

Estimating travel times in work zones using re-deployable traffic management systems

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Abstract

Empirical studies have shown that work zones are responsible for a large proportion of non-recurrent congestion and have higher crash rates than similar roadways without work zones. Consequently, a great deal of attention has been focussed over the past several years on the management of traffic and safety within work zones. A key component of traffic management in work zones is the ability to notify travellers of the travel time they will experience if they elect to travel through the work zone.

The currently available work zone FTMS use relatively crude travel time estimation algorithms. Furthermore, these systems are able to provide estimates only of the current travel time not the travel time that drivers entering the work zone will experience (i.e. predictive travel time).

This paper examines the issues associated with estimating current and predictive travel times in work zones and reviews approaches that have been suggested in the literature. Several potential travel time prediction algorithms are presented, including one that makes use of Kalman Filtering.

A field database for work zones containing sensor data from re-deployable FTMS and true vehicle travel time data is not currently available. Consequently, the algorithms presented in this paper are evaluated using data generated from the INTEGRATION traffic simulation model. The evaluation considers a number of factors including traffic conditions and sensor accuracy.

Keywords:

travel time, prediction, traffic, management, ATIS, ATMS

1 Introduction

The management of traffic in highway work zones is of increasing concern to motorists and to highway authorities. There are several likely reasons for this increasing concern, including:

1. Motorists are generally experiencing longer and more congested trips than they have in the past.
2. Aging infrastructure is requiring more frequent and/or more extensive rehabilitation, resulting in increased frequency and duration of work zones.
3. The high level of traffic demands on most urban freeways throughout a long portion of the day means that lane closures associated with work zones cause a much higher user delay cost than has been the case in the past.

The continuing development of ITS technologies has led to the recent development of commercially available re-deployable FTMS. These systems typically consist of trailers on which there are mounted changeable message signs (CMS), traffic sensors, such as video or microwave radar, wireless communication devices, solar panels and/or a generator, and computer control device. These systems are considered to be re-deployable as they can be brought to a field site and made operational without any permanent installation. After the construction project is finished and the FTMS is no longer needed, the entire system can be removed from the site and deployed elsewhere.

Highway officials have recognized that one of the most frustrating aspects of work zones for motorists is the highly variable and therefore often unexpected delays that result from the work zone activities. One means of mitigating this frustration is to provide motorists with a real-time estimate of the travel time they can expect to experience traversing the work zone. Providing this information has two main effects:

1. Motorists have the option to select an alternative route (though in most instances they may have little information about the conditions on alternative routes).
2. Motorists tend to find the delay less disruptive when they know how long the delay will be.

Most existing re-deployable FTMS that provide estimates of travel time do so on the basis of historical information. These systems typically estimate the travel time of vehicles that have traversed the roadway section and post this travel time on the CMS at the upstream end of the road segment. This can be illustrated in Figure 1 which depicts individual vehicle trajectories over space and time. The vehicles are approaching a work zone that acts as a capacity bottleneck. The vehicle arrival rate is higher than the capacity of the work zone resulting in the formation of a queue, which is indicated in Figure 1 by the change in speed of

vehicles as they transition from the uncongested traffic stream approaching the work zone to the congested queue that grows upstream from the work zone.

Consider a vehicle denoted as V_1 which experiences a travel time of tt_1 . If this travel time is measured, or approximated on the basis of measured traffic conditions, and is posted on a CMS at sensor station S_1 , then the vehicle V_2 will pass the CMS at the time that the travel time is posted. However, as the queue is growing, the travel time that vehicle V_2 experiences (tt_2) is actually considerable longer than the travel time posted on the CMS.

There are many studies reported in the literature related to the area of travel time prediction. These studies can be divided into two categories, namely (1) those that directly measure travel time using specialized infrastructure such as Automatic Vehicle Identification (AVI) or cellular telephone tracking [1,2,3] and (2) those that indirectly estimate travel time on the basis of traffic characteristics such as volume, speed and occupancy obtained from traditional traffic sensors such as loop detectors [4,5,6,7,8]. Even though “direct” travel time prediction techniques generally improve travel time prediction accuracy, the specialized infrastructure these methods require are not yet widely deployed.

