Estimating Freeway Travel Times Using the General Motors Model

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Travel time is a key transportation performance measure because of its diverse applications. Various modeling approaches to estimating freeway travel time have been well developed due to widespread installation of intelligent transportation system sensors. However, estimating accurate travel time using existing freeway travel time models is still challenging under congested conditions. Therefore, this study aimed to develop an innovative freeway travel time estimation model based on the General Motors (GM) car-following model. Since the GM model is usually used in a microsimulation environment, the concepts of virtual leading and virtual following vehicles are proposed to allow the GM model to be used in macroscale environments using aggregated traffic sensor data. Travel time data collected from three study corridors on I-270 in Saint Louis, Missouri, were used to verify the estimated travel times produced by the proposed General Motors travel time estimation (GMTTE) model and two existing models, the instantaneous model and the time-slice model. The results showed that the GMTTE model outperformed the two existing models due to lower mean average percentage errors of 1.62% in free-flow conditions and 6.66% in two congested conditions. Overall, the GMTTE model demonstrated its robustness and accuracy for estimating freeway travel times.

Travel time, regardless of transportation modes, is a key transportation performance measure because of its diverse applications. These applications include (*a*) measuring the level of congestion (*1*); (*b*) measuring the level of facility accessibility in urban contexts (*2, 3*); and (*c*) helping travelers make route decisions using public media (e.g., dynamic message signs, radios, and social media). Moreover, due to the availability of travel time information, travel time reliability measures have recently been discussed and developed [see, for example, Yang et al. (*4*)]. These applications require high-quality travel time information that can be either collected directly from the field or indirectly estimated through other data sources. Essentially, most existing freeway travel time data collection approaches can be categorized as either direct measurement or indirect measurement. Commonly used methods of direct measurement include test vehicles, vehicle observation, vehicle signature matching methods, platoon matching methods, and probe vehicles (*5*). Travel time measured from direct measurement approaches is often referred to as measured travel time. In contrast, indirect measurement approaches produce estimated travel time using existing traffic data collection infrastructure (e.g., microwave radar sensors and passive infrared sensors). Indirect measurement approaches have two primary advantages over direct measurement approaches: first, data collection is much easier because data is estimated using large volumes of data automatically reported by the intelligent transportation system sensors. In contrast, direct measurement approaches are generally time-consuming and labor-intensive. Data collection personnel are needed to serve as drivers, observers, or interviewers to either recognize vehicle-specific features (e.g., license plates) or record travel times in test vehicles. The second advantage of indirect measurement approaches is the ease of implementing models with satisfying results. Most previous studies indicate that the results from these robust travel time estimation models present accurate travel times (*6–8*).

Existing freeway travel time estimation models can be categorized as speed-based and vehicle-trajectory–based. Speed-based models are inspired by an intuitive concept: travel time equals roadway length divided by speed. This concept takes the mathematical form shown in Equation 1.

$$\text{traveltime}(i, t_j) = \frac{2 * l_i}{v(i_{\text{up}}, t_1) + v(i_{\text{down}}, t_2)} \tag{1}$$

where

traveltime(i, t_j) = estimated travel time on ith link with the departure time t_j;
$v(i_{\text{up}}, t_1)$, $v(i_{\text{down}}, t_2)$ = upstream and downstream speeds on the ith link at time t_1 and t_2, respectively;
t_1, t_2 = random departure time variables that vary between models; and
l_i = length of link.

The speed information variables, $v(i_{\text{up}}, t_1)$ and $v(i_{\text{down}}, t_2)$, can be either measured directly from traffic sensors (e.g., dual loop and radar-based sensors) or estimated on the basis of the volume and occupancy information collected from single-loop sensors (*9, 10*).

Three commonly used speed-based models for estimating travel time include the instantaneous model, the time-slice model, and the dynamic time-slice model (*11*). These models are based on Equation 1. The differences between them result from the selection of t_1 and t_2. The instantaneous model assumes that both t_1 and t_2 equal the departure time at the start point t_j, and thus the departure times of following links are set as t_j shown in Equation 2. The time-slice model uses Equation 3 to determine t_1 and t_2 under the assumption that the departure times on the consecutive links equal the summation of t_j and the total travel time on previous links. Last, Equation 4 shows the expression of t_1 and t_2 in the dynamic time-slice model.

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This equation takes a recursive formulation to update the estimated travel time by approaching actual speeds downstream.

$$t_1 = t_2 = t_j \tag{2}$$

$$t_1 = t_2 = t_j + \sum_{i=2}^{N} \text{traveltime}\left(i-1, t_j\right)$$

where

$$\text{traveltime}\left(1, t_j\right) = \frac{2 * l_1}{v\left(1_{\text{up}}, t_j\right) + v\left(1_{\text{down}}, t_j\right)} \tag{3}$$

$$t_1 = t_j \qquad t_2 = t_j + \text{traveltime}\left(i, t_j\right) \tag{4}$$

Because the three speed-based models all assume a linear change in speed as vehicles move from upstream to downstream sensor locations, the average of the upstream and downstream speeds can mathematically represent the linear change. However, this linear change may fail to capture speed changes within links, and therefore travel times may not be accurately estimated. To consider speed changes within links, van Lint and Van der Zijpp proposed the piecewise linear-speed–based model by incorporating a linear transformation to estimate speeds between upstream and downstream locations (*12*). Those authors stated that the results of the piecewise linear-speed–based model outperformed typical linear-speed–based models. Li et al. reviewed and implemented the same four models for estimating travel time and compared their performances with ground truths collected from the field (*7*). Several key findings were observed by Li et al.: (*a*) the performance differences between the four models were minor; (*b*) travel times were underestimated; and (*c*) the level of congestion greatly affected the estimations.

In addition to those four speed-based models, vehicle-trajectory–based models were developed to improve further the accuracy of estimations of travel time (*6, 13, 14*). Coifman proposed a model for estimating travel time on the basis of a two-regime traffic flow model (*6*). This model was developed to reconstruct a vehicle trajectory on a corridor by using loop sensor data, and then travel time could be inferred from the trajectory. As expected, the estimated travel time from the model was consistent with ground truth travel time under uninterrupted traffic conditions. However, Coifman stated that his model fails "when a queue partially covers a link" (*6,* p. 362).

Ni and Wang summarized previous research on speed-based models for estimating travel time and proposed a new model in which a "speed surface" was constructed as a function of space and time to infer vehicle trajectory (*13*). The travel time could then be calculated by using the vehicle trajectory. Next generation simulation program data sets were used to verify the model empirically because the detailed vehicle trajectory information in the data set can help infer accurate speed surfaces. Results showed that the model outperformed both the piecewise linear-speed–based model and the instantaneous model (*12*). An additional test was conducted during off-peak and peak hours (free-flow and congested conditions). However, only a relative comparison between the proposed model and the instantaneous model was conducted, without verification with ground truths. Similar to results from Li et al., the conclusions from the relative comparison showed that (*a*) few differences existed between the two models under free-flow conditions, but (*b*) large differences were found under congested conditions (*7*).

