DEVELOPING AND APPLYING ARTERIAL CORRIDOR TRAVEL TIME INDEX ESTIMATION MODELS

by

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INTRODUCTION

Traffic congestion is a growing problem that many communities throughout the United States, both large and small, experience daily. According to the *2009 Urban Mobility Report*, congestion within the United States in 2007 was estimated to cause 4.16 billion hours of travel delay (*1*). Congestion hinders the economy, and it is imperative that it is regularly monitored and steps are taken to alleviate it through proactive planning. Mobility monitoring allows transportation professionals to track changes from year to year, prepare for future growth, and implement the most efficient congestion mitigation measures. Direct mobility monitoring on a regular basis can be time consuming and expensive; therefore, models can be used to estimate parameters associated with congestion; including volume, travel time, and delay.

Arterial congestion is growing as freeways become congested; thus, it is important to monitor and mitigate arterial congestion. Travel time is a vital statistic for transportation system performance that is easily communicated to both technical and non-technical audiences. Common planning applications such as mobility monitoring can benefit from methods to estimate the travel time index (TTI). The travel time index relates the actual (peak) travel time relative to an off-peak travel time. The TTI has proven valuable for mobility analysis and quantifying transportation system performance (*1*).

EXISTING MODELS

Existing published models for arterial studies incorporate many desirable features, but all have some limitations for transportation planning purposes. This section evaluates models typically used by transportation professionals for estimating speed or travel time along arterials.

Mobility in the arterial environment is best understood when conveyed in terms of arterial travel time. Previous research for the National Cooperative Highway Research Program (NCHRP) states, "Measures related to travel time and speed are the most flexible and useful for a wide range of analyses. . . Travel time measures are consistent, address transportation and land use systems, and are responsive to concerns of residents, businesses, and travelers" (*2*). The interrupted arterial environment poses many obstacles and possesses other parameters not seen on uninterrupted facilities, so travel time models developed for freeways are not very useful for applications on arterials. In recent years, various arterial travel time models have been developed, but they often utilize the equations in the *Highway Capacity Manual (3)* and have similar numerous inputs. A model to estimate arterial travel time is desired that requires limited data collection while remaining useful to transportation engineers and planners.

The *HCM* is a common source transportation professionals reference for estimating travel time on an arterial. The *2000 Highway Capacity Manual (HCM)* uses street classification, segment length, and free-flow speed to determine the running time on an urban street (*3*). The arterial travel time is estimated using the running time combined with the three types of signal delay: uniform delay, incremental delay, and initial queue delay. During over-saturated conditions, the high variability of travel time makes deterministic *HCM* results questionable. In addition, the information needed to calculate these delay values can be difficult to locate or expensive to collect in many situations. The *HCM* model is an operational model with extensive input requirements. The variables that are needed to calculate delay using the *HCM* model include the progression adjustment factor, volume, road capacity, capacity and green time for each lane group, cycle length, adjustment factors for actuated control and filtering or metering, initial queue, and duration of analysis period and the unmet demand. Additionally, assumptions that are used for the *HCM* model are not universal for all intersections. Permitted left turns, protected-permitted left turns, progression, multiple green displays, and protected-permitted right turns are just some of the situations where alterations must be made for the *HCM* model to work (*4*).

Chapters 15 (Urban Streets) and 16 (Signalized Intersections) of the *2000 HCM* outline in detail how to determine the travel time on an arterial by calculating running time on an arterial and control delay at signalized intersections. First, the functional class of the arterial must be classified based on the functional category (principal or minor arterial) and design category (high-speed, suburban, intermediate, or urban). The balance between access and mobility, types of intersecting streets, and trip types are used to distinguish whether a road is a principal or minor arterial. The design category uses the following criterion: access density, arterial type, parking, presence of left-turn lanes, signal density, speed limit, pedestrian activity, and density of roadside development. Engineering judgment is necessary when a street does not clearly fit into one category. The street classification, along with free-flow speed and average segment length, are used to find the segment running time.

In addition to calculating the running time, the signal effects must also be included. The *HCM* method for calculating signal delay is a very long and detailed process that requires a large amount of data and knowledge about each intersection. Equations considering uniform and incremental delay are used to calculate the control delay at a single intersection. When the queue at an intersection does not clear each cycle, another equation is used to calculate the initial queue delay. The estimated delay will be added to the running time of the approach link to derive the travel time of the link, therefore this arterial travel time evaluation is link-based.

The HCM method requires a significant amount of information about each intersection and many calculations for an estimate of arterial travel time. For a given corridor, the running time for the entire corridor as well as the uniform, incremental, and initial queue delay at each signalized intersections would need to be calculated, which would require a tremendous amount of field data collection and present a significant challenge for a planning application. In addition, because the input data are link-based, the estimated delay from the *HCM* method is link-based in nature, rather than representing a corridor.

Another limitation of the *HCM* model is that the delay values increase rapidly as the volume approaches and exceeds the capacity. Rouphail has recognized this problem and written several papers relating to signalized intersections and arterial travel times over the past two decades (*5-27*). During the 1990s, he published several papers proposing changes to the delay parameters used in the *HCM*, and some of those recommendations have been used in the updated versions of the *HCM* (*10*). In one of his more recent publications, he proposed an alternate method to extracting delay from the queue accumulation diagram, which does not require the many assumptions and inputs, but produces similar results to those from the *2000 HCM* method. The proposed use of this model is to incorporate it into the *HCM* along with lane-by-lane analysis (*4*). While this may be an accurate method for looking at each lane at every intersection along a corridor, implementation can be very cumbersome for arterial travel time calculation. This model is most useful for individual intersections or signal analysis.

