

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

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1 ABSTRACT

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

18

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

1 INTRODUCTION

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

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

23 Motivation

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

37 Even with suitable data, the limited amount of time may not allow the analyst to set up and
38 run a 24-hour traffic micro-simulation model to determine RUC, as micro-simulations tend to be
39 time-consuming. For a simple intersection with minor congestion, the run time of a 24-hour model
40 can be around 30 minutes. Under heavier traffic volume or/and congestion when the number of
41 vehicles to be simultaneously simulated is high, the simulation may take hours to complete. This
42 issue becomes more severe when retiming of traffic signals is required. Aside from the actual
43 number of simulation runs needed to find an optimal timing plan, ten simulation runs are required
44 under the default settings of VISSIM to confirm that a timing plan is optimal. With a “during

1 construction” model, retiming of traffic signals is typically required and congestion tends to occur.
2 In this case, the completion of signal retiming within the micro-simulation package may take days
3 rather than hours. Furthermore, due to randomness of the microscopic simulation model itself,
4 even with the model properly set up and calibrated, numerous runs are typically required, rendering
5 a 24-hour simulation an even less favorable option. On the other hand, the simulation run time for
6 a one-hour model is typically 2 to 5 minutes, hence greatly reducing the amount of time required
7 to obtain reasonable results.

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

16 **Objective and Methodology**

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

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

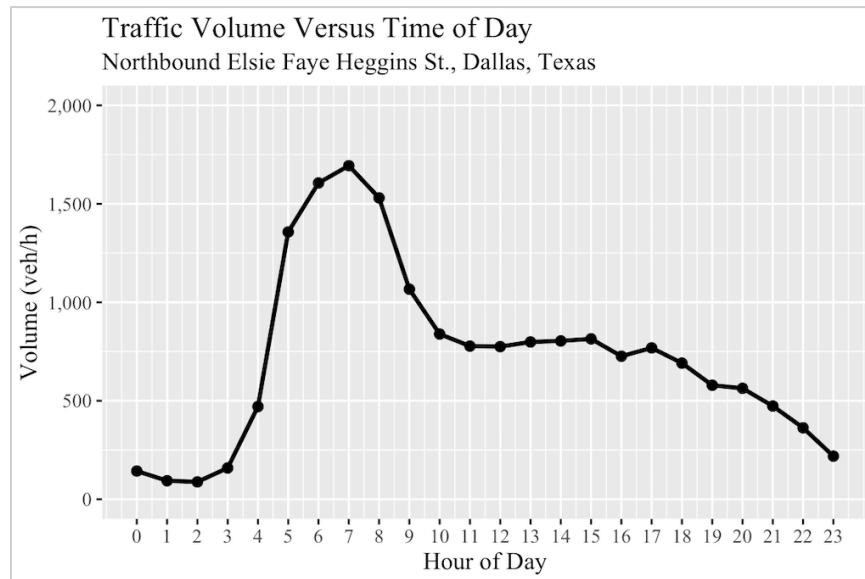
32 **Outline**

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

36 **BACKGROUND**

37 Increased RUC caused by traffic diversion and reduced capacity during construction are
38 recognized as significant components of total cost. Micro-simulation is a popular tool for
39 estimating user delays associated with urban construction particularly since in most cases, the
40 construction schedule must include handling existing traffic demands during construction.
41 Existing and future geometry, traffic control and traffic demands can be specified in a micro-
42 simulation environment and reasonable estimates of traffic flow, speeds, delays and travel times
43 can be produced for any specified condition. However, although estimates of *daily* impacts are

1 usually needed, traffic volumes are rather variable across the 24 hours of a typical day and most
 2 measures of effectiveness (MOE) are determined by the traffic demands. Figure 1 is a typical
 3 example of how traffic demand varies across the 24 hours of a typical day.