Sun et al. proposed a vehicle-trajectory–based model by using a piecewise truncated quadratic function to estimate freeway travel time (*14*). To verify the model, the estimated travel time was compared against ground truth travel time. However, the model was verified only by a limited number of ground truths through the *t*-test instead of a measure of accuracy (e.g., mean absolute error). Without a measure of accuracy, the differences between travel times cannot be quantitatively compared at a specific time.

From the literature review, the current authors found that speed-based and vehicle-trajectory–based models perform similarly under free-flow conditions, but noticeable differences between estimated and ground truth travel times arise under congested conditions. Therefore, the objective of this paper's study was to develop an innovative freeway travel time estimation model that can accurately estimate travel times across all flow conditions. The rest of this paper is organized as follows. First, a new travel time estimation model integrated with the General Motors (GM) car-following model is proposed. Next, the model is verified with real-world traffic data and a robustness test. Last, several key findings are discussed in the conclusion.

GM-BASED TRAVEL TIME ESTIMATION MODEL

Car-following models are generally used to measure the kinetic response of vehicles to the movement of leading vehicles by taking into account acceleration rates, current speeds, and headway between leading and following vehicles. The GM model is one of the most popular ones to measure car-following behaviors (*15, 16*). The GM, macroscopic traffic flow, and travel time estimation models have interchangeable relationships (Figure 1). The relationship between macroscopic traffic flow models and the GM model was investigated. Several macroscopic traffic flow models have been derived from the GM model, including Greenshield's model, the Greenberg model, the Underwood model, and the Northwestern model (*15, 17*). The relationship between macroscopic traffic flow models and travel time estimation models was also discussed in Coifman's study (*6*). Coifman used a two-regime macroscopic traffic flow model to construct vehicle trajectories and infer travel time. However, little research has been conducted to estimate travel time by means of the GM model. Therefore, the travel time estimation model proposed in the current study was developed on the basis of the GM model to complete the relationships shown in Figure 1. The proposed model described in the rest of this paper is thus named the General Motors–based travel time estimation (GMTTE) model.

The details of the GMTTE model are further described in the following subsections: (*a*) understanding the GM car-following model, (*b*) introducing the concept of virtual leading and following

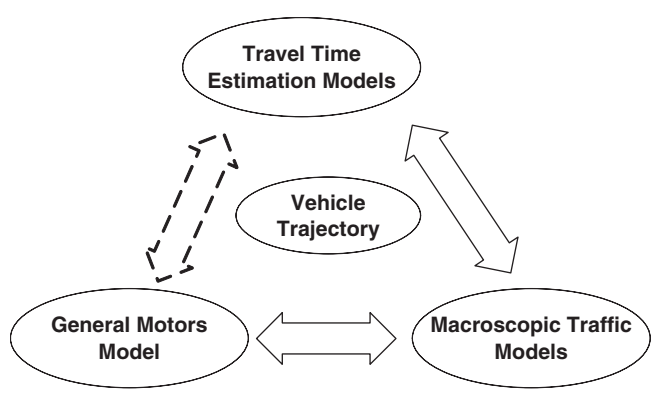


FIGURE 1 Relationships between travel time estimation models, GM model, and macroscopic traffic models.

vehicles, (*c*) producing link and corridor travel time estimation, and (*d*) parameter selection.

GM Car-Following Model

The GM model is described in Equations 5 through 7. The input parameters of the GM model include the initial relative position, acceleration, and speeds of the leading and following vehicles. These parameters are updated every time interval by using Equations 5 through 7. Here, 0.1 s is selected as the time interval so that the kinetic response of the following vehicle can be estimated every 0.1 s. The driver's response time is already considered in the original GM model formulation and is usually set at 1.5 s. To simplify freeway travel time estimation with the GM model, the driver's response time was ignored in the current study.

$$v_n^t = v_n^{t-\Delta T} + a_n^{t-\Delta T} * \Delta T \tag{5}$$

$$x_n^t = x_n^{t-\Delta T} + v_n^{t-\Delta T} * \Delta T + \frac{1}{2} a_n^{t-\Delta T} \Delta T^2 \tag{6}$$

$$a_{n+1}^t = \left[\frac{\alpha_{l,m} \left(v_{n+1}^t\right)^m}{\left(x_n^{t-\Delta T} - x_{n+1}^{t-\Delta T}\right)^l} \right] * \left(v_n^{t-\Delta T} - v_{n+1}^{t-\Delta T}\right) \tag{7}$$

where

v_n^t = instantaneous speed of *n*th vehicle at time *t*,
a_n^t = instantaneous acceleration rate of *n*th vehicle at time *t*,
ΔT = time interval (0.1 s selected),
x_n^t = traveling distance of *n*th vehicle at time *t*,
l = distance headway exponent between [−1, 4],
m = speed exponent between [−2, 2], and
$\alpha_{l,m}$ = sensitivity coefficient.

Three primary variables, namely instantaneous speeds (v_n^t), traveling distances (x_n^t), and instantaneous acceleration rates (a_n^t), can be calculated at each time interval for individual vehicles. Both vehicle trajectories (also known as time–space diagrams) and individual vehicle travel times can be inferred from the three variables. The GM model was designed to ensure the fidelity of simulated vehicle movements at a microscale level. Theoretically, the GM model could be used in real-world situations to estimate vehicle trajectories and travel times by using traffic data. However, most traffic sensor data are aggregated to a certain period (e.g., 20 or 30 s) with no individual vehicle information. The challenge of applying the GM model to estimate travel time by using aggregated traffic sensor data can be solved through the concept of virtual vehicles proposed below.

Virtual Leading and Following Vehicles

To use the GM model to estimate travel times, the concept of virtual leading (VL) and virtual following (VF) vehicles is proposed to bridge aggregated traffic sensor data and the GM model. This concept is demonstrated in Figure 2. Only the two virtual vehicles travel on the freeway link, and no other vehicles are considered on that link. The freeway link in Figure 2 is defined as the segment bounded by two traffic sensors, *Sa* and *Sb*. The two sensors consistently report vehicle counts, average speed, and occupancy data at each time interval, T_i. The initial distance headway between the VL and VF vehicles is the length of the link. The characteristics of the VL and VF vehicles include these:

- Definition of travel time on a link. "Travel time" is defined as the time that the VF vehicle travels from *Sa* to *Sb*. Therefore, the travel time of the VL vehicle has no effect on estimating the link travel time.
- Movements of VL and VF vehicles. The VF vehicle moves toward *Sb* with certain kinetic attributes (e.g., speed and acceleration rate) affected by the movement of the VL vehicle until the VF vehicle arrives at *Sb*. The VL vehicle can freely move forward. The locations of the VL and VF vehicles at departure time *t* are denoted x_{VL}^t and x_{VF}^t, respectively. The distance between the two vehicles at time *t*, denoted gap_t, can be calculated through $x_{\mathrm{VL}}^t - x_{\mathrm{VF}}^t$.
- Kinetic attributes of VF vehicles. The movement rules of the VF vehicle are the same as those of the GM model. Because the VF vehicle's kinetic attributes primarily depend on the movement of the VL vehicle, the instantaneous speed (v_{VF}^t), acceleration rate (a_{VF}^t), and traveling distance (x_{VF}^t) can be calculated by using Equations 5 through 7 when the kinetic attributes of the VL vehicle are known.
- Kinetic attributes of VL vehicles. Equation 5 indicates that current speed is determined by the speed and acceleration rate of the previous time interval. Because of the difficulty in measuring the acceleration rate a_n^t, Equation 5 may not be suitable to calculate the VL vehicle's kinetic attributes. Measured speed from Sensor *Sb* provides an alternative method to estimate the kinetic attributes of the VL vehicle. Sensor *Sb* reports the aggregated vehicle speed information at a time interval T_i (denoted as $v_{Sb}^{T_i}$). The VL vehicle's speed and traveling distance at time *t* (denoted as v_{VL}^t and x_{VL}^t, respectively) can be estimated by using Equations 8 and 9 instead of Equations 5 and 6.

$$v_{\mathrm{VL}}^t = \frac{v_{Sb}^{T_{i+1}} - v_{Sb}^{T_i}}{T_{i+1} - T_i} * (t - T_i) + v_{Sb}^{T_i} \left(T_i \le t \le T_{i+1}\right) \tag{8}$$

$$x_{\mathrm{VL}}^t = x_{\mathrm{VL}}^{t-\Delta T} + \frac{1}{2}\left(v_n^{t-\Delta T} + v_n^t\right) * \Delta T \tag{9}$$

Equation 8 shows that the speed of the VL vehicle changes linearly by using the time series speed data collected from *Sb*. Equation 7

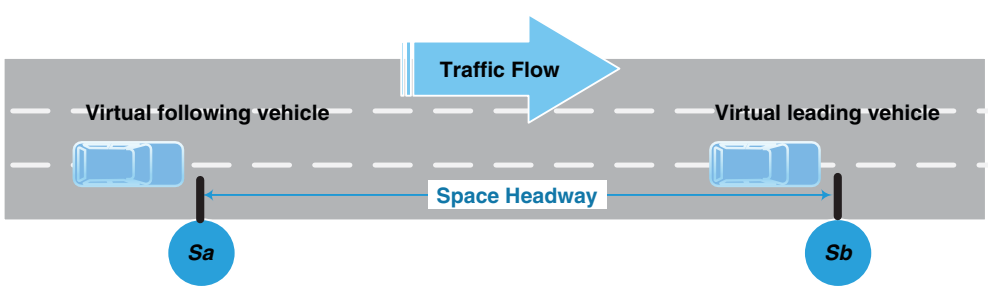


FIGURE 2 Settings for virtual following and leading vehicles.

indicates that the kinetic attributes of the VF vehicle are not related to the acceleration rate of the VL vehicle.

Link and Corridor Travel Time Estimation

The VF vehicle trajectory can be created from the GM model by using aggregated traffic sensor data. The link travel time can be inferred from the trajectory of the VF vehicle as it moves from *Sa* to *Sb*. The initial speed of the VF vehicle is defined as the speed of *Sa* at time T_0 ($v_{Sa}^{T_0}$). After speed initiation of the VF vehicle, its kinetic attributes follow the GM model through the VL vehicle.

The procedure for estimating corridor travel time is similar to the link travel time estimation, for which travel time is also inferred from the VF vehicle trajectory. However, the difference between the two is the initialization of the speed of the VF vehicle at the beginning of the downstream links. Figure 3 depicts a corridor consisting of two links, *Sa–Sb* and *Sb–Sc*. The initial VF vehicle speed at *Sa* equals $v_{Sa}^{T_0}$. By assuming the VF vehicle's travel times on link *Sa–Sb* and *Sb–Sc* are TT_{ab} and TT_{bc}, respectively, the initial speed of the VF vehicle at *Sb* is specified as $v_{Sb}^{TT_{ab}}$, and the initial speed at *Sc* is then $v_{Sc}^{(TT_{ab})+(TT_{bc})}$. This speed initialization means that the VF vehicle moves with continuous speed in the time and space domain. This movement is similar to actual vehicle movement. Unlike the VF vehicle, which has continuous speed along a corridor, the VL vehicle moves forward and leads traffic with the speed measured by the sensors. The relevant kinetic attributes of the VL vehicle at a specific time can be calculated by using Equations 8 and 9.

Parameter Selection

Because estimated travel time is "sensitive to the level of congestion," parameters are selected depending on the congestion scenario (*7*). Three parameters in the GMTTE model, (*a*) the distance headway exponent, *l*; (*b*) the speed exponent, *m*; and (*c*) the sensitivity coefficient, $\alpha_{l,m}$, can be representative of the level of congestion. After various sets of parameter values were tested, two sets of parameters were empirically selected to represent, first, free-flow conditions ($l = 0.5$, $m = 0.8$, $\alpha_{l,m} = 12$) and, second, congested conditions ($l = 1$, $m = 0.1$, $\alpha_{l,m} = 8$).

STUDY DATA

Table 1 shows detailed information for three study corridors in Saint Louis, Missouri, used for model verification. All the corridors are located on I-270 in the Greater Saint Louis area. Corridor 1 is a 7.2-mi section of I-270 southbound that suffers from severe recurrent congestion on Tuesdays, Wednesdays, and Thursdays but not on Fridays. Therefore, Friday, December 12, 2014, along Corridor 1 was used as a free-flow scenario in the verification procedure. Corridors 2 and 3, consistently suffering from traffic congestion on all weekdays, were both used for congested scenarios. More than 700 radar-based traffic sensors had been installed on major freeways in the Greater Saint Louis area at an average spacing of approximately 1 mi. The study data were collected throughout the selected periods from those traffic sensors that lie along the three corridors. In addition to the traffic sensors, previously installed surveillance cameras were used to collect ground truth travel times by the signature-matching method (*5*). This method collected ground truth travel times by manually matching identical vehicles from upstream and downstream video feeds. Because the vehicle-matching process was fairly time-consuming, the matching process aimed to select sampled vehicles evenly throughout the testing period. The number of ground truth samples is listed in Table 1.

MODEL VERIFICATION

Measures of Accuracy

Two measures of accuracy, including mean absolute error (MAE) and mean absolute percentage error (MAPE), were used to verify the GMTTE model's performance (*18*). The MAE provided an overview of all errors and showed the space headways between the estimated and the ground truth travel times. The MAPE showed the error as a percentage and was a scale-independent measure of accuracy. Equations 10 and 11 show the definitions of the two measures:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|g_i - e_i| \tag{10}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|g_i - e_i|}{e_i} \tag{11}$$

where g_i is the ground truth travel time at time *i* and e_i is the estimated travel time at time *i*.