For planning applications, another common place for speed estimates is the original Bureau of Public Roads (BPR) Curve that is shown in Equation 1 (*2*,*28*).

$$S = \frac{S_0}{1 + a\left(\frac{v}{c_1}\right)^b} \qquad \textit{Equation 1}$$

Where:
S_0 = free-flow travel speed;
S = travel speed at volume v; and
C_1 = practical capacity ≅ 80% of maximum capacity.

The values of *a* and *b* were 0.15 and 4, respectively. Many regions have modified these coefficients for local conditions. While the simplified nature of the BPR function facilitates understanding and application, it is also a link-based model and typically only used for links of uninterruptible-flow facilities. The model does not inherently include variables considering green time distribution, coordination, or access point density except to the extent that these considerations can be incorporated into the capacity estimate used by the practitioner. The arterial model described in this report to estimate the travel time index directly considers these signal and access characteristics.

Research sponsored by the National Cooperative Highway Research Program (NCHRP) developed relationships to estimate speed based upon signal density and average daily traffic per lane by arterial Class (as defined by the 1994 *HCM*) (*2*). The models provide a very general guideline for practitioners. The models do not consider signal coordination or access density considerations. The R^2 values for the models were low, varying from 0.07 to 0.35. The planning-level model described in this report considers access density and signal coordination parameters, yet the inputs to the developed model include data that are readily available, or easily obtained, by practitioners.

Summary of Existing Models

The selection of the most common models here provides a representative sample of the general limitations of existing models. The limitations of existing speed estimation arterial models generally include one or more of the following:

- Link-based vs. arterial (corridor)-based: Some existing models are based on a link or individual intersection rather than being a true arterial model. Generally, link-based models do not effectively consider signal coordination or other driver interference (e.g., driveway density) that may occur along an arterial corridor. Corridor-based models allow for consideration of driver interference, which is improved with access management treatments.
- Require multiple Inputs: Some existing models require multiple inputs that may not be readily available and may be costly to collect.
- Not calibrated/validated with field data: Some existing models have not been adequately calibrated or validated with actual field data.
- Do not explain variability: Some existing models do not have very good estimation ability (e.g., low R^2, high root mean square error) and do not estimate arterial travel time well under a variety of traffic volume conditions (e.g., congested and uncongested).

RESEARCH OBJECTIVES

The primary objective of the research upon which this report is based is to develop and validate an arterial model to estimate the travel time index (TTI). In light of the limitations of current models listed previously, the research documented here describes the development of an arterial model that is:

- Corridor-based with consideration of signal coordination and motorist interference (e.g., driveway density).
- A function of generally available independent variables for estimating the travel time index along the corridor.
- Calibrated and validated with extensive field data.
- Able to explain a relatively high degree of variability as measured by R^2 values over relatively low volume, high volume, and extreme (special event) situations.

The resulting models described in this report provide an estimate of the travel time index (the ratio of the average peak period travel time to the travel time at free-flow conditions) with consideration of driveway density. The models can be easily implemented by transportation professionals for TTI estimation for planning applications. Using an index has several advantages, including comparability between long and short arterials and transferability between different geographic locations or corridors. Comparison of the TTI estimates between different corridors can assist transportation professionals in prioritizing mobility improvements.

STUDY CORRIDORS

Researchers used data from four case studies to perform this research. One site (College Station, Texas) was used to develop the model, while three additional sites (in Virginia) were used to validate the model transferability. Table 1 provides a summary of key characteristics of the sites.

The following sections describe the process to develop the model using the College Station, Texas site and then subsequent sections describe validation of the resulting models using the three (3) Virginia sites.

DATA COLLECTION AND REDUCTION FOR MODEL DEVELOPMENT SITE

Researchers performed extensive data collection along the College Station, Texas corridor for model development. Data collection included travel time runs, volume counts, video, and obtaining signal timings.

Table 1. Study Site Characteristics.

Corridor	Location	Case Study Use	Length (Miles)	Median Type(s)	Total No. of Lanes	No. of Signals	Signal Density (Signals/Mile)	Driveway Density (Driveways /Mile)	Primary Land Uses
FM 60 (University Drive)	College Station, Texas	Model Development	2.6	Raised median, TWLTL	6	12	4.6	27	Retail, University
US 60 (Midlothian Turnpike)	Chesterfield, Virginia	Model Validation	2.3	Grassy depressed, TWLTL, undivided, painted	4	6	2.6	24	Retail, Undeveloped
US 29 (Seminole Trail)	Charlottesville, Virginia (Albermarle County)	Model Validation	2.8	Raised	6-8	11	3.9	21	Retail, Undeveloped
US 29 (Lee Highway)	Centreville, Virginia (Prince William County)	Model Validation	8.0	Grassy depressed median, Jersey barrier, undivided	4	13	1.6	9	Undeveloped, state forest, retail, residential

Traffic Volume Data

Researchers collected extensive traffic volume data along the College Station corridor. Using pneumatic tubes, directional traffic volumes were collected at 40 different locations along University Drive (FM 60). Traffic counts were generally taken between the major signalized intersections and cross streets along University Drive, as well as north and south of the major signalized intersections. Researchers collected traffic data from November 6, 2006 (Monday) to November 13, 2006 (Monday).