4
 5 **FIGURE 1 Hourly traffic volume versus hours of the day.**

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

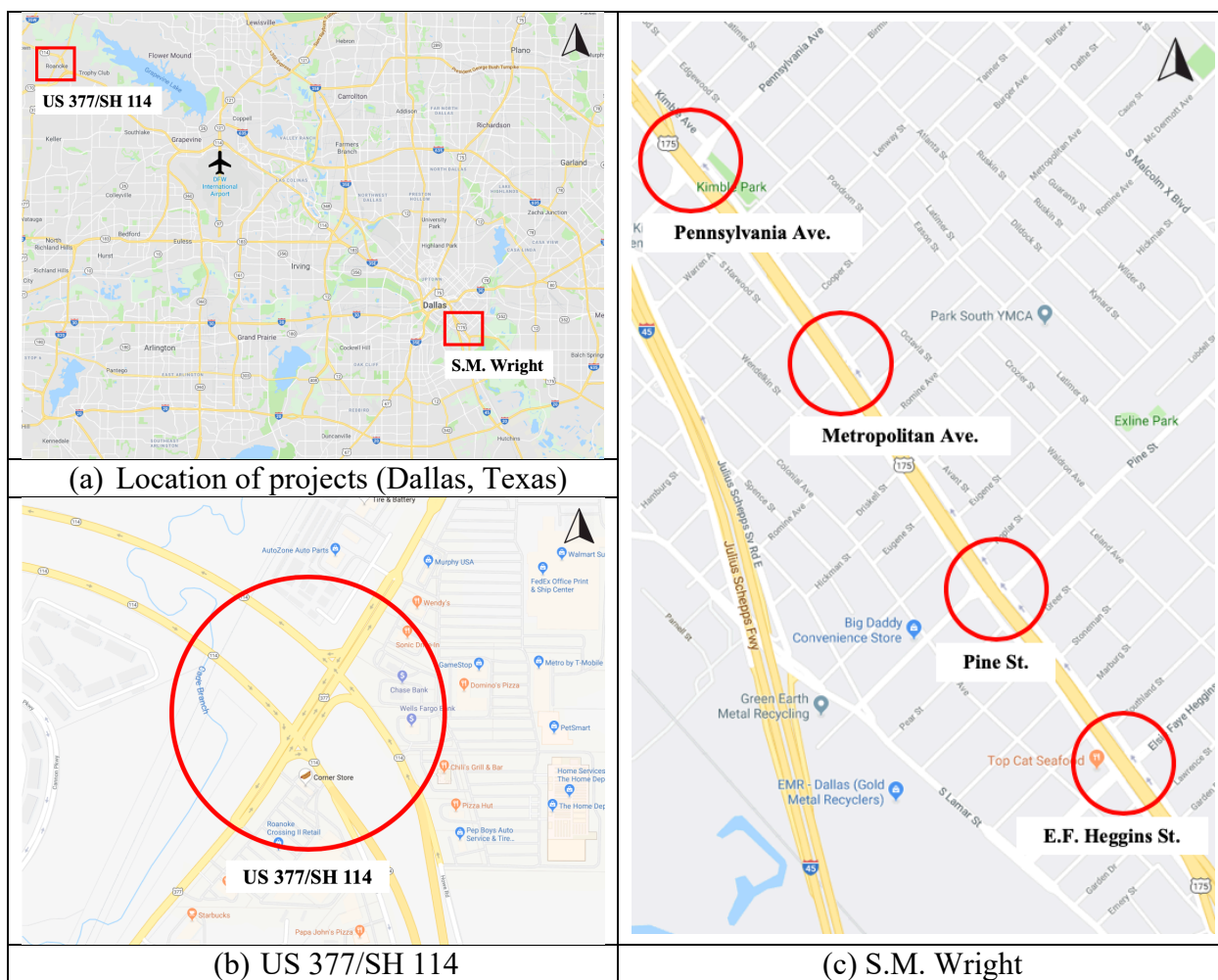
10 The fraction of *daily traffic volume* in the *peak-hour* has been examined by many authors.
 11 For example, almost 60 years ago, Carll and Homburger (2) examined the characteristics of hourly
 12 traffic volume distributions across hours of the day at locations in the Bay Area during the early
 13 1960's (2). The American Association of State Highway and Transportation Officials (AASHTO)
 14 Geometric Design Policy (3) suggests "Two-way DHVs (i.e., the 30 HV, or its equivalent) may be
 15 determined by applying a representative percentage (usually 8 to 12 percent in urban areas) to the
 16 ADT." A frequently used interpretation of this statement is that the peak-hour volume is usually
 17 8 to 12 percent of the daily total volume. In fact, the peak-hour volume shown in Figure 1 is 9.7
 18 percent of the daily total. Therefore, based upon the AASHTO suggestion, one could estimate the
 19 daily total traffic volume if one knows the peak-hour volume by simply dividing the peak-hour
 20 volume by the percentage that AASHTO says is 8 to 12 percent and in the Figure 1 example, this
 21 would be approximately 10 percent. Traffic volumes tend to exhibit significant timewise changes
 22 among days of the week, months and seasons. Bernard (4) explored the daily, weekly and seasonal
 23 trends in traffic volume of Atlanta freeways and recommended that time series analyses is an
 24 important part of traffic volume analyses (4).