Most of the existing indirect travel time prediction methods assume speed data are available from traffic sensors. However, re-deployable FTMS have roadside sensors that generally cannot measure speed accurately. Consequently, many existing travel time estimation methods are not applicable to work zone FTMS.

The TIPS system (Travel Time Prediction System) [9] is one notable work zone FTMS that is able to provide travel time estimates. This system consists of microwave radar traffic sensors, trailer mounted changeable message signs (CMS), micro controller, 220 MHz radios for transmitting traffic data and an on-site PC with TIPS software. The TIPS system has been widely deployed in the US [10] for work zone traffic control.

A review of the literature revealed one field evaluation of the accuracy of the TIPS travel time estimation capability [11]. This study was conducted at a single work zone on northbound direction of I-75 in the Dayton, Ohio area. I-75 consists of three lanes in this area. The work zone activities resulted in the closure of one lane over a length of approximately 6.5 km. The TIPS system consisted of 3 CMS with the first located approximately 20 km upstream of the work zone. The remaining two CMS were spaced approximately 16 km upstream and 12 km upstream of the work zone respectively.

The TIPS system was configured to provide estimates of the travel times drivers would experience from the location of the CMS to the end of the work zone. Estimates were to the nearest 4 minutes and estimates were updated every 3 minutes.

The evaluation was conducted by the Ohio DOT over a period of 3 days. Three floating vehicles were used to travel through the work zone area and record the predicted travel time posted on each of the CMSs and the actual travel time

experienced. A total of 119 runs were conducted over the 3 days. The authors of the study report that 88% of all the predicted travel times recorded as part of the evaluation were within 4 minutes of the recorded true travel time. The authors conclude that the TIPS system provides significant improvement over any static non-real time display assuming proper placement of the microwave sensors. However they also note that errors in travel time prediction can be quite large relative to the observed travel time under certain conditions.

In light of the findings from this field evaluation of TIPS [11], the objective of this research is in to investigate the potential for improving upon the travel time prediction accuracy of the TIPS system.

This paper is organized as follows. The next section describes the existing TIPS travel time estimation methodology and the proposed methods. Section 3 describes the evaluation of the travel time prediction methods. Conclusions and recommendations are provided in Section 4.

2 Travel time estimation methods

2.1 TIPS

The TIPS travel time prediction method estimates travel time on the basis of calibrated speed versus weighted occupancy relationships and known roadway lengths. Weighted occupancy is computed on the basis of individual lane occupancies as defined in Equation 1.

$$O_w = \sum_{i=1}^n \lambda_i O_i \quad (1)$$

where:

- O_w = weighted occupancy (%)
- O_i = measured occupancy in lane i (%)
- λ_i = weight factor for lane i ($0 \leq \lambda \leq 1$)
- n = number of lanes

The weight factors are computed using Equation 2.

$$\lambda_i = \frac{O_i}{\sum_{i=1}^n O_i} \quad (2)$$

The TIPS system makes use of microwave radar traffic sensors that are not capable of measuring traffic speeds. Consequently, the calibration of the speed versus weighted occupancy relationship was conducted by collecting vehicle travel time data [9]. Video cameras were positioned approximately 2 km apart upstream of a work zone on I-70 and the travel times of individual vehicles were extracted manually by identifying vehicles as they entered and exited the section. The travel times were converted to an average travel speed by dividing the section length by the travel time. These average travel speeds were used to

calibrate the speed versus weighted occupancy relationships. Approximately 15 hours of data were collected.

Two exponential relationships were calibrated; a single regime and a three-regime model. Each model was of the form in Equation 3. Parameter values are provided in Table 1 and the relationships are illustrated in Figure 2. The authors concluded that the 3-regime model provides better prediction accuracy and recommended its use. It must be noted, that a single set of parameter values is used for all sensor stations.

$$S_j = \theta e^{\beta O_w} \quad (3)$$

where:

- S_j = average speed computed for sensor station j (ft/sec)
- θ, β = calibration coefficients
- O_w = weighted occupancy (%)

Figure 3 illustrates the calculation method used to estimate the travel time between two successive TIPS sensor stations. The weighted occupancy is computed at each sensor station and is applied to the three-regime speed versus occupancy relationship to estimate speed. The travel time for the road segment between the two sensor stations is computed as in Equation 4.