Researchers also collected video data along the primary signalized intersections along the corridor. Students reduced the data to obtain turning movements and queue length information at the signalized approaches. Data collection by video or digital video recorder was performed at all but one of the signalized intersections along the corridor. Researchers performed video data collection from the top of tall buildings along the corridor or by using video trailers or digital video recorders connected into the signal systems.

Travel Time Data

Researchers collected travel time data on two normal weekdays: Wednesday (November 8, 2006) and Thursday (November 9, 2006). Travel time data were collected from 7:00 a.m. to 10:00 a.m. and from 4:00 p.m. to 7:00 p.m. on Wednesday and Thursday. Travel time runs were collected in both directions, and instrumented test vehicles performed travel time runs in a circuit in both directions. Researchers used the "floating car" test vehicle driving style and were instructed to "float" with the traffic by attempting to safely pass as many vehicles as pass them (*29*). Researchers also included travel time runs on November 11, 2006 (Saturday) from 10:00 a.m. to 1:00 p.m. prior to a Texas A&M University home football game. This provided an opportunity to obtain travel time data during special event traffic conditions.

Researchers used test vehicles equipped with global positioning system (GPS) instrumentation. Researchers instrumented each vehicle with a GPS antenna connected to an on-board laptop computer. Each laptop had software on it, which the test vehicle drivers used to collect the travel time data. Researchers collected 15 hours of travel time data. Researchers used commercially-available software to reduce and analyze the travel time data.

Reducing the travel time data was a lengthy process. The test vehicle drivers completed travel time run data collection sheets before and after each run to document information such as name, driver, vehicle information, weather conditions, incident conditions and other queuing information. These sheets were used to keep track of the approximately 600 travel time runs performed. Some runs were removed because drivers did not make a complete run through the entire corridor (e.g., driver starting the run after the first designated checkpoint).

Researchers used extensive data collection and reduction procedures that are documented elsewhere in a study performing GPS data collection (*30*). The interested reader is encouraged to review this other study for detailed data collection and reduction processes, including a guide used for travel time run data reduction.

After performing quality control and cleaning out any runs with errors, there were 283 runs in the eastbound direction and 280 runs in the westbound direction. After reducing all of the runs, headways were found to be between 2.95 minutes and 3.36 minutes for each direction and each day. To maintain these approximately three-minute headways, researchers operated between six and eight test vehicles along the corridor. Figure 1 shows the speed profile for the afternoon eastbound test vehicles including both Wednesday and Thursday data.

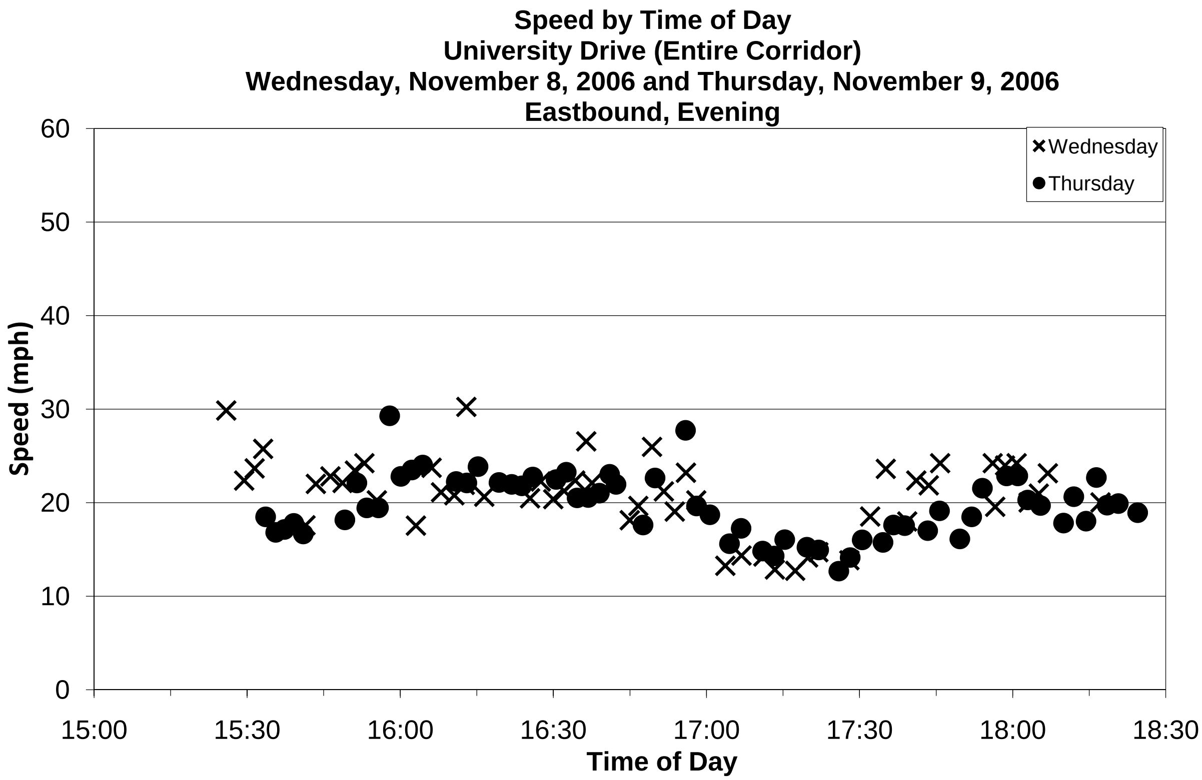

Figure 1. Afternoon Eastbound Test Vehicle Speeds.