Both measures of accuracy were applied to compare the performance quantitatively between the proposed GMTTE model, the instantaneous model, and the time-slice model.

Comparisons of Travel Time Estimation

Figures 4 through 6 show the estimated travel times for the three corridors for the GMTTE model, the instantaneous model, and the

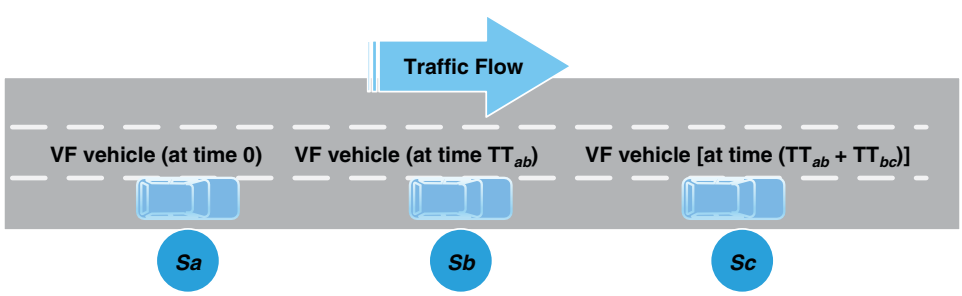
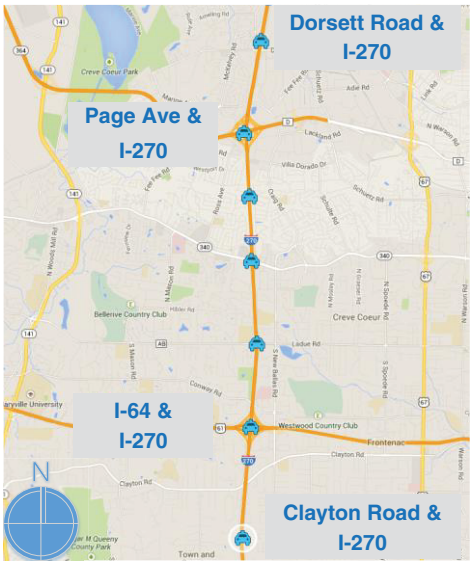
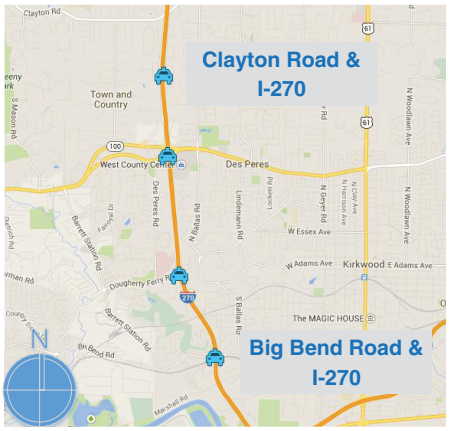
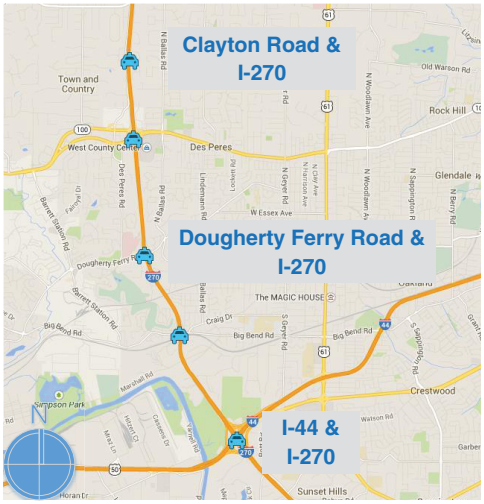


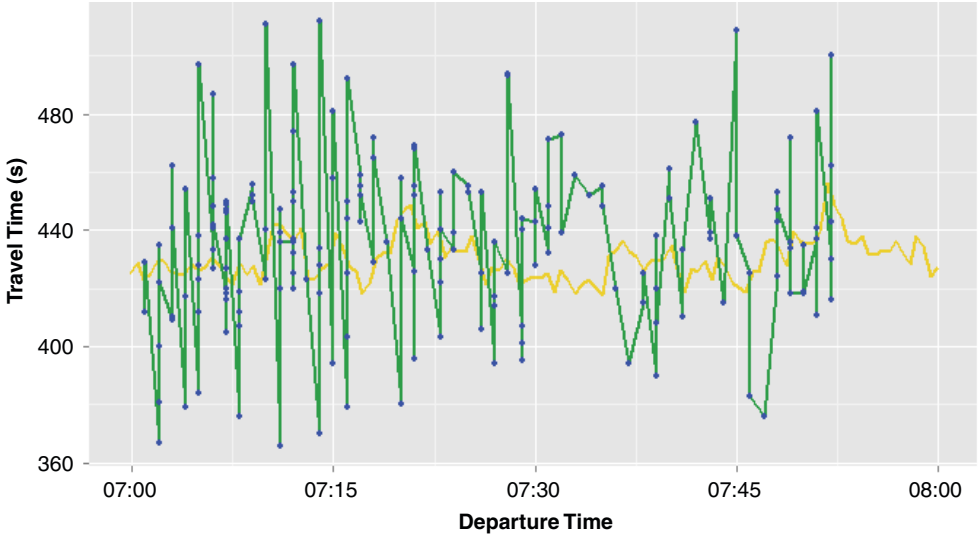
FIGURE 3 Estimation of corridor travel times.

TABLE 1 Study Corridors

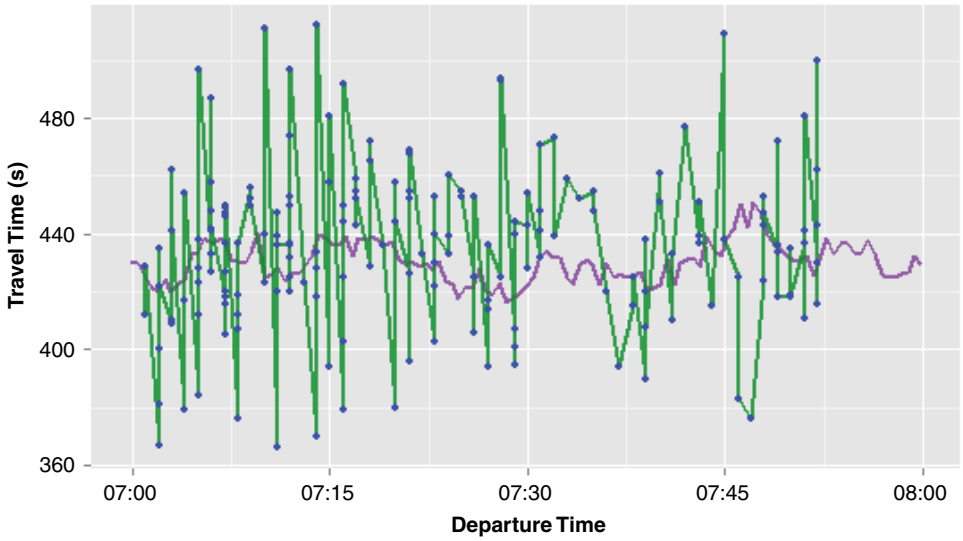
Study Corridor	Time Period	Location	Number of Ground Truth Samples
Corridor 1: I-270 southbound (7.2 mi)	7:00–8:00 a.m. Friday, December 12, 2014		180
Corridor 2: I-270 northbound (3.7 mi)	7:50–8:50 a.m. Tuesday, December 16, 2014		282
Corridor 3: I-270 northbound (5.5 mi)	7:00–8:00 a.m. Wednesday, December 17, 2014		122