$$T_{j,j+1} = \frac{0.5d_{j,j+1}}{S_j} + \frac{0.5d_{j,j+1}}{S_{j+1}} \quad (4)$$

where:

- $T_{j,j+1}$ = travel time from sensor j to sensor $j+1$
- $d_{j,j+1}$ = distance from sensor j to sensor $j+1$
- S_j = speed measured at sensor j
- S_{j+1} = speed measured at sensor $j+1$

2.2 Variation of TIPS

This method is a simple variation of the TIPS method described in the previous section. In this variation, a speed versus weighted occupancy relationship is calibrated for each sensor station rather than using a single set of parameter values for all sensor stations. This is the only difference from the TIPS method described in the previous section.

2.3 Kalman Filter

Kalman Filtering, one of the most advanced methods in modern control theory, is based on theory proposed by Kalman [12] and may be applied to short term stationary or nonstationary stochastic phenomena. In traffic it can be applied for demand and travel time prediction to obtain increased accuracy.

Traditional estimation methods are able to only provide estimates of the current travel time through the road section, rather than the travel time that vehicles will experience (predictive travel times). Kalman filtering makes use of previous and current observations to provide predictions of future travel times.

In this study, Kalman Filtering is used to predict travel time based on real-time travel time information provided by the TIPS system using the 3-regime speed versus occupancy relationship.

The Kalman filter method is based on two primary relationships denoted the process equation (Equation 5) and the observation equation (Equation 6).

$$X_k = F_{k,k-1}X_{k-1} + w_{k-1} \quad (5)$$

$$y_k = H_k X_k + v_k \quad (6)$$

where:

- X_k = travel time at time interval k
- $F_{k,k-1}$ = transition parameter which is externally determined.
- w = a noise term that has a normal distribution with zero mean and a variance of Q_{k-1} .
- y_k = travel time for interval k provided by TIPS system or other proposed methods.
- v = observation error at time interval k which is assumed to have a normal distribution with zero mean and a variance of R_k .
- H_k = identity matrix, which in this application is a single dimension and consequently has a value of 1.

Parameters, $F_{k,k-1}$, Q_{k-1} and R_k , are predetermined in advance from empirical data. If no value is available for Q_{k-1} and R_k , it is customary to express them as diagonal matrices [13].

Based on the objective of minimum state error, the travel time prediction equation can be expressed as:

$$\hat{X}_k = \hat{X}_k^- + G_k (y_k - X_k^-) \quad (7)$$

where:

- G_k = Kalman gain value which is adjusted continuously by the recursive process
- $\hat{X}_k^-$ = the optimum estimate of X_k before y_k is obtained
- $\hat{X}_k$ = the travel time at time interval k to be predicted

The actual method of implementing the above equations, beginning at time $k=0$, is specified below:

Step 1. Let error covariance $P(0) = E[(X(0) - \hat{X}_0)^2]$ and $\hat{X}_0 = E[X(0)]$

Step 2. State estimate extrapolation $\hat{X}_1^- = F_{1,0} \hat{X}_0$

$$\text{Error covariance extrapolation } P_1^- = F_{1,0} P(0) F_{1,0}^T + Q_0$$

Step 3. Calculate Kalman Gain Value

$$G_1 = P_1^- (P_1^- + R_1)^{-1}$$

Step 4. Calculate the new state estimate and error covariance

$$\hat{X}_1 = \hat{X}_1^- + G_1 (y_1 - \hat{X}_1^-)$$

$$P_1 = (I - G_1) P_1^-$$

Step 5. Let $k=k+1$ and go back to Step 2 until the preset time period ends

The next section describes the quantitative comparison of the TIPS system (section 2.1) with the variant of the TIPS system (section 2.2) and the Kalman filter (section 2.3).

3 Evaluation of travel time estimation methods

3.1 Test network

At the time of this study, a field database containing both sensor data (i.e. volume and occupancy) for a work zone and the corresponding actual travel times was not available. The collection of such data is time consuming and costly. Furthermore, it is difficult to control external factors (such as weather, demand, incidents, etc.) when collecting field data. Consequently, in this study, a microscopic simulation model was used to generate the data (sensor and travel time) that were used to evaluate existing and proposed travel time estimation algorithms. For this study, the INTEGRATION traffic simulation model was used, however, any microscopic simulation model capable of modelling freeways and recording individual vehicle travel times could have been used.