Additional Data Collection and Reduction

In addition to the extensive traffic volume and travel time data collection described above, researchers also performed the following data collection activities:

- Used GPS travel time data to determine lengths between intersections for developing a micro-simulation operations model of the corridor.
- Collected signal timings and coordination, if any, for both peak and off-peak periods from each signal cabinet (and permitted/protected left-turn phasing).
- Obtained "as built" drawings of corridor from the Texas Department of Transportation (TxDOT) to determine turn-bay lengths.
- Documented changes in speed limit throughout the corridor.
- Documented driveway locations and counts for density measure along the corridor.
- Computed turning movement volumes and percentages from video recordings of signal approaches for the micro-simulation model input.
- Computed queue lengths for each lane and approach of the signalized intersections to validate the micro-simulation model. This was computed by watching the video of each signalized intersection approach and pressing "pause" before the green started and counting the queue.

MICRO-SIMULATION MODEL DEVELOPMENT

To ultimately develop a model to estimate the travel time index for an arterial corridor, additional observations of travel time index values were desired to obtain a broader range of the dependent variable (travel time through the corridor). Because micro-simulation is a stochastic model, multiple replications can be used to capture variability in the response variable of travel time.

To obtain the additional replications ("observations"), researchers calibrated a CORridor SIMulation (CORSIM) micro-simulation model. Researchers used the traffic counts, turning movements reduced from video, signal timings, "as built" drawings, and posted speed limits to develop the calibrated model. The model was calibrated for both directions of travel. Researchers used the queue length information to validate the micro-simulation model. Intersection approaches were investigated cycle-by-cycle to investigate queuing parameters (e.g., average, maximum). Researchers calibrated parameters such as link speeds and queue discharge characteristics to ensure the calibrated model was performing within approximately five percent of field data for maximum queues and travel times.

After development of the CORSIM micro-simulation model, the research team used the model to produce additional replications ("runs") of travel time index estimates given the range of operational inputs (e.g., traffic volumes during different times of the day).

Researchers set up the micro-simulation model to produce additional replications of each 30-minute time period for which travel time data were available. Because there were 15 total hours of data collection, there were 30, 30-minute time periods. Calibrated and validated models were produced for each of these 30, 30-minute time periods by direction. Note that this "validation" refers to validation of the CORSIM micro-simulation model, not validation of the TTI models that are developed and described in subsequent sections of this report and uses the three case studies from Virginia mentioned in Table 1. Traffic volumes, turning percentages, signal timings, and geometric data were input into the model. Researchers replicated the micro-simulation model ten (10) times for each 30-minute time period except Wednesday and Thursday afternoon from 6:00 p.m. to 7:00 p.m. As described later in the report, this time period was not used in the final analysis. These time periods were replicated four (4) times each. Also, researchers do not anticipate that the lower number of replications would affect the ultimate model to estimate the travel time index as the standard deviation of the corridor travel times for those original cases run ten times and those run four times were relatively similar. The replications resulted in 276 additional replications of the original dataset. Researchers ultimately had 30 original cases and an additional 276 replications of the total corridor travel time and average link volume along the corridor from the CORSIM output.

DEVELOPMENT OF A MODEL TO ESTIMATE THE TRAVEL TIME INDEX

After performing replications of the validated CORSIM model, researchers had a populated database with numerous variables from which to develop a model to estimate the travel time index. Initially, all data were in the database at the link ("signal-to-signal") level. Because the creation of a corridor-based model was desired, the research team aggregated the link-based information to the segment level. Researchers created six segments (three in each direction) along the corridor because of different signal coordination settings along the arterial.

Researchers defined the variables in Table 2 as predictor (independent) variables for estimating the travel time index. Table 2 provides the variable names and descriptions. In general terms, the independent variables consider volume, access density, signal density, signal coordination, and the proportion of green time to total cycle time (g/C).

Equation 2 shows the general form of the travel time index. Note that the travel time index is written in the form of travel rate (minutes per mile). When the actual travel rates compared in the ratio are over the same length, the length simply cancels out, and the TTI is computed as a ratio of the travel time in the peak to the travel time in the off-peak. The denominator of Equation 2 is the travel rate at the free-flow speed. For this research, an average (statistical mean) off-peak free-flow travel rate was used in the denominator for all the calculations.

