A SYSTEM FOR DISPLAYING TRAVEL TIMES ON CHANGEABLE MESSAGE SIGNS

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ABSTRACT

We present a system that displays travel time predictions in real time on changeable message signs (CMS) in California. Using loop detector data, this system calculates predicted travel times on designated routes every five minutes. An automated process displays the current travel time predictions on the appropriate CMS's. We demonstrate the benefits of real time travel time prediction. Historical analysis show that route decision based on CMS almost always identifies the quickest route when alternates are available. Regardless of whether alternate routes exist, prediction reduces travel time uncertainly which is quantified by buffer time. The buffer time is the total time one must budget to guarantee a certain probability of being on-time, such as 90%. We verify the accuracy of loop detector data-based travel time estimates by comparing with probe vehicle travel times. There is a close agreement between the two when the data quality is high, and large errors when quality is low. Therefore, data quality of CMS routes must be verified by probe vehicle tests before deployment.

INTRODUCTION

Changeable message signs (CMS's) along freeways can display dynamic information to help drivers choose the best route and plan for delays. Currently, operators in the Traffic Management Center (TMC) type messages about incidents, road conditions, and events onto the signs. Increasingly, CMS's are also used to display automatically generated travel time information. Such services exist in Europe and in US cities including Houston, San Antonio, and Atlanta. Real time traffic data and computer algorithms are used to generate and display the CMS content.

This paper describes the implementation of an automated CMS service in California. The goal of this pilot project is to display predicted travel times from the message sign to several destinations along the route. A computer program processes real time data from loop detectors and calculates the predicted travel times. The predictions are sent to the TMC, where another program displays them onto the message signs.

We chose several origin-destination pairs for our pilot program based on the existence of competitive alternate routes and large variability in travel time. Our analysis shows that using real time information, drivers reduce average travel time by choosing the quickest route. They also benefit by being able to predict the length of delays much better than is possible with only historical information.

We compare the accuracy of our travel time estimates with probe vehicle measurements. When the data are good, there is good agreement between probe travel time and estimates. But the data quality is often poor. Therefore, it is important to verify estimates with probe measurements before deploying the system. Detailed probe vehicle data can also be used to detect and diagnose detector failures.

We expect to field test the system in September 2003.

BACKGROUND

Many state Departments of Transportation (DOTs) provide real time traffic information. In Washington state, a network of loop detectors measures link speeds. These data are used to calculate instantaneous travel times, which are posted on the Central Puget Sound Travel Times web site (*1*). Changeable message signs deliver traffic information directly to drivers on many freeways. Often, traffic operators type messages onto the signs from the TMC, alerting drivers of lane closures or accidents ahead. Users of the TransGuide system in San Antonio "consider the [changeable message signs] to be more useful and reliable than radio or other sources of traffic information because of the signs proximity to traffic congestion and their higher level of accuracy" (*2*).

Increasingly, changeable message signs are displaying automatically generated travel time information. The Georgia Navigator is a network of detectors and message signs built for the 1996 Atlanta Olympic games (*3*). It computes link travel times using video traffic detectors and publishes route travel times on CMS's as well as on a web page. The Houston Transtar system (*4*) uses Automatic Vehicle Identification (AVI) technology to measure travel times and posts them on CMS's. AVIs offer a more direct measurement than stationary detectors, but the accuracy depends on the level of penetration (*5*). Our system uses loop detector data because they are the only data widely available in California. Therefore, our travel time estimates are not directly measured and need to be verified with ground truth. The WSDOT observed good agreement between loop detector-based and probe vehicle travel times (*1*). Our own probe measurements show that accuracy of loop data-based estimates is good given good data quality.

Most CMS systems, including those mentioned above, simply present instantaneously measured values, rather than predictions of the future travel time. But instantaneous travel time can be deceiving. Van Zwet (*6*) showed that especially during the transition between free flow and congestion, prediction that uses both historical and real time information performs much better than that using current measurements alone. We implemented the prediction algorithm in van Zwet, which uses linear regression with coefficients fitted to historical and real time data. There are other ways to predict travel time (7). Our method is both simple and effective, but other algorithms may be used in the same framework.

POTENTIAL BENEFITS OF CMS

Problem Formulation

Changeable message signs are ideal for delivering real time information to drivers. If there are two alternate routes to the same destination, displaying their predicted travel times enables the driver to choose the quicker one; if travel time is abnormally high, the driver may decide to delay his trip and do something else instead. We quantify the benefit of real time travel time on several freeway routes. The benefits include average travel time savings and the reduction in uncertainty.