A typical freeway work zone was modelled as illustrated in Figure 4. The freeway segment consists of an off-ramp and on-ramp junction followed by the work zone. The freeway, consisting of 7 links, has 3 lanes except in the work zone where the cross section is reduced to 2 lanes. Furthermore, the capacity of the freeway lanes in the work zone is reduced from the 2,200 pcu/h/lane to 2,000 pcu/h/lane as a result of reduced lateral clearances and/or reduced lane widths. There are 8 sensor stations (labelled $S1, S2, \dots, S8$) located along the freeway section. Consistent with the objective of re-deployable traffic management systems, it is assumed that these sensors are roadside sensors (e.g. radar or video) rather than in-pavement sensors such as loop detectors.

The INTEGRATION model requires the specification of the four parameters that define Van Aerde's steady-state macroscopic speed-flow-density relationship.

The parameter values used in this study are provided in Table 2 while Figure 5 illustrates the corresponding macroscopic speed-flow relationships.

A temporally varying traffic demand was created to be representative of a typical peak period in which traffic demands are initially sufficiently low that no congestion results upstream of the work zone. However, as demand increases, congestion begins to form at the bottleneck caused by the lane reduction at the work zone and this congestion spills back upstream and eventually interferes with traffic entering and exiting the freeway at the ramps. The congestion does not spill off the upstream end of the network before the traffic demand declines and the congestion dissipates before the simulation period ends. The temporal variation, in terms of the fraction of the base rate, is the same for all three origin-destination combinations (i.e. mainline to off-ramp; mainline to mainline; and on-ramp to mainline) and is illustrated in Figure 6. Vehicles are generated with random (i.e. shifted negative exponential headways).

The application of these traffic demands to the test network results in a travel time profile as illustrated in Figure 7. In this figure, the x-axis represents the time at which vehicles passed the start of link 2. The y-axis represents the time the vehicle required to travel from the start of link 2 to the end of link 6. Naturally, only vehicles that are travelling from the mainline to the mainline are included within these results. Vehicles that enter or exit the freeway via the ramps do not traverse all of links 2, 3, 4, 5, and 6 and therefore are not depicted.

INTEGRATION models loop detectors that provide speed, volume, and occupancy output at a user defined polling interval duration. In this study we have used a polling interval duration of 90 seconds. Unlike field sensors, the simulation output does not contain measurement errors. Unfortunately, the magnitude and distribution of these measurement errors for various sensor technologies, and in particular microwave radar, does not appear to be reported in the literature. Consequently, we have represented the error in terms of Gaussian noise having a mean of zero and a standard deviation that is specified by the coefficient of variation (COV). Three levels of sensor error were considered; COV = 10%, 15%, and 20%. Increasing values for COV imply decreasing sensor accuracy and therefore we refer to three levels of sensor accuracy as 90% accurate, 85%, and 80%. Consequently, Equation 8 was used to transform all sensor output from the simulation to sensor measurements containing random errors.

$$X_m = X + z\sigma \quad (8)$$

where:

$$\begin{aligned} X_m &= \text{traffic characteristic containing sensor measurement error} \\ X &= \text{traffic characteristic containing no error} \\ z &= \text{normally distributed random variable with mean of 0 and} \\ &\quad \text{standard deviation of 1} \\ &= \sum_{i=1}^{12} U_i - 6 \end{aligned}$$

U_i = uniformly distributed random variable ($0 \leq U_i \leq 1.0$)
 σ = standard deviation of measurement error ($\sigma = COV \times X$)

In the course of the research, it was observed that the speed versus weighted occupancy data produced by the simulation model exhibited substantially different characteristics than did those data used by Pant [9] for calibrating the TIPS relationships. To provide a consistent evaluation between the travel time prediction methods it was decided to recalibrate the exponential speed versus weighted occupancy relationships on the basis of the simulated data. This calibration was conducted for each level of sensor accuracy data separately. The resulting parameter values are provided in Table 3.