It is also important to note that the travel time index expressed in Equation 2 is sometimes referred to as a travel rate index when incident conditions are not included in the calculation (*31*). Note that throughout this document, the authors use the "travel time index" terminology to avoid confusion in the nomenclature. In the arterial environment investigated here, the differences between the travel rate index and the travel time index (i.e., the incident factor) are considered negligible.

$$\begin{matrix} \mathit{Travel\ Time} \\ \mathit{Index} \end{matrix} = \frac{\begin{matrix} \mathit{Average\ Travel\ Rate} \\ (\mathit{minutes\ per\ mile}) \end{matrix}}{\begin{matrix} \mathit{Free\text{-}flow\,Travel\ Rate} \\ (\mathit{minutes\ per\ mile}) \end{matrix}} \qquad \mathit{Equation}\ 2$$

Researchers normalized (by length) or weighted many of the variables shown in Table 2. Normalizing some of the variables by length (VMT/LN-MILE, DRIVEDENS, SIGDENS) ensures they are scalable to corridors when the model is applied elsewhere. Weighting driveway density (DRIVEDENSWT) by through VMT ensures that the model is scalable. It also incorporates the intuitive fact that driveway density should affect roadway operation as a function of the number of through vehicles, length of the given link, and the number of lanes. Similarly, weighting g/C by through volume on the link is meant to capture the intuitive affect that g/C along a corridor should be averaged to the segment level as a function of how many vehicles are influenced by each link g/C value.

Table 2. Candidate Predictor (Independent) Variables for Travel Time Index.

Potential Predictor Variable	Variable Name in Model	Description
VMT/Lane-mile	PHV/LANE	• Continuous variable • Vehicle-miles of travel (VMT) of through vehicles per lane-mile. • This value reduces to the peak hour volume per lane. It is shown as PHV/LANE in the remainder of this report.
Driveway Density of Segment	DRIVEDENS	• Discrete variable • One value for each segment • Number of access points in given direction and segment / length of segment
Driveway Density of the Segment Weighted by Link Through Volume	DRIVEDENSWT	• Continuous variable • Computed as: $\frac{\sum_{link} (\# \, Access_{link} \times Through\,VMT_{link}) / length_{link}}{\sum_{link} (Through\,VMT_{link})}$
Signal Density of Segment	SIGDENS	• Discrete variable • Number of links / length of segment • Only one value for a pair of segments (eastbound and westbound)
Signal Coordination	COORD	• Discrete variable • Favored (There is coordination of signals, traveling during the peak, and in the peak direction). • No coordination (There is no coordination of signals). • Unfavored (There is coordination of signals, traveling during the peak, and in the off-peak direction).
Weighted Average Green Time to Cycle Time for Through Direction	g/C	• Continuous variable • Average traffic signal green time per total cycle time in direction of travel • Weighted by through volume of the link • Computed as: $\frac{\sum_{links} [Through\,Vol \times g/C]}{\sum_{links} Through\,Vol}$

Determination of Peak and Off-peak Traffic Conditions

Researchers investigated speed graphics by segment and direction as shown in Figure 1. Researchers also investigated travel time and TTI graphics by time-of-day to investigate the ranges of the TTI values over time. Researchers computed TTI values relative to the average and 15th percentile travel time, however the relationships using the average values ultimately resulted in the most appropriate models, and are simpler for practitioners to understand and implement. Researchers selected the time periods for the peak and off-peak analysis and model development with consideration for the following:

- <u>Signal timing plan</u>: Researchers ensured that the peak and off-peak periods used for the TTI computation included the same timing plan (e.g., morning peak period or afternoon peak period) to ensure comparison to an off-peak travel time in the arterial environment with similar operational constraints.

- Speed and travel time profiles: Researchers created graphics as shown in Figure 1 to investigate the speed (and travel time) profiles along the corridor, and the segments, to identify peak conditions.
- Travel time index profiles: Researchers investigated plots of TTI by segment and time period.

After consideration of these factors, researchers determined that there are two "ranges" of congestion level in the data. There appears to be what might be termed "light" congestion conditions from 7:30 a.m. to 8:30 a.m. (TTI values up to approximately 1.35), and conditions of what might be termed "moderate" congestion (TTI values up to approximately 2.8) from 5:00 p.m. to 6:00 p.m. Researchers used the morning data to develop a model representing light congestion conditions, and the afternoon data were used to develop a model representing the moderate congestion conditions. Average speeds in the peak direction during the "light" congestion period (morning) were approximately 25 mph, and during the "moderate" congestion period (afternoon) were approximately 18 mph.

The off-peak (denominator in Equation 2) was computed as the average off-peak travel rate from 7:00 a.m. to 7:30 a.m. in the light congestion conditions model and from 4:00 p.m. to 4:30 p.m. in the moderate congestion conditions model. Note that the Saturday (special event) data were not used in the model development as the congestion levels were generally not as high throughout the corridor as those during the morning and afternoon commutes.

It should be noted that the database included TTI values that were occasionally below 1.00. At first this might seem counterintuitive to traditional TTI computation because this implies that during the peak period, motorists are able to get through the corridor faster, in some cases, than in the off-peak period. Due to the unique operating conditions in the interrupted flow environment of arterial streets, this can occur. One example would be that during the peak period signals coordination leads to reduced travel time in the favored direction even though the flow in this direction is higher than the off-peak flow.

After determining these two time periods and the two corresponding models to pursue, researchers investigated numerous models, and the results are provided in the sections that follow.