Suppose there are n alternate routes between a given origin-destination pair. Let $X_i(d,t)$ be the travel time on the ith route on day d and time of day t. Model $X_i(d,t)$ as a random variable whose distribution depends on i and t but is independent and identically distributed (iid) in d. At any time (d,t), we can make a prediction of $X_i(d,t)$, call this $\hat{X}_i(d,t)$. Notice that we don't know the actual value of $X_i(d,t)$ until some time after (d,t), the departure time. The CMS displays the prediction $\hat{X}_i(d,t)$ for each route i.

We compare two strategies. The first chooses the route with historically the lowest average travel time; the second chooses the route with the lowest predicted travel time. Let T_0, T_1 be the actual travel time realized following the two strategies. We hypothesize that the second strategy is better because it uses more information. The travel time realized is T_1, the actual travel time of the route with the shortest predicted travel time, where

$$T_1(d,t) = X_k(d,t),\ k \text{ s.t. } \hat{X}_k(d,t) \le \hat{X}_i(d,t)\ \forall i \le n \tag{1}$$

In the first strategy, drivers only know the historical average travel time at each time of day t, which is their "prediction" of the current travel time since no other information is available. Thus,

$$\hat{X}'_i(t) = \mathrm{E}[X_i(1,t)]\ \forall\, i \le n,\ \forall d \tag{2}$$

is the predicted travel time on each route. Then

$$T_0(d,t) = X_k(d,t),\ k \text{ s.t. } \hat{X}'_k(t) \le \hat{X}'_i(t)\ \forall i \le n \tag{3}$$

From historical data, we can find $\hat{X}_i(d,t)$ and $\hat{X}'_i(t)$ and estimate T_0, T_1 and their distributions.

For a thorough comparison, we introduce a third, hypothetical travel time T_2, which is the travel time on the actual fastest route,

$$T_2(d,t) = \min\left\{X_i(d,t) :\ i \le n\right\}. \tag{4}$$

T_2 is the lower bound of travel time of any routing strategy.

Route Description

The performance of these route selection strategies is evaluated using data from San Diego freeways. There are two alternate routes between the I-5/I-805 interchange and the I-5/I-163 interchange. One can stay on I-5 SB for the entire trip or take I-805 SB and then I-163 SB. We number the routes 1 and 2 respectively. They have similar traffic characteristics. See Table 1.

We compute travel times $X_i(d,t)$, where $i = 1, 2$, for departure times between 5:00 AM and 10:00 PM on 8/1/2002 through 8/31/2002. There are 22 weekdays included in the study. Travel times are computed for 1320 departure times over the study period at every 17 minutes. For each departure time, we calculate a trajectory in space and time that satisfies the measured speeds by "walking" through the speed surface in time and space. For more details on the calculation of historical travel times see the SYSTEM IMPLEMENTATION section, Chen (*8*), or Oda (*9*).

The scatter plot of route 1 and route 2 travel times is shown in Figure 1. Each point represents travel times on the two routes with the same departure time; there are 1320 points. Travel times on the two routes are comparable, suggesting that they are realistic alternatives. However, for any given departure time, either route may have the shorter travel time.

Route Selection

Let $R_0(t) \in \{1, 2\}$ be the route taken based on strategy 0, i.e.

$$R_0(d,t) = \underset{r}{\operatorname{argmin}} \operatorname{E}\left[X_r(1,t)\right].$$

$R_0(d,t)$ is fixed for each time of day t and does not depend on d because it uses only historical information. Let $R_1(t)$ to be the choice based on real time prediction, i.e.

$$R_1(d,t) = \underset{r}{\operatorname{argmin}} \hat{X}_r(d,t).$$

This is a random variable that depends on t but is assumed to be iid in d. Similarly, the route choice under full knowledge is

$$R_2(d,t) = \underset{r}{\operatorname{argmin}} X_r(d,t).$$

R_0 does not depend on real time data and therefore depends only on t, the time of day. But R_1 depends on the current information, therefore it depends on both d and t. Figure 2 shows for each time of day, the probability that route 1 is chosen based on strategy 1. Recall that strategy 1 chooses the route with the minimum predicted travel time based on current information. Route choice is clearly affected by the real time information. On average, during the morning, route 1 is chosen on most days; during the afternoon peak at 18:00, about 40% of the time route 1 is chosen, and the other 60% of the time route 2 is chosen.

We now compare the performance of real time route selection versus route choice based only on historical knowledge. We calculate the reduction in average travel time and buffer time, a measure of uncertainty. The use of real time information also successfully avoids routes with abnormally high delays.