3.2 Evaluation results

Four methods of estimating travel times were compared using the root-mean-squared error (RMSE) between the actual and predicted travel times. The performance of the methods was examined for the entire simulation period as well for selected sub-periods within the simulation so that the performance of the methods could be examined for various traffic conditions (e.g. congestion forming, congestion dissipating, etc.). Rather than provide the error as an absolute measure (in seconds) the RMSE was divided by the mean true travel time to represent the error as a portion of the true travel time. The results of these comparisons are provided in Table 4 for an assumed sensor accuracy of 90%.

The single regime TIPS method provides predicted travel times that under estimate or over estimate the true travel time by 17% on average. During uncongested periods, the method is more accurate and during periods of congestion or congestion forming, the errors are larger.

The three-regime TIPS method provides better performance with an average error of 15.5% of the mean. Again, the method performs better during periods of uncongestion and provides less accurate estimates during periods of congestion and when congestion is forming.

The TIPS variant, in which separate speed versus weighted occupancy functions are used for each sensor station, provided performance that was essentially the same as the single-regime TIPS model. Consequently, this method was not considered for further analysis.

The Kalman filter method provided the best results overall with an average prediction error equal to 14% of the mean travel time. This method also exhibited the most consistency in the prediction accuracy through out all the traffic conditions.

The estimated travel times for the single-regime and three-regime TIPS methods and the Kalman filter method are depicted in Figure 8.

The results discussed above indicate that the Kalman filter provides improved travel time predictions. However, we are also interested to know how sensitive these results are to the accuracy of the sensors. Consequently, we repeated the

travel time predictions for two additional sensor accuracies, namely 80% and 85%. Figure 9 illustrates the resulting overall errors for the two TIPS methods and the Kalman filter method as a function of sensor accuracy. Error is again quantified in terms of the RMSE divided by the mean true travel time.

From these results it is clear that the Kalman filter method is least affected by the accuracy of the sensors, while the single-regime TIPS method is very sensitive to the sensor accuracy. These results appear to confirm the previous results that the Kalman filter provides more accurate travel time predictions than do the existing TIPS methods.

4 Conclusions and Recommendations

The testing conducted as part of this study has demonstrated that the application of the Kalman filter to the problem of predicting travel times improves the estimates of the three-regime TIPS method by approximately 10%. More importantly, the Kalman filter provides more accurate travel time predictions during periods of congestion forming, congestion, and congestion dissipating – the exact conditions for which predicted travel times are most valuable.

The conclusions stated herein are made on the basis of a limited number of simulation results. Consequently, it would seem appropriate that these conclusions be confirmed for a wider range of traffic conditions and beyond that, with actual field data.

It is also worth stating that the Kalman filter method used in this study is not restricted to re-deployable FTMS but can also be applied for the estimation of travel times on permanent FTMS.

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Figures

Figure 1: Historical versus predicted travel times

Figure 2: Single regime and three-regime models used by TIPS

Figure 3: TIPS calculation of travel time for each link

Figure 4: Schematic of hypothetical freeway segment

Figure 5: Macroscopic speed-flow-density relationship used in the simulation

Figure 6: Temporal profile of traffic demands

Figure 7: Individual vehicle travel times (Link 2 to end of link 6)

Figure 8: Estimated and actual average travel times as a function of simulation time (sensor accuracy = 90%)