Equation 3 shows the general form of the fitted models developed in this report. The βs are the regression coefficients, and Xs are potential predictors.

$$TTI = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots\dots\dots + \beta_n X_n \qquad \textit{Equation 3}$$

Not all of the variables shown in Table 2 ultimately ended up as significant for inclusion in each model after the statistical analysis. Researchers used the following typical criteria and guidance in the regression model determination:

1. Correlation among independent variables: Ensuring that there is no significant correlation among the selected independent variables to ensure there is no collinearity problem in the regression analysis.
2. Parameter significance: Ensuring that only predictor (independent) variables were kept that are statistically significant.
3. Coefficient sign: Ensuring signs on the coefficients were intuitive in the fitted model.
4. Residual investigation: Ensuring that there were no significant patterns in the residual plots (plots of the predicted value compared to the difference between the predicted

value and actual value). Any patterns present in the residuals indicate that one or more of the underlying assumptions for the regression are violated.

Moderate Congestion Level Model of Travel Time Index

For the model to estimate the TTI for the moderate congestion level, researchers investigated numerous combinations of the independent variables shown in Table 2. Researchers ultimately vetted the models to satisfy the four criteria identified above. The general model form is shown in Equation 4. This model satisfied the criteria and provided the best fit (R^2=0.94). All independent variables shown in Equation 4 are significant at the $\alpha = 0.05$ significance level.

$$\begin{aligned} TTI = {} & 2.936 + 0.00226(PHV/LANE) + 0.011(DRIVEDENSWT) \\ & - 6.770(g/C) - 0.019(COORD[Favored]) + 0\,(COORD[Unfavored]) \\ & + 0.364(COORD[Uncoordinated]) \end{aligned} \qquad \textit{Equation 4}$$

For the moderate congestion level conditions, the best-fit model is a function of peak-hour volume per lane (PHV/LANE), weighted driveway density, g/C, and coordination (favored, unfavored, or uncoordinated). In Equation 4, only one term is used to estimate TTI for the signal coordination variable (e.g., if coordination is "favored," only the "-0.019(COORD[Favored])" term is used, and the other COORD terms are ignored; if coordination is "unfavored," a term for coordination is not used because the coefficient is zero). The signs on all terms are intuitive. For example, increased peak-hour volume per lane (PHV/LANE) or DRIVEDENSWT yield higher TTI values (positive sign), and higher values of g/C yield lower TTI values (negative sign). The other variables shown in Table 2 were not statistically significant or did not result in a meaningful model.

Researchers investigated the plot of the residual by predicted value for the moderate congestion conditions model, and there were no significant patterns present (i.e., residuals are generally centered around zero); therefore, the assumptions for regression are not violated. Researchers also investigated exponential models, but the linear models provided comparative TTI predictability, and they are easier for practitioners to implement.

Light Congestion Level Model of Travel Time Index

For the light congestion level model to estimate TTI, researchers investigated numerous combinations of the independent variables shown in Table 2. Researchers ultimately vetted the models to satisfy the four criteria identified above. The model shown in Equation 5 satisfied the criteria and provided the best fit (R^2=0.68). All independent variables shown in Equation 5 are significant at the $\alpha = 0.05$ significance level.

$$TTI = 1.341 + 0.00041(PHV/LANE) - 0.781(g/C) \qquad \textit{Equation 5}$$

For the light congestion conditions, the best-fit model is a function of only the peak-hour volume per lane (PHV/LANE) and the ratio of through-vehicle green time to total cycle time (g/C). It seems intuitive that at the lower congestion levels, the COORD term may not affect the model because traffic is flowing relatively smoothly. Similarly, access terms (DRIVEDENS or DRIVEDENSWT) do not seem to be significant for this model. As with the moderate congestion level model, researchers investigated residuals, and there were no significant patterns present (i.e., residuals are generally centered around zero); therefore, the underlying assumptions about errors for regression are not violated. Researchers also investigated exponential models for the light congestion level also, but the linear models provided comparative TTI predictability, and they are easier for practitioners to implement.

VALIDATION OF MODEL TRANSFERABILITY

Researchers investigated the transferability and use of the developed models by applying them to three case study locations in Virginia. The characteristics of these three roadways in Virginia were previously shown in Table 1.

Data Collection at Validation Study Corridors

Researchers required extensive data to validate the light and moderate congestion models. Researchers identified the three Virginia case studies because they had access to the detailed data required. It is important to note that the level of data detail required for validation is more extensive than that required for practitioner use of the models. Table 3 includes all of the data collected for each validation site.

Model Validation Procedure

Researchers summarized the needed model inputs for each link and at the corridor level for all three validation study corridors. Researchers computed the model independent variables based upon the descriptions in Table 2 and Equations 4 and 5. Researchers estimated the TTI for the light congestion model and the moderate congestion model after computing the independent variables.

Ground truth (field measured) average travel time and free-flow travel time are needed to estimate the TTI per Equation 2. Researchers used the field travel time runs and Synchro to estimate the average travel rate in the numerator of Equation 2. Researchers used two methods to estimate the free-flow travel rate shown in the denominator of Equation 2. The method was dependent on the site itself. For US 60 (Chesterfield) and US 29 (Albermarle County), researchers reduced the traffic volumes in the calibrated Synchro model by 50 percent because the Synchro file is created for a peak-hour condition and the reduction from the peak-hour flow represents an approximation of the free-flow traffic condition. Along US 29 in Prince William County, researchers used the running time data as a function of the link distance divided by speed.

With these estimates of the average travel rate and the free-flow travel rate, researchers computed the "ground truth (field measured)" TTI value as the ratio shown in Equation 2. This ground truth TTI value was compared to the TTI estimate from the models shown in Equation 4 and Equation 5. It needs to be pointed out that when travel time measurements for free-flow conditions are available, they can be used directly and the estimation of free-flow travel times will be no longer needed.