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

1 **CASE STUDY**

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

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



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

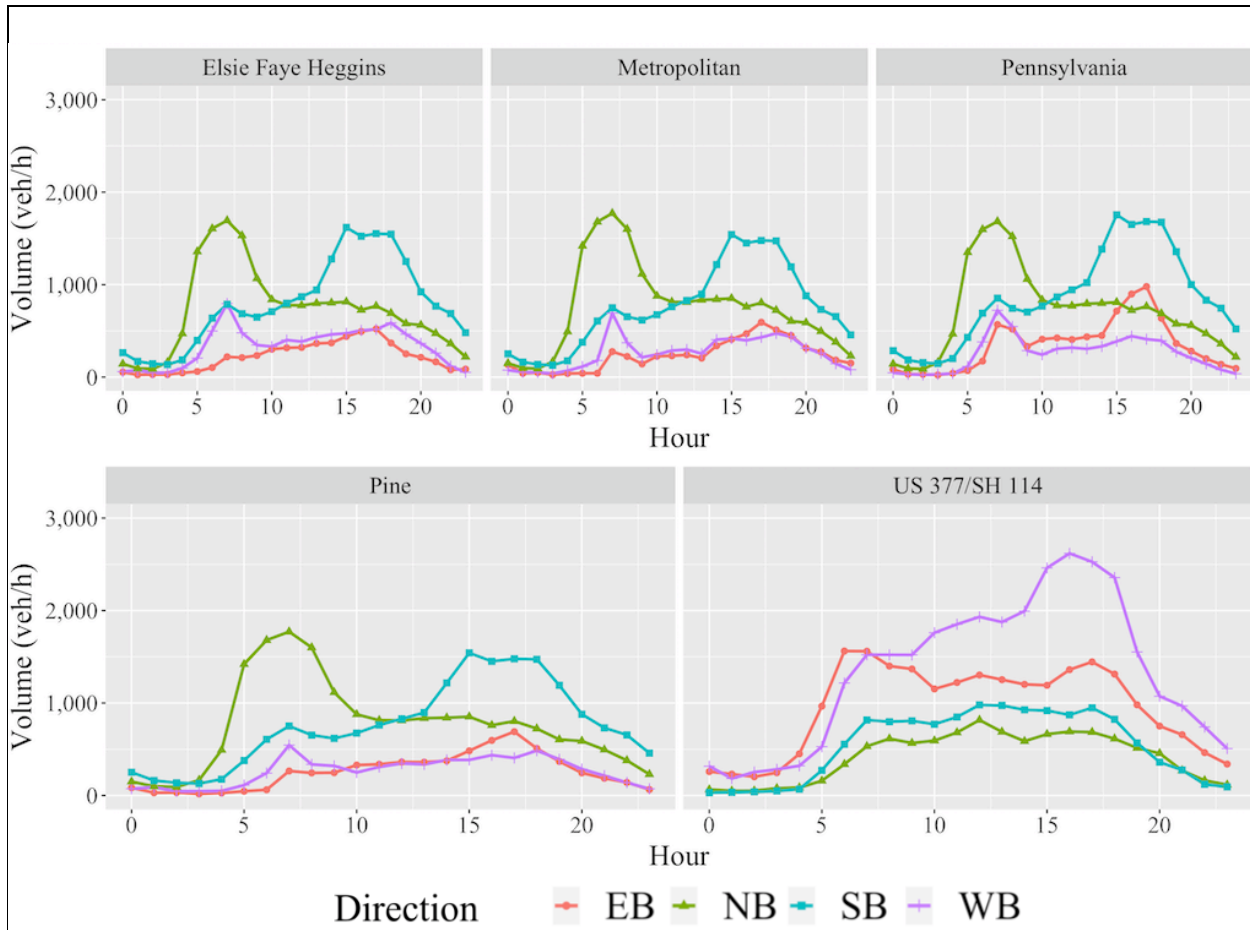
1 **TABLE 1 Description of construction cases.**