Figure 9: Travel time prediction error as a function of sensor accuracy

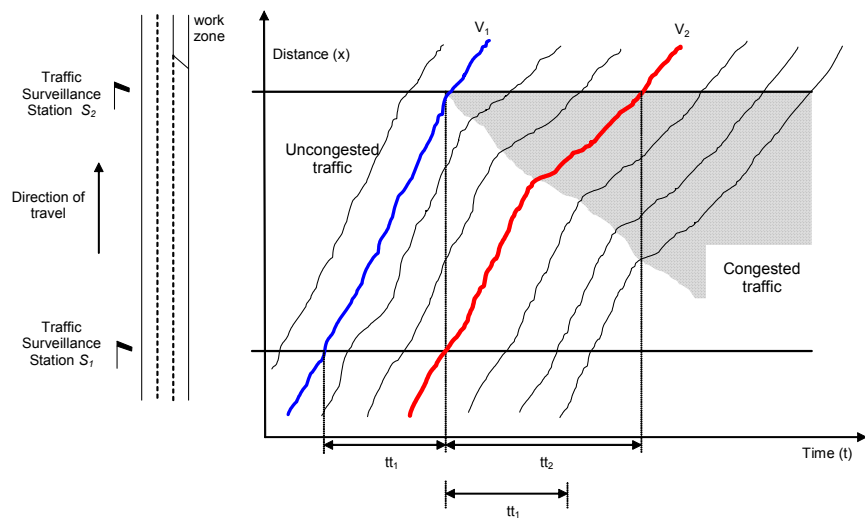


Figure 1: Historical versus predicted travel times

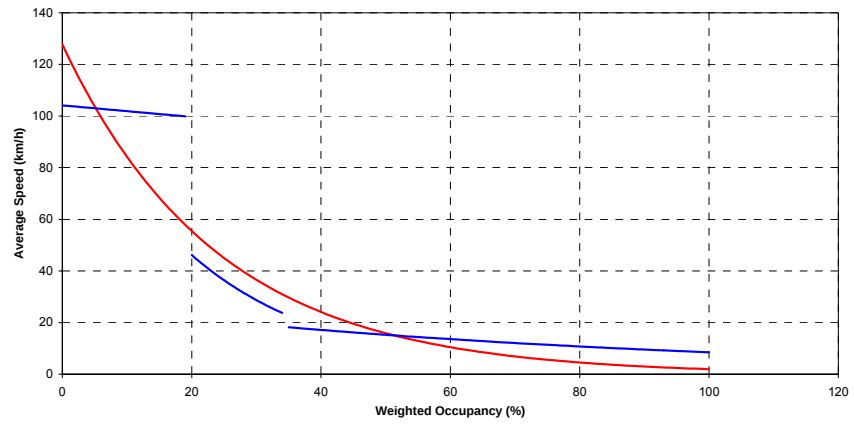


Figure 2: Single regime and three-regime models used by TIPS

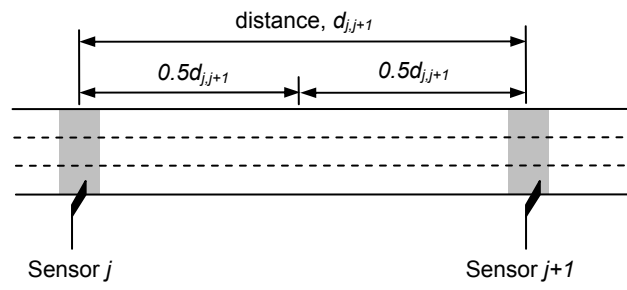


Figure 3: TIPS calculation of travel time for each link

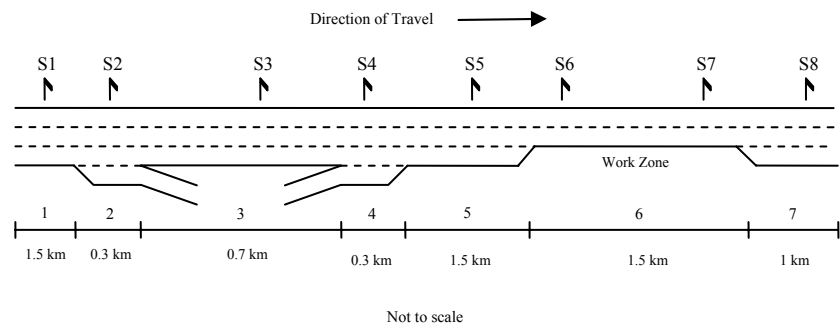


Figure 4: Schematic of hypothetical freeway segment