Researchers computed an error term as the absolute difference between the model estimate from Equation 4 or Equation 5 and the field measured TTI value as shown in Equation 6.

$$Error = \left| \textit{Model TTI Estimate} - \textit{“Ground Truth (Field Measured)” TTI Value} \right| \qquad \textit{Equation 6}$$

Table 3. Data Available for Model Validation Sites in Virginia.

Data Element	US 60 (Chesterfield)	US 29 (Albermarle County)	US 29 (Prince William County)
ADT, K-factor and D-factor	Yes	Yes	Yes
Calibrated Synchro Models	4 models[1] (2008)	Morning and afternoon models peak (2007)	Morning and afternoon peak models, mid-day off-peak model (2009)
Field travel time runs (during peak hours)	Yes	Yes	Yes
Number/location of driveways	Yes	Yes	Yes
Predominant land use	Yes	Yes	Yes
Speed limit	Yes	Yes	Yes
Photographs/Video Logs	Yes	Yes	Yes

[1]The four Synchro files include models calibrated with field data for a base case (peak and off-peak), which includes a coordinated timing plan in the field without an adaptive split feature, and an adaptive split feature case (peak and off-peak), which includes a coordinated timing plan in the field with an adaptive split feature. An adaptive split feature means that the split (percentages of green times in a cycle) changes according to the arriving volumes of different movements, and the split may change from cycle to cycle.

Findings of Model Validation

Table 4 shows the results of applying the light and moderate congestion level models along the entire US 60 corridor by available Synchro model condition and direction. The light congestion model has a smaller error than the moderate congestion model. Researchers found similar results at the US 29 Albermarle study corridor.

Table 4. Model Validation Results for the US 60 Study Corridor.

Condition[1]	Direction	TTI Model Estimate	Ground Truth (Field Measured) TTI Value	Error[2]
Light Congestion Model				
Without ASF (off-peak)	EB	1.11	1.12	0.01
	WB	1.02	1.08	0.06
With ASF (off-peak)	EB	1.13	1.11	0.02
	WB	1.05	1.09	0.04
Without ASF (peak)	EB	1.08	1.10	0.02
	WB	0.99	1.11	0.12
With ASF (peak)	EB	1.13	1.12	0.01
	WB	1.05	1.09	0.04
Moderate Congestion Model				
Without ASF (off-peak)	EB	4.00	1.12	2.88
	WB	2.83	1.08	1.75
With ASF (off-peak)	EB	2.84	1.11	1.73
	WB	2.85	1.09	1.76
Without ASF (peak)	EB	2.87	1.10	1.77
	WB	2.80	1.11	1.69
With ASF (peak)	EB	2.91	1.12	1.79
	WB	2.85	1.09	1.76

[1]ASF = Adaptive split feature signal timing. See Table 3 for a description of ASF.
[2]Error defined as shown in Equation 6. Differences within 0.01

For all three validation study sites, researchers investigated the error term when estimating the TTI using both the light congestion model and the moderate congestion model. Figure 2 shows the relationship between g/C, peak-hour volume per lane, and error when using the light congestion model (points shown as solid circles) and the moderate congestion model (points shown as hollow circles). The points represent link-level data. All directional links from all three validation corridors are shown. Researchers found the following:

1. Green time allocation (g/C) appears more critical than traffic volume. A roadway link (or corridor) can have relatively high volume, but if motorists are provided with the green time needed, they can flow with limited congestion.
2. When g/C is less than 0.45, the moderate congestion model performs better (average error of 0.32) than the light congestion model (average error of 0.49).
3. When g/C is greater than or equal to 0.45, the light congestion model performs better (average error of 0.21) than the moderate congestion model (average error of 1.33).