| 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 | - | | | | | | | |

2

3 Since comparative estimates of daily travel time were desired for the eleven cases, daily
4 traffic volume distributions like Figure 1 were developed. The hourly volume distribution was
5 obtained from 24-hours volume counts, openly available at the North Central Texas Council of
6 Governments (NCTCOG) website¹. The hourly volume distribution was used to approximate the
7 distribution of the traffic during the construction and pre/post-construction phases using the
8 projected traffic volumes for the projects. Figure 3 presents a summary of the inbound volume
9 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>



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

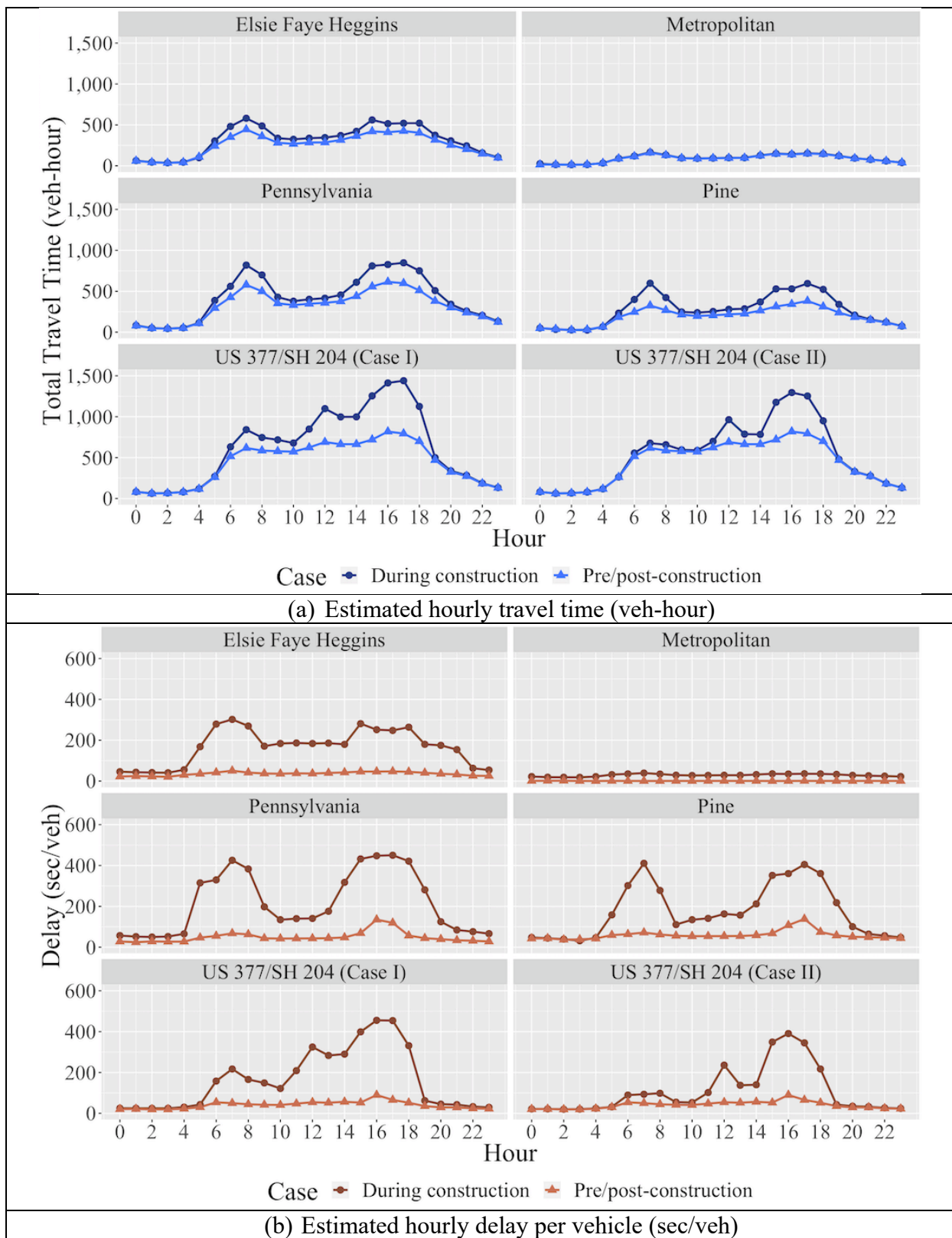
2 **METHODOLOGY**

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

5 **Micro-Simulation**

6 Two micro-simulation software packages were used in this study. CORSIM was used for the
7 projects along S.M. Wright while VISSIM was used for US 377/SH 114. The models consisted