 traffic sensor locations

SOURCE: Background images from Google Maps.



(a)



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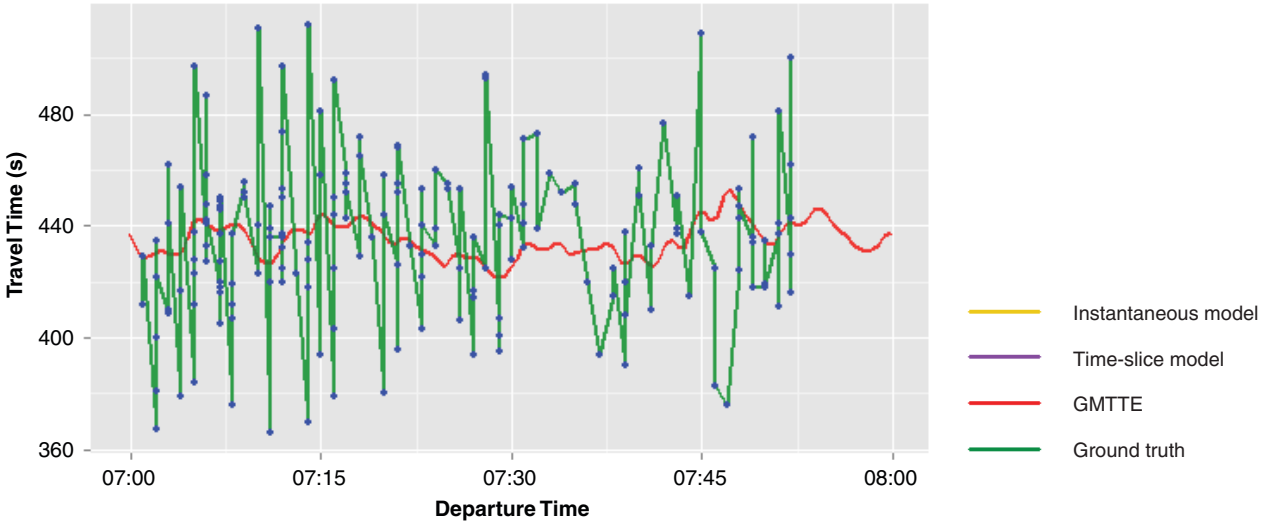
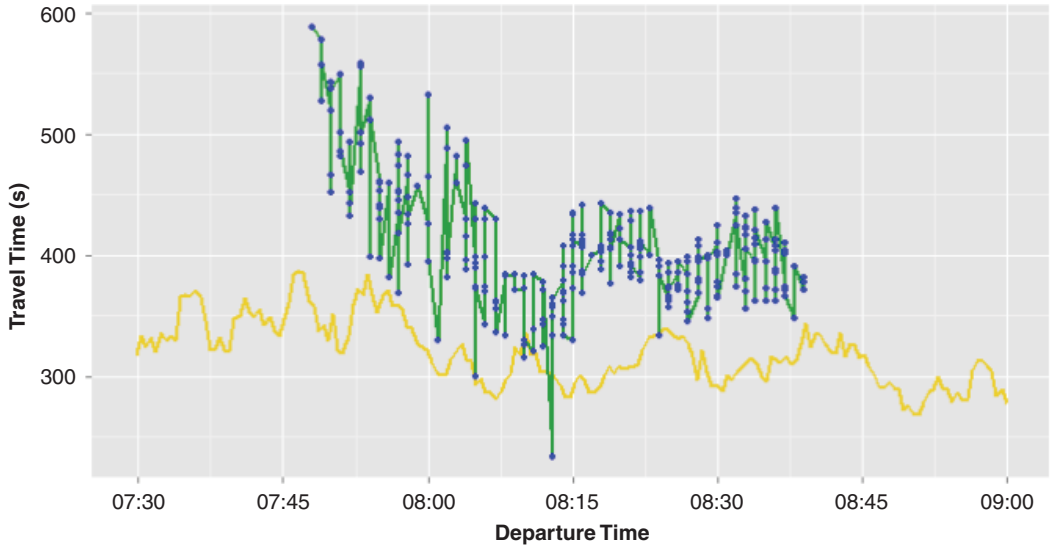
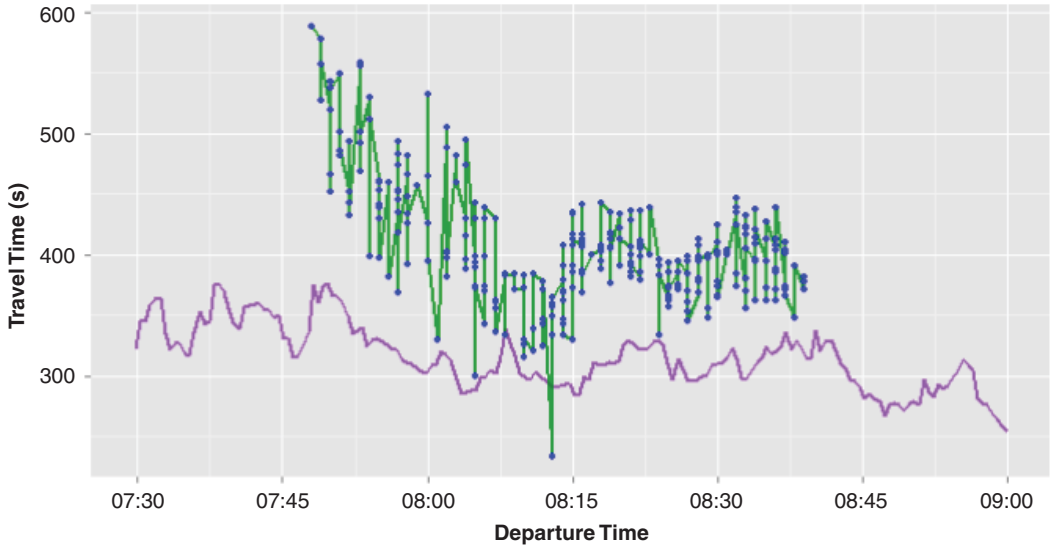


(c)

FIGURE 4 Estimation of travel times for Corridor 1 (7:00 to 8:00 a.m., Friday, December 12, 2014): (*a*) ground truth versus estimated travel time (instantaneous model), (*b*) ground truth versus estimated travel time (time-slice model), and (*c*) ground truth versus estimated travel time (GMTTE model).