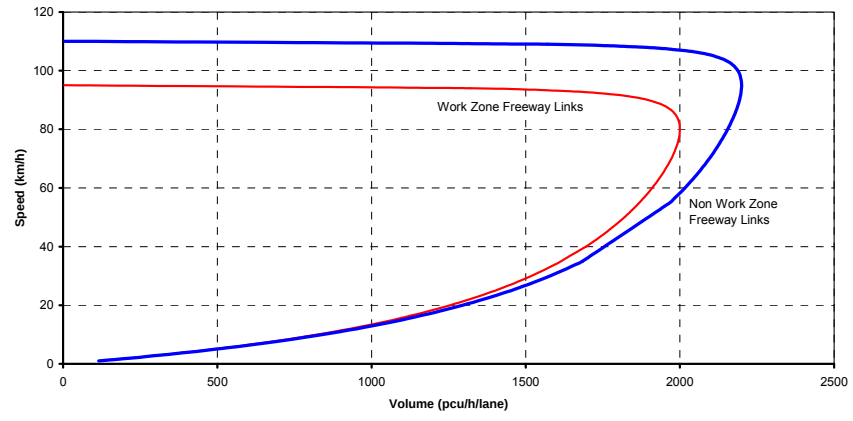


Figure 5: Macroscopic speed-flow-density relationship used in the simulation

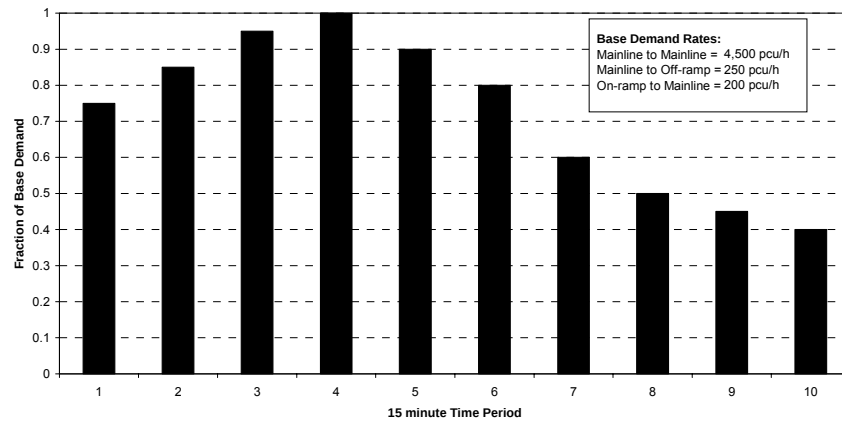


Figure 6: Temporal profile of traffic demands

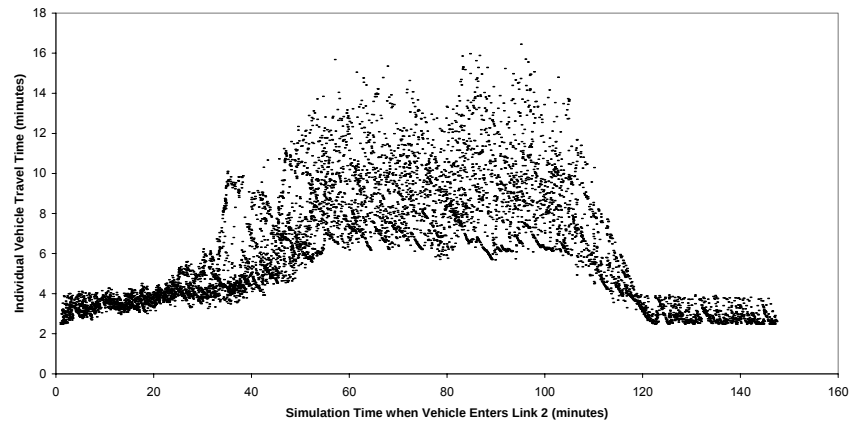


Figure 7: Individual vehicle travel times (Link 2 to end of link 6)

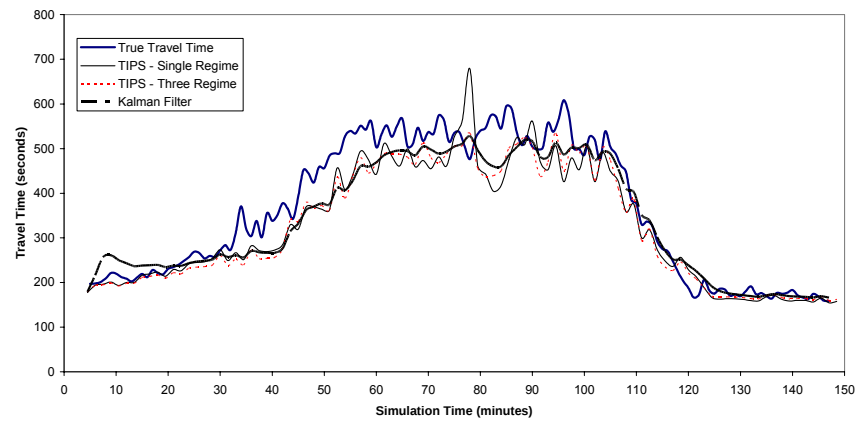


Figure 8: Estimated and actual average travel times as a function of simulation time (sensor accuracy = 90%)