Average Travel Time Reduction

Real time travel time predictions $\hat{X}_i$ on routes $i = 1, 2$ are computed for every departure time. The details of travel time prediction is given in the SYSTEM IMPLEMENTATION section. We also compute T_0, T_1, and T_2 – the achieved travel times of the three route decision strategies. Figure 3 shows the average travel times for each departure time of day during the test period. The quicker route according to CMS takes about 2 minutes less than the historically quicker route during the afternoon peak period, or about 9% of the average. The achieved CMS travel times are very close to the minimum possible travel time shown by the dotted line. This shows that CMS almost always picks the route with minimum travel time.

The improvement in average travel time may seem moderate because CMS reduces travel time only when the historically quicker route is the slower one on a given day. But individual trip savings can be great. Figure 4 shows the scatter plot of $T_1(d,t)$ vs. $T_0(d,t)$ for all 1320 departure times (d,t). There are 60 departures per day over 22 days, representing one point every 17 minutes on each day and 1320 total points. For (d,t) when $R_0(d,t) = R_1(d,t)$, $T_0(d,t) = T_1(d,t)$ as well and the points fall on the diagonal. This is the case when the decisions based on historical and current information are the same. Most of the trips fall on the diagonal. But there are also many trips with $T_1 < T_0$. On these trips, using real time information leads to a shorter travel time. There are also a few trips that have $T_1 > T_0$: on these trips, the predicted travel times do not identify the shortest route, *and* historical prediction makes the correct decision. But even on these trips, the difference in the achieved travel times is small compared to the difference in the other cases. These results show that almost all trips would have been shorter using the CMS predictions.

Buffer Time Reduction

Even when no alternate route is available, accurate prediction of travel time reduces uncertainty and allows people to better plan activities that depend on their arrival time. Studies have found that drivers place a cost on the variability of travel time (*10*) and value the ability to make informed decisions even if no alternate routes are available (*2*). Therefore, the reduction of uncertainty through accurate prediction of travel time provides a useful service in itself.

The cost of uncertainty in travel time is quantified by buffer time. This is the total time that must be budgeted in order to arrive on-time with a certain probability, and can be much larger than average travel time. The Texas Transportation Institute's Mobility Study uses 95% level as the buffer time (*11*); we use 90% here because our data set is small.

When only historical information is available, the 90% buffer time is the 90^{th} percentile of historical travel time, which depends on time of day. When real time information is used, the buffer time depends also on current measurements. The 90% buffer time $y^{90}(s,t)$ given predicted travel time t and departure time s is estimated from historical data. Given n historical trips and let s_i be the departure time of the ith trip, T_i be its actual travel time, and t_i be the predicted travel time. The ith prediction error is $\epsilon_i = T_i - t_i$. We estimate $y^{90}(s,t)$ using the weighted 90th percentile of ϵ_i, where the weights are given by

$$w_i(s,t) = k_1(s - s_i)k_2(t - t_i), \tag{5}$$

and k_1 and k_2 are Gaussian kernels with mean zero and variance chosen experimentally. The weighted $100p$th percentile of a sorted set $\{x_i : \ i = 1, 2, \ldots, n, \ x_i \leq x_i + 1 \ \forall i\}$ with weights w_i is

$$y = \begin{cases} \frac{1}{2}(x_i + x_{i+1}) & \text{if } \sum_{j=1}^{i} w_j = pW \\ x_{i+1} & \text{if } \sum_{j=1}^{i} w_j < pW < \sum_{j=1}^{i+1} w_j \end{cases} \tag{6}$$

where $W = \sum_{i=1}^{n} w_i$ is the sum of the weights. The interpretation of $y^{90}(s,t)$ is that given the predicted travel time at s is t, the prediction error is less than $y^{90}(s,t)$ with 90% probability.

The buffer time given a time of day s and travel time prediction t is the sum of the 90th percentile error and the predicted travel time:

$$T^{90}(s,t) = y^{90}(s,t) + t. \tag{7}$$

Figure 5 shows the average buffer times at different times of day. The first plot shows the buffer times when only route 1 is available. During the afternoon peak, the 90% buffer time when using real time information is five minutes less than that using only historical information, a saving of 17%. The second plot shows the savings when only route 2 is available, with similar results. This means that even when no alternate routes exist, prediction using real time information is worthwhile by significantly reducing the buffer time. The third plot in this series shows the effect of combining route selection with real time prediction. The saving in this case is slightly larger, about seven minutes at the peak.