(a)



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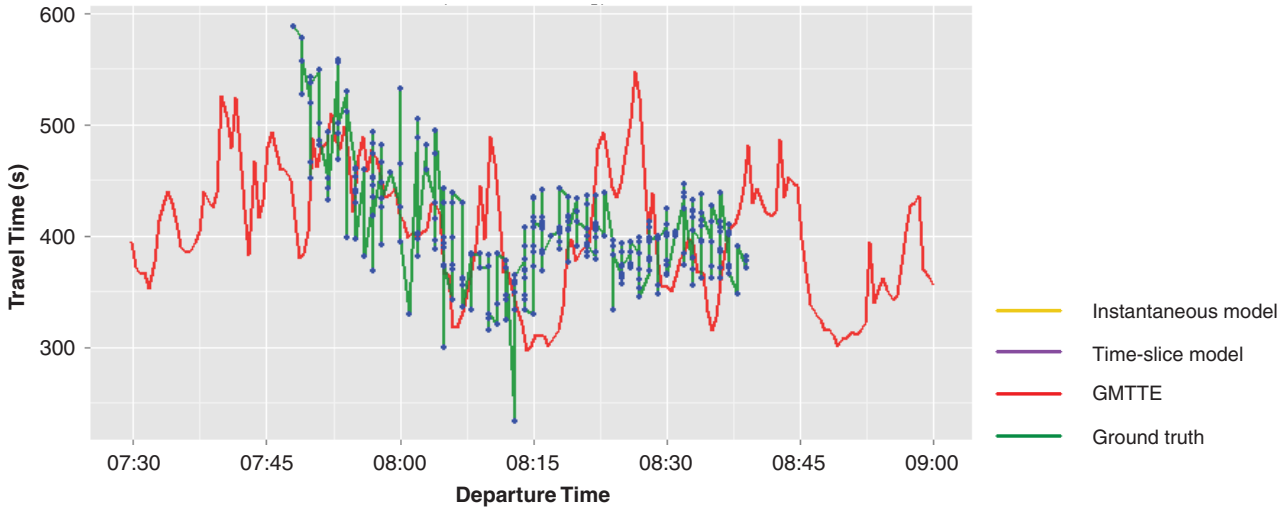


(c)

FIGURE 5 Estimation of travel times for Corridor 2 (7:50 to 8:50 a.m., Tuesday, December 16, 2014): (*a*) ground truth versus estimated travel time (instantaneous model), (*b*) ground truth versus estimated travel time (time-slice model), and (*c*) ground truth versus estimated travel time (GMTTE model).

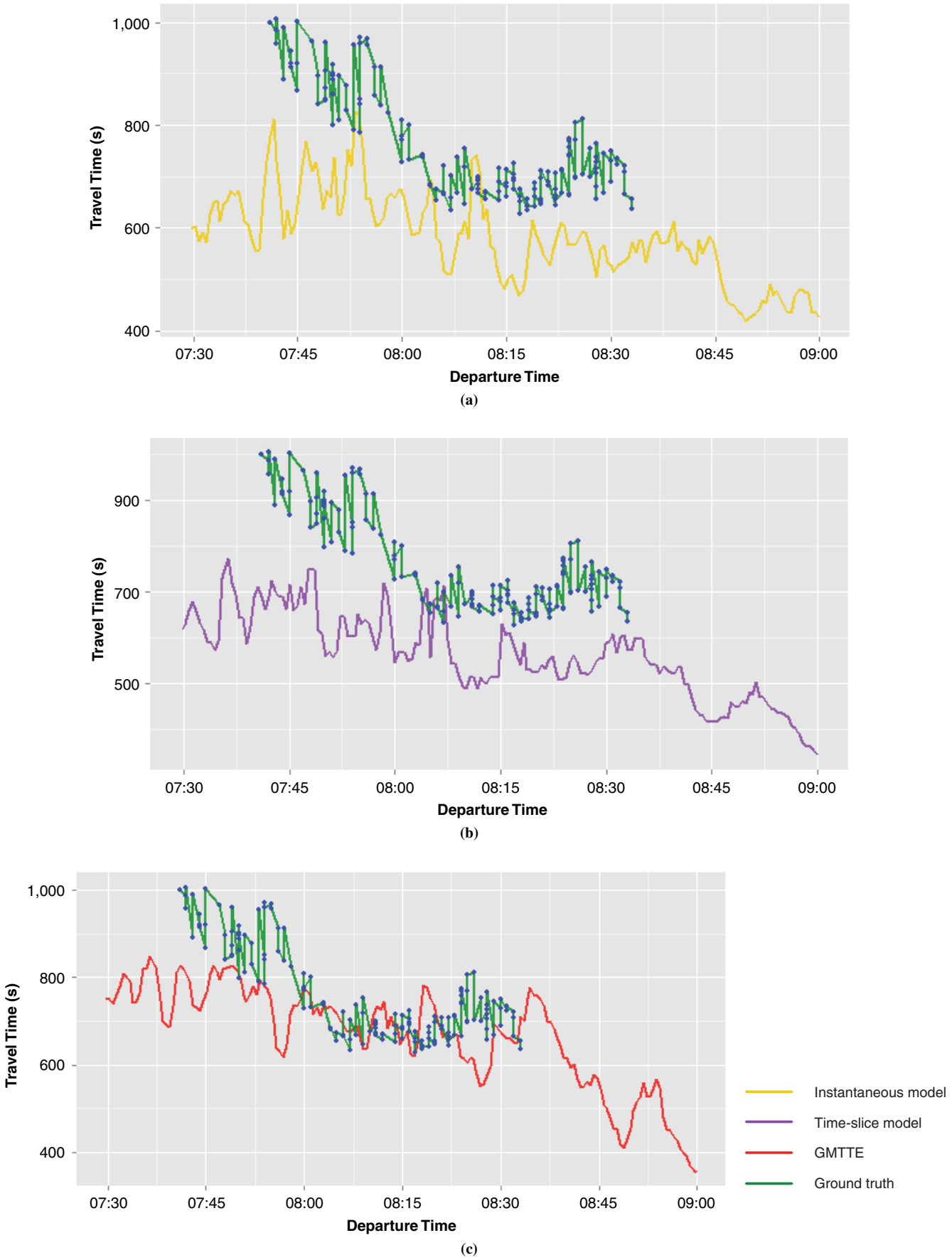


FIGURE 6 Estimation of travel times for Corridor 3 (7:50 to 8:50 a.m., Wednesday, December 17, 2014): (*a*) ground truth versus estimated travel time (instantaneous model), (*b*) ground truth versus estimated travel time (time-slice model), and (*c*) ground truth versus estimated travel time (GMTTE model).

time-slice model. The solid lines in Figures 4 through 6 are the estimated travel times, and the dot-connected lines are ground truth travel times. Table 2 shows quantitative comparisons between these models. Key findings are listed and discussed next.