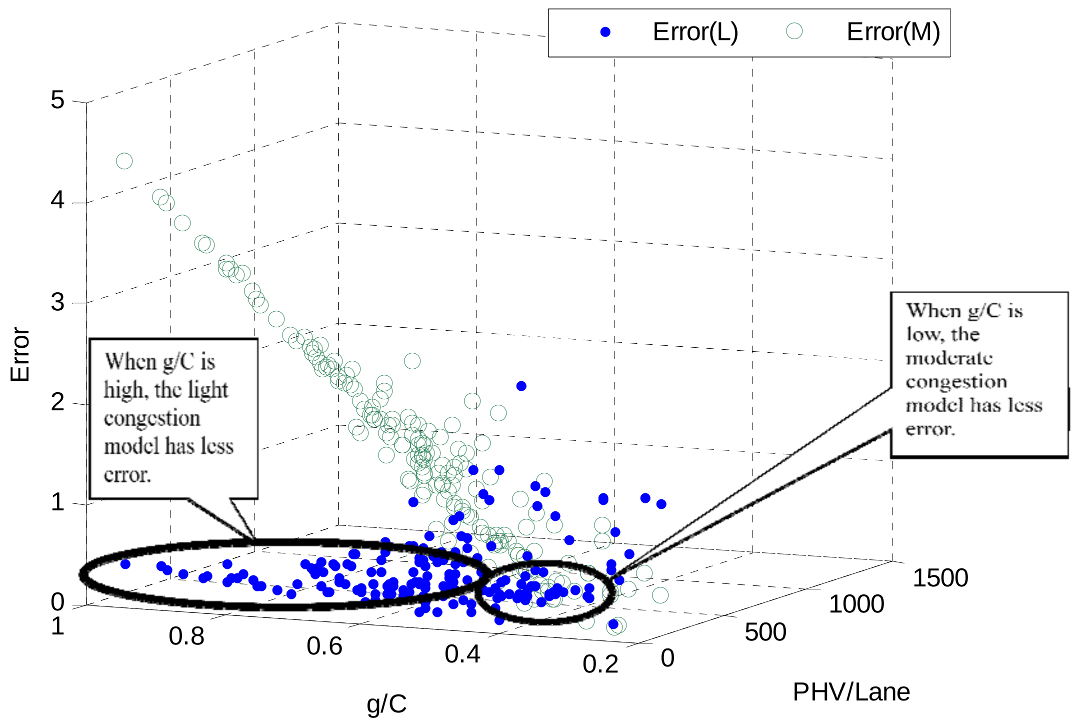

Figure 2. Illustration of g/C and PHV/Lane and Error (Link Data for All 3 Virginia Corridors).

Researchers found that the US 29 (Prince William County) study corridor had the lowest link g/C values. These relatively low g/C values were at the links adjacent to I-66 along US 29. It appears that when there are cross-streets that require significant green time (g/C of 0.55 or more on the cross street), link-level analysis is more appropriate with the moderate model adjacent to those cross streets. The model can then be used at the corridor level (i.e., combining similar-condition links) with the light model where the green time is increased on the primary roadway. Because of relatively similar operational and geometric conditions, researchers combined all links to the corridor level for the US 60 and US 29 (Albermarle County) sites.

Ultimately, the models provide an adequate sketch-planning tool to assist in identifying directional roadways for more detailed analysis. Such an analysis is most appropriate when transportation professionals are performing a comparative analysis to prioritize roadway or operational improvements and want to identify critical areas. The TTI is a proven measure for performing such comparative mobility analyses.

These models appear useful for transportation professionals in small to medium-sized communities for mobility analysis, and/or in the "fringe" areas of cities where there may be limited, if any, mobility monitoring infrastructure in place.

CONCLUSIONS AND DISCUSSION

This report describes the development and validation of two models to assist transportation professionals in estimating the travel time index in the arterial environment during light and moderate congestion conditions. These models are valuable at the sketch-planning level for transportation professionals when monitoring congestion and performing comparative mobility analysis of corridors to prioritize where infrastructure improvements are potentially needed. To address limitations of existing models, the models presented in this report 1) consider driveway density, 2) are corridor-based, 3) are a function of generally-available or easy-to-obtain independent variables, 4) are calibrated and validated with extensive field data, and 5) explain a relatively high degree of variability. The use of TTI also makes the models more transferable. The following are the key conclusions from this research:

1. The model for moderate congestion conditions (TTI values up to approximately 2.8) is a function of traffic volume, driveway density, signal green time relative to the cycle time (g/C), and signal coordination condition. The moderate congestion level model has an R^2 of 0.94. The model for light congestion conditions (TTI values up to 1.35) is based upon traffic volume and g/C along the corridor. The light congestion conditions model has an R^2 of 0.68. The independent variables in these models are generally available or relatively easy to obtain for transportation professionals.
2. The research described here found that the level of driveway density is an important predictive variable for speed-related performance measures in the arterial environment for relatively higher congestion levels. This is intuitive because at relatively higher traffic volumes added driveways provide more opportunity for interference along the corridor. The fact that driveway density is significant in the model indicates the importance of considering access management for TTI estimation in the arterial environment.
3. The results show that the effect of driveway density on TTI values can vary throughout the day by traffic volume and driveway (business) activity. Traditional *HCM* methods set one representative speed to try to capture driveway density impacts. The results here demonstrate that setting one speed does not fully account for the real impact because the results here demonstrate that driveway density impacts can vary throughout the day. The results demonstrate the need to model different traffic levels and time periods separately.
4. Researchers tested the transferability of the models on three (3) case study corridors in Virginia with promising results. The results indicate that green time (g/C) allocation is more critical than traffic volume. In other words, an arterial roadway segment can have high volume, but if there is adequate green time provided, there can be relatively limited congestion.
5. Researchers found that when the g/C is less than 0.45, the moderate congestion model performs better (average error of 0.32), and when the g/C is greater than or equal to 0.45, the light congestion model performs better (average error of 0.21). Researchers found that when there are cross-streets that require significant greet time (g/C of 0.55 or more), link-level analysis is more appropriate with the moderate model adjacent to those cross streets. The model can then be used at the corridor level (i.e., combining similar geometric and/or operational links) with the light model where the g/C is increased beyond 0.45 on the primary roadway.
6. The models appear to provide an adequate sketch-planning tool to assist in identifying roadways/locations for more detailed analysis (comparative analysis). There is application by transportation professionals in “fringe” areas and/or in communities where monitoring infrastructure are not currently in place.
7. The case studies used for model development and validation are suburban arterials. While the models were developed with roadways with links covering a range of g/C and peak-hour volume per lane values, researchers have yet to test the models along

corridors that have several cross streets that require significant green time (g/C of 0.55 or more). Model performance in these conditions is a future research need

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