8 of one-hour simulations using volumes and configurations discussed in the previous section. The
9 micro-simulators were run for each of the 24-hourly traffic demand conditions, and with three
10 replicate runs for each case, this became 72 simulations for each of the eleven cases or a total of
11 792 simulations.

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



1 **FIGURE 4 Results from micro-simulations.**

1 Modeling

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

$$7 \quad y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \epsilon_i \quad \text{Equation (1)}$$

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

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

$$22 \quad H_0: \beta_p = 0 \quad \text{Equation (2)}$$

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

$$31 \quad H_0: Var(\epsilon|\mathbf{X}) = \sigma^2 \quad \text{Equation (3)}$$

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

$$36 \quad w_i = \frac{y_i^\lambda - 1}{\lambda} \quad \text{Equation (4)}$$

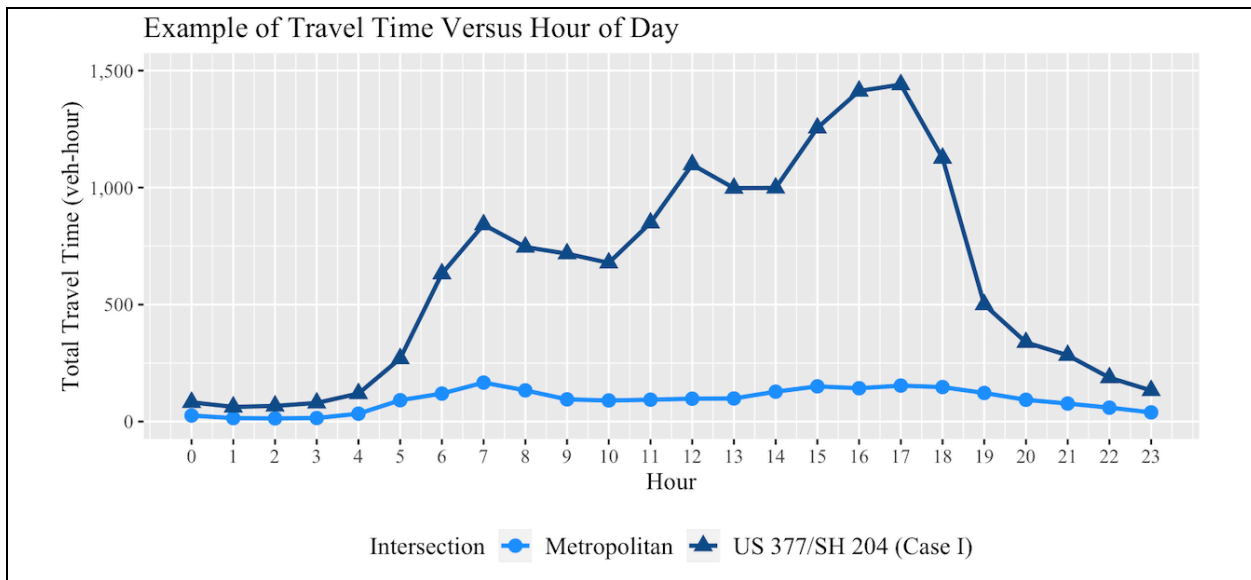
37 Where, $\lambda > 0$.