1. The GMTTE model outperformed both the instantaneous and the time-slice models. The MAEs and MAPEs of the GMTTE model were smaller than those of the two existing models. Compared with the MAEs of the two existing models, the MAEs of the GMTTE model were reduced by approximately 13% under free-flow conditions and 60% under congested conditions. Although the differences between the estimated and ground truth travel times during free-flow conditions were small and could be disregarded, the results from both MAEs and MAPEs indicated that the GMTTE model still performed slightly better. The results showed that the effectiveness of the GMTTE model was most significant under congested conditions; the MAPEs of the two existing models were more than 20%, while the MAPEs of the GMTTE model were less than 7%. In addition, the MAE values of the GMTTE model for Corridors 1, 2, and 3 were 7.0, 31.5, and 59.6 s, respectively. These low values indicate the strong similarity between the ground truth and estimated travel times, and thus the estimated travel time adequately represented the ground truth travel times.
2. The instantaneous and the time-slice models underestimated travel times, especially under congested conditions. Although all the travel time profile trends were similar, the two existing models underestimated travel time consistently during the study periods, as shown in Figures 5, *a* and *b,* and 6, *a* and *b.* The ground truth travel time profiles are shown beside the estimated travel time profiles. This underestimation was consistent with the conclusions by Li et al. (*7*).
3. The GM model, usually implemented in simulation environments, was compatible with aggregated traffic sensor data in the real world. The concept of virtual leading and following vehicles connected the GM model and aggregated traffic data seamlessly. The relationship in Figure 1 between the GM model and travel time estimation models that had been previously unexamined was formed.

Robustness of GMTTE Model

Traffic data errors have negative effects on the evaluation of performance measurement and have been widely investigated in different studies (*19, 20*). If travel time estimation models could be made robust (less sensitive) and impervious to low-quality traffic data, the results generated from them would be more accurate. In this section, the impacts of empty-value speed data on travel time estimation were investigated because this error type is commonly observed in data from intelligent transportation systems. Empty-value speed data represent sensor errors for which erroneous speed data values, typically zero, are produced.

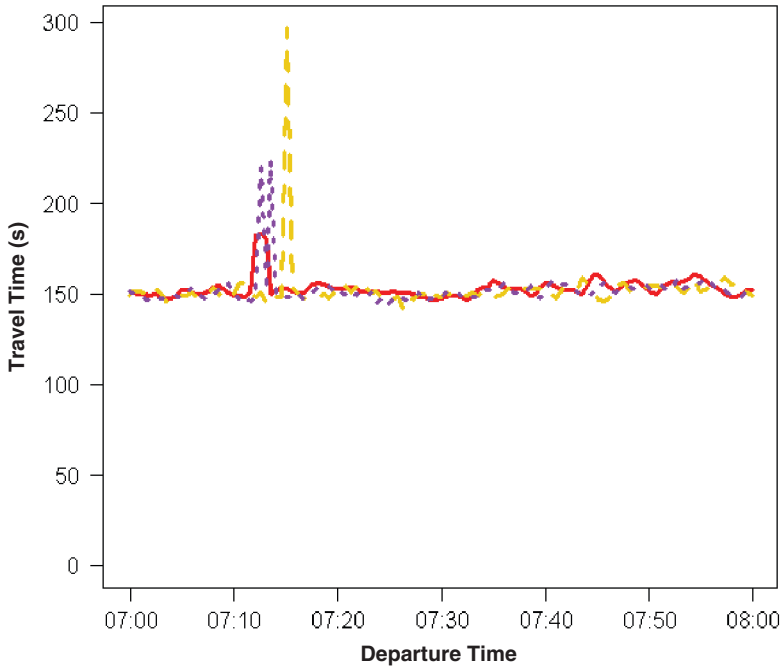
To create scenarios for testing robustness of the proposed model when empty values are encountered, the first two freeway links on Corridor 1 (free-flow condition) were selected as the study area. Empty-value speeds were intentionally produced at the middle intelligent transportation system sensor between the links. Three scenarios were created to evaluate the robustness of the GMTTE model:

- Scenario 1, pulse zero. The middle sensor reported an empty-value speed only once, at 7:15 a.m.
- Scenario 2, 5-min zeroes. The middle sensor reported empty-value speeds from 7:15 to 7:20 a.m.
- Scenario 3, 10-min zeroes. The middle sensor reported empty-value speeds from 7:15 to 7:25 a.m.

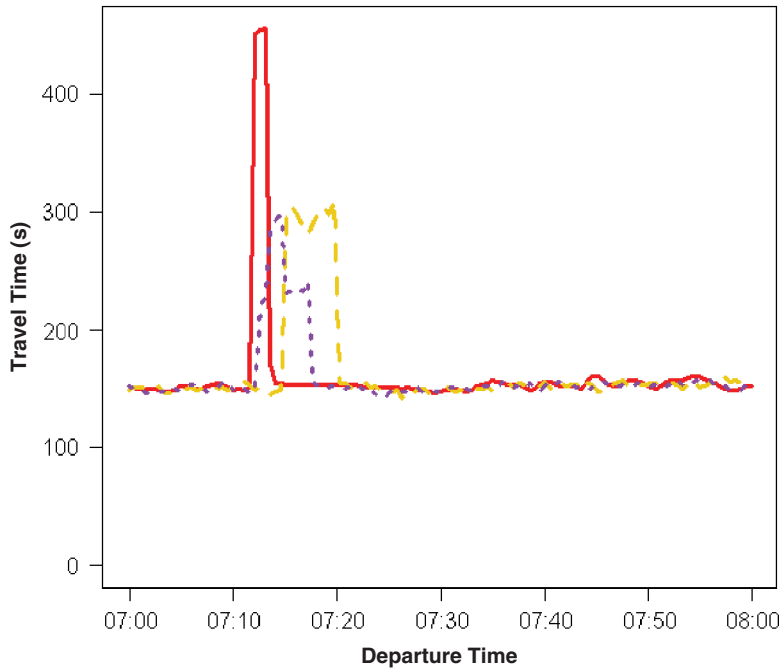
Figure 7 shows estimated travel times from the instantaneous, the time-slice, and the GMTTE models. The earlier section on comparisons of travel time estimation proved that, under free-flow conditions, these models performed similarly and that their estimated travel times can represent ground truth. Therefore, on the basis of the model estimations, the ground truth travel time in the study area was 150 s, and estimated travel times greatly different than 150 s were considered as outliers. The findings indicated that the longer was the duration of impact, the more outliers the models produced. In Scenario 1, the travel time estimated by the instantaneous model was approximately 297 s, and the duration of impact lasted only as long as the pulse, while, for the time-slice model, the duration of impact was 1.5 min, and the maximum estimated travel time was 224 s. As expected, the result produced by the GMTTE model was less affected by the zero speed: the maximum travel time was 183 s, and the duration of impact was also 1.5 min. Figure 7, *b* and *c,* and Table 3 suggest that (*a*) the impact of empty-value speeds on the estimated travel times produced by the instantaneous and the time-slice models lasted longer than those by the GMTTE model, and (*b*) the estimated travel times produced by the instantaneous and the time-slice models had relatively stable maximum estimated travel times, while the maximum estimated travel time produced by the GMTTE model increased with increasing duration of empty-value speeds. The GMTTE model had a short duration of impact because the VL vehicle in the GMTTE model used speed data at departure times and afterward, while the instantaneous and the time-slice models used speed data only at departure