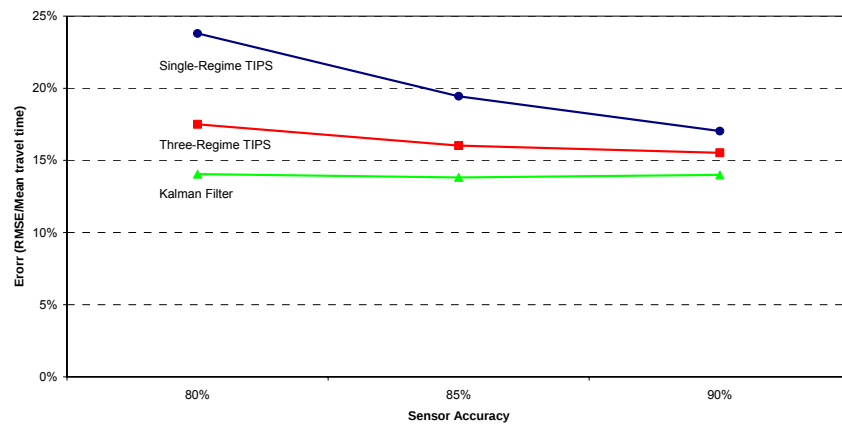


Figure 9: Travel time prediction error as a function of sensor accuracy

Tables

Table 1: TIPS speed versus weighted occupancy parameter values

Table 2: Simulation speed-flow-density relationship parameters

Table 3: Recalibrated parameter values for the TIPS speed versus weighted occupancy relationship

Table 4: Prediction errors for sensor accuracy of 90%
(Error = RMSE/mean travel time)

Table 1: TIPS speed versus weighted occupancy parameter values

	θ	β
Single Regime Model	127.82	-0.0417 $0 \leq O_w \leq 100\%$
Three-Regime Model	95	-0.0022 $0 < O_w \leq 20\%$
	108.995	-0.0475 $20 < O_w \leq 35\%$
	25	-0.0117 $35\% < O_w \leq 90\%$

Table 2: Simulation speed-flow-density relationship parameters

Parameter	Non-Work Zone	Work Zone	Ramps
Free Speed, S_f (km/h)	110	95	60
Speed at capacity, S_c (km/h)	90	80	45
Jam density, D_j (pcu/lane-km)	120	120	120
Capacity, V_c (pcu/h/lane)	2,200	2,000	1,800

Table 3: Recalibrated parameter values for the TIPS speed versus weighted occupancy relationship

Level of Accuracy	90%		85%		80%	
Parameters	θ	β	θ	β	θ	β
Single regime	116.71	-0.0495	113.63	-0.0463	109.06	-0.0417
Three-Regime	110.24	-0.0416	109.99	-0.0409	110.42	-0.0409
	232.32	-0.0763	229.01	-0.075	181.56	-0.0649
	24.548	-0.0086	24.77	-0.0083	27.094	-0.0092

Table 4: Prediction errors for sensor accuracy of 90%
(Error = RMSE/mean travel time)

Period	TIPS: Single regime	TIPS: Three regime	TIPS Variant	Kalman Filter
Uncongested (0-30 min)	6.1%	8.0%	6.3%	10.8%
Congestion forming (30-72 min)	16.0%	16.7%	16.8%	15.9%
Congested (72-96 min)	17.9%	13.6%	17.8%	11.6%
Congestion Dissipating (96-120 min)	15.6%	14.0%	15.3%	10.0%
Uncongested (120-150 min)	10.1%	8.4%	7.7%	9.1%
Overall	17.0%	15.5%	17.2%	14.0%