More Results

Similar studies are carried out on four other origin-destination pairs. In each case, the benefits of using real time information are shown in terms of mean travel time and 90% buffer time in Table 2. The peak average travel time is computed by first calculating the average travel time by time of day over the test period of one month, and then taking the peak value over all times of day. The reduction in average travel time is similarly computed and represents the peak hour. For most O-D pairs, the average travel time reduction information is small, because often there are few competitive alternative routes available. But in most cases, using real time information results in a large reduction in buffer time. This reduction is between 7% and 31% for the five locations studied.

SYSTEM IMPLEMENTATION

Data Source

Real time and historical data for the CMS project are provided by the Freeway Performance Measurement System (PeMS), which collects data from traffic sensors in California (*12*). Located on the University of California, Berkeley campus, PeMS has several years of data on-line, which are used to calibrate the prediction model and evaluate its performance.

Historical travel times are computed from speed data using an algorithm described by Chen (*8*). Given a route of length L with detector locations $x_1, \ldots, x_n$ where $0 \le x_1 \le \cdots \le x_n \le L$, the measurements are average speeds at $v(x_i, t_i)$ at discrete times t_i and detector locations x_i. Although we use single loop detectors, accurate speeds can be obtained from volume and occupancy measurements using an algorithm that estimates the average vehicle lengths (*13*). To compute the travel time at departure time s_0, we estimate the trajectory $y_0, y_1, \ldots$ at times $s_0, s_1, \ldots$ that obeys the measured speeds. The trajectory is found by iterating:

$$\begin{aligned} y_0 &= 0; \\ s_i &= s_0 + i\Delta; \\ y_{i+1} &= y_i + \Delta \hat{v}(y_i, s_i),\ i = 1, 2, \ldots \end{aligned} \tag{8}$$

where $\hat{v}(x,t)$ is the interpolation of $v(x_i, t_i)$ at (x, t). The time increment Δ is 10 seconds. The travel time $X(s_0)$ on $[0, L]$ is the time it takes for the trajectory to reach L:

$$X(s_0) = \min\{s_i \ :\ y_i \ge L\} - s_0. \tag{9}$$

Travel Time Prediction Module

Travel time predictions are computed using linear regression, a method developed by van Zwet (*6*). A route is divided into n segments of length $l_i,\ i = 1, 2, \ldots, n$, where the segment boundaries are located at the midpoints between adjacent detection detectors. For a given time t, define the instantaneous travel time $T^*(t)$ as

$$T^*(t) = \sum_{i=1}^{n} \frac{l_i}{v(x_i, t)}, \tag{10}$$

where $v(x_i, t)$ is the speed measured by the ith detector at t. T^* represents the current state of the route; it is a predictor of the actual travel time $T(t)$ in this linear model:

$$X(t) = \alpha(t, s) + \beta(t, s) T^*(s) + \epsilon(t, s),\ s \le t \tag{11}$$

where t is the intended departure time, s is the time of most recent data, and $\epsilon(t,s)$ is iid noise. The coefficients α and β are functions of t and s. They are estimated from historical data and stored in the database shown as "Prediction coefficients" in Figure 6. The travel time prediction at current time t is found using the estimates of α and β:

$$\hat{X}(t) = \hat{\alpha}(t,t) + \hat{\beta}(t,t)T^*(t). \tag{12}$$

Architecture And Communications

Figure 6 shows the system block diagram. Travel time prediction is implemented in Perl. At every five minutes, this process uses the most recent five-minute speed data and stored prediction coefficients to compute the travel times for the current departure time. The prediction for each route is written to a text file. Another process in the TMC reads this file and displays its contents onto the designated message signs. The software responsible for displaying messages on CMS's is called Satellite Operation Center Command System (SOCCS). SOCCS communicates with CMS's via telephone lines.

ACCURACY OF TRAVEL TIME ESTIMATE

We use local speed measurements to estimate historical travel times rather than direct measurements. For the results to be accurate, the detector data must be valid and detector spacing must be small enough to capture the true speed profile of the vehicles. Since detectors often fail, producing bad data or no data at all (*14*), one must verify travel times based on loop data against those directly measured with probe vehicles.

Probe vehicle measurements were carried out on two routes. One is on Interstate 80 between the Carquinez Bridge and the Bay Bridge in the San Francisco Bay Area, a section of about 20 miles; the other is on I-5 between El Toro and Buena Park in Orange County, also about 20 miles long. Travel times estimates on I-5 agree with probe measurements, but travel times on I-80 are often affected by missing and bad data. We are currently