1 **RESULTS AND DISCUSSION**

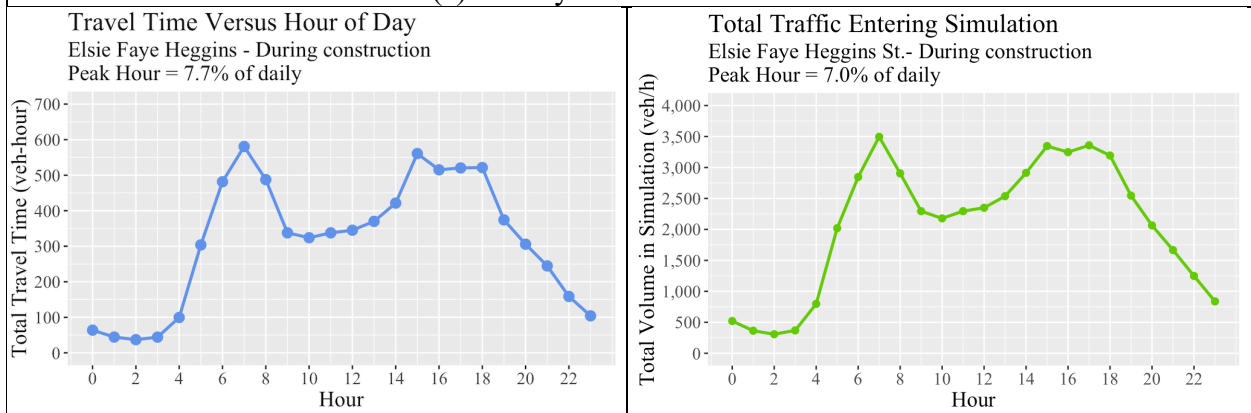
2 In this section, we present the primary results and provide discussion that leads to the main
 3 findings. We first analyzed the hourly wave-form of the performance metrics and then we
 4 evaluated predictive relationships.