TABLE 2 Quantitative Comparison Between Ground Truth and Estimated Travel Times

Corridor	Time Period	Length (mi)	Model	MAE (s)	MAPE (%)
Corridor 1 (free flow)	7:00–8:00 a.m., Friday, December 12, 2014	7.2	GMTTE	7.0	1.62
			Instantaneous	8.6	1.95
			Time slice	8.0	1.84
Corridor 2 (congested)	7:50–8:50 a.m., Tuesday, December 16, 2014	3.7	GMTTE	31.5	6.86
			Instantaneous	93.2	22.00
			Time slice	100.8	23.62
Corridor 3 (congested)	7:00–8:00 a.m., Friday, December 17, 2014	5.5	GMTTE	59.6	6.46
			Instantaneous	153.0	19.71
			Time slice	168.4	21.55



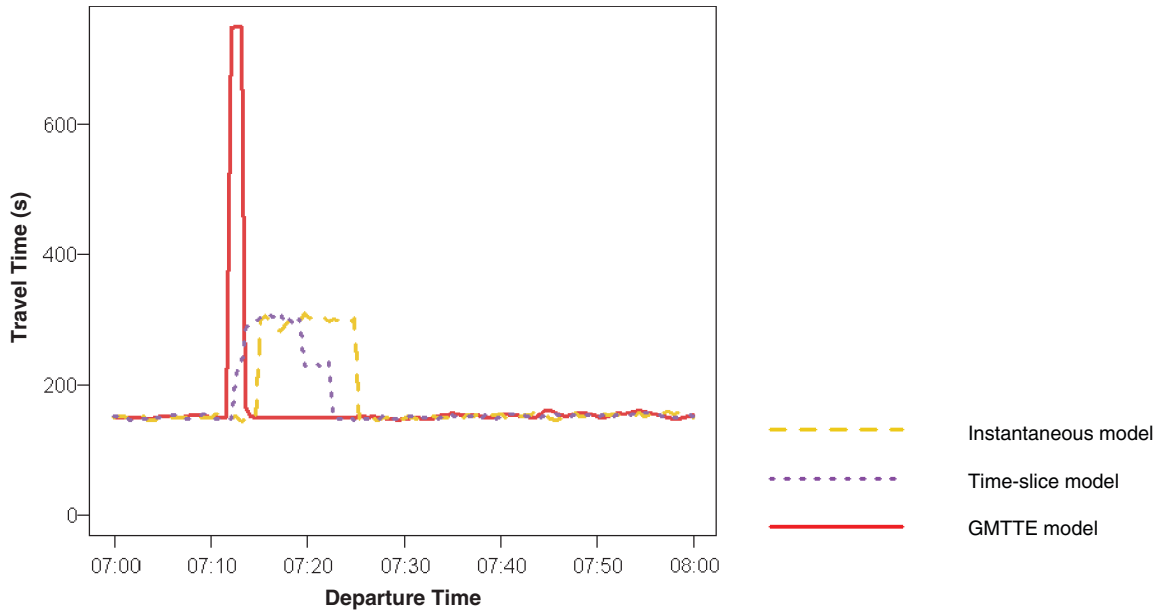
(a)



(b)

FIGURE 7 Estimation of travel times by using zero-value speed: (*a*) Scenario 1 and (*b*) Scenario 2.

(continued)



(c)

FIGURE 7 *(continued)* Estimation of travel times by using zero-value speed: (*c*) Scenario 3.

times. Therefore, the GMTTE model was able to incorporate data unaffected by the empty values.

When the GMTTE model is used, the outliers caused by empty-value speeds can be mitigated by taking the median value of estimated travel times because of the short duration of impact. However, the outlier travel times produced by the instantaneous and the time-slice models may be smaller because of the longer duration of impact.

CONCLUSIONS AND RECOMMENDATIONS

Travel time, as a key measure of transportation performance, serves a fundamental role in transportation-related studies. The travel times on freeways provide not only basic traffic information for individual drivers but also advanced traffic analysis for transportation agencies to improve system performance. A considerable amount of research has been conducted to estimate travel time. However, estimating travel time under congested conditions has remained a challenge.

TABLE 3 Effects of Empty-Value Speed

Scenario	Model	Duration of Impact (min)	Maximum Estimated Travel Time (s)
Scenario 1, pulse zero	Instantaneous	Pulse	297
	Time slice	1.5	224
	GMTTE	1.5	183
Scenario 2, 5-min zeroes	Instantaneous	5	310
	Time slice	5	297
	GMTTE	1.5	456
Scenario 3, 10-min zeroes	Instantaneous	10	310
	Time slice	10	311
	GMTTE	1.5	750

To estimate travel times on freeways accurately, especially under congested traffic conditions, this paper proposed a model based on the GM car-following model. Because the GM model incorporates the kinetic responses of following vehicles, it typically has been implemented in simulation environments. This paper proposes the concept of virtual following and leading vehicles to allow the microscale model to use aggregated real-world data.

Ground truth travel times collected from three corridors along I-270 in the Greater Saint Louis area were used to verify the estimated travel times from the GMTTE model and two existing models: the instantaneous model and time-slice model. The results showed that the MAPEs of the GMTTE model were less than 7%, even under congested conditions, while the MAPEs of the two existing models were greater than 20%. Overall, the GMTTE model more accurately estimated freeway travel times in both free-flow and congested conditions. In addition, the robustness test with empty-value speed data showed that the proposed GMTTE model was minimally affected by erroneous data values.

Even though the GMTTE model demonstrated its estimation accuracy and robustness, the model can be further improved by refining model parameters on the basis of the level of congestion. In this study, two sets of parameter values (l, m, and $\alpha_{l,m}$) were used to represent free-flow and congested conditions. However, these values were empirically selected without mathematical proof. Further investigations of parameter selection should be conducted to fit the specific level of congestion (e.g., congestion onset and dispersion).

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