percentage of daily travel time during peak-hour (Y)***					
	Y		***Ln Y***		***Box-Cox Y***	
	Est.	(p-value)	Est.	(p- value)	Est.	(p-value)
Demand (β_1)						
Percentage of daily traffic volume during peak-hour	1.35	(0.00)**	0.32	(0.00)**	0.07	(0.00)**
Capacity (β_2)						
Number of inbound lanes serving traffic during scenario	-0.14	(0.05)*	-0.02	(0.07)*	-0.01	(0.61)
Adjusted R^2	0.88		0.89		0.88	
Standard Error	0.82		0.11		0.01	
F-statistic	546.04	(0.00)**	1997.64	(0.00)**	10850.82	(0.00)**
Breush-Pagan test	3.92	(0.05)*	4.53	(0.03)**	0.09	(0.76)

Note: conditions to reject the null hypothesis with a 90 percent (*) and a 95 percent (**) confidence level.

[2] Note that the model is using a zero-intercept value, or $\beta_0 = 0$.

SUMMARY AND CONCLUSIONS

Fractions of daily travel time accumulations occurring during the peak hour have been examined. Micro-simulation (both CORSIM and VISSIM) was used to estimate accumulated travel time across each of the 24-hours of typical weekdays and these hourly values were summed producing daily travel time accumulation totals. Percentages of the daily totals occurring during the peak hour were estimated and found to range from 7.2 to 9.9 percent. The arithmetic mean of the 11 cases investigated is 8.2 percent and the 95 percent confidence interval is 7.6 to 8.9 percent.

Wave-forms of accumulated travel time versus time of day and traffic volume versus time of day were found to be similar. This finding is re-assuring since travel time accumulation must be directly related to traffic volume.

The fraction of daily accumulated travel time occurring during the peak hour tends to fall within the AASHTO suggested range of 8 to 12 percent for the peak hourly traffic volume as a fraction of daily volume. The 11 cases described here tend to fall nearer to the lower end of the AASHTO suggested range (arithmetic mean 8.2 percent). Predictive relationships for the daily travel time were developed, and a robust evaluation of the models was presented.

Although robust, the current analysis is based on a limited sample (eleven cases), further research is recommended to include a wider variety of cases and locations to provide generalization of the results. Results and methods presented in this research are intended to provide transportation agencies with a methodological framework to develop such relationships, and to demonstrate empirical results that can potentially be applied in data-limited and time-constrained scenarios. Additional limitations of this research include the use of micro-simulation results and the lack of field validation. We recommend future research to evaluate scenarios with field validations tests such as probe vehicles.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Machemehl, R.B., Zuniga-Garcia, N., Khawaja, N.A., Pruner, K.D. and, Fu, M.; Methodology: Machemehl, R.B., Zuniga-Garcia, N., Khawaja, N.A., Pruner, K.D., and Fu, M.; Analysis and interpretation of results: Machemehl, R.B., Zuniga-Garcia, N., Khawaja, N.A., Pruner, K.D., and Fu, M.; Manuscript preparation: Machemehl, R.B., Zuniga-Garcia, N., Khawaja, N.A., Pruner, K.D., and Fu, M. All authors reviewed the results and approved the final version of this manuscript.

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