5 **Wave-forms**

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



(a) Hourly travel time wave-forms



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

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

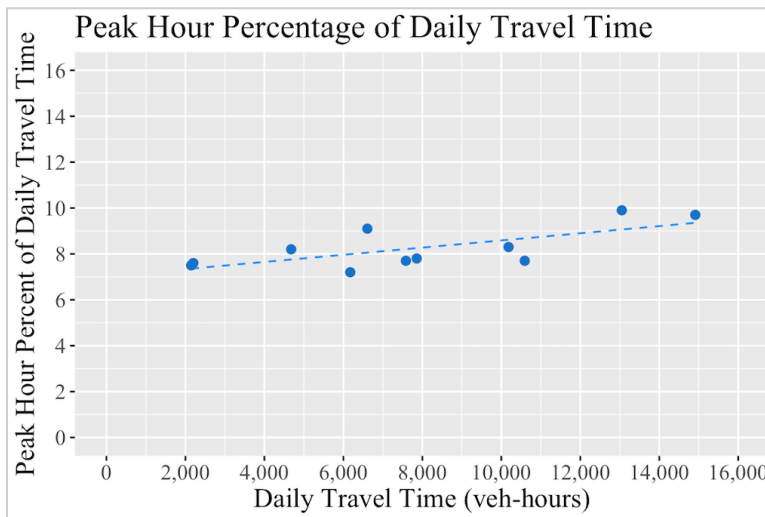
1 One might be curious about how similar traffic volume and travel time wave-forms might
 2 be. Figure 5b provides such a comparison showing travel time and traffic volume versus time of
 3 day for one of the intersections along the urban freeway conversion project. The travel time chart
 4 provides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

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

26 **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 |
| <i>Min.</i> | <i>7.2</i> | <i>160.6</i> | <i>2,144.8</i> | <i>89.4</i> | <i>47.2</i> | <i>9.6</i> | <i>52.4</i> |
| <i>Max.</i> | <i>9.9</i> | <i>1,439.9</i> | <i>14,912.6</i> | <i>621.4</i> | <i>271.5</i> | <i>55.4</i> | <i>98.6</i> |
| <i>Mean</i> | <i>8.2</i> | <i>668.1</i> | <i>7,816.8</i> | <i>325.7</i> | <i>170.6</i> | <i>34.8</i> | <i>61.0</i> |
| <i>Std. Dev.</i> | <i>0.9</i> | <i>412.3</i> | <i>4,109.0</i> | <i>171.2</i> | <i>80.8</i> | <i>16.5</i> | <i>13.4</i> |

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



8
 9 **FIGURE 6 Peak-hour fractions of daily travel time.**
 10

11 Predictive Relationships

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

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

$$26 \quad Y_i = \beta_1 X_{Demand\ i} + \beta_2 X_{Capacity\ i} \quad \text{Equation (5)}$$

27
 28 Where,

29 Y_i = Percentage of daily travel time during peak hour for scenario i .

30 $X_{Demand\ i}$ = Percentage of daily traffic volume during peak-hour for scenario i .

31 $X_{Capacity\ i}$ = Number of inbound lanes serving traffic during scenario i .

1 Review of the residuals for the equation indicated a possibility of heteroskedasticity or
 2 non-constant variance so Breush-Pagan's test for detection of heteroskedasticity was performed in
 3 each of the cases. Additionally, two measures to correct heteroskedasticity were implemented.
 4 The first one includes transformation of the dependent variable using the natural logarithm. The
 5 second includes the Box-Cox transformation (Equation 4). Therefore, a total of three models were
 6 evaluated using R software and Microsoft Excel. Results for the models are summarized in Table
 7 3, including the estimate and the p-value for the β_1 and β_2 parameters² along with the model
 8 summary and the Breush-Pagan test results.

9 The model estimation results show adjusted R² values within 0.88 and 0.89, indicating a
 10 high linear relationship between the variables. The Breush-Pagan's test indicates that only the
 11 travel time model using logarithmic transformation (second column) was not statistically
 12 significant at the 10 percent probability level, while the travel time model without variable
 13 transformation (first column) was significant at a five percent probability level. This result implies
 14 that these two cases may present problems with heteroskedasticity at those specific significant
 15 levels because it rejects the null hypothesis of equal variance (Equation 3).

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

22
 23 **TABLE 3 Estimation result for the models.**

| Variables | <i>Percentage of daily travel time during peak-hour (Y)</i> | | | | | |
|---|---|-----------|-------------|-----------|------------------|-----------|
| | <i>Y</i> | | <i>Ln Y</i> | | <i>Box-Cox Y</i> | |
| | 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.

24
 25

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

1 **SUMMARY AND CONCLUSIONS**

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

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

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

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

24 **AUTHOR CONTRIBUTION STATEMENT**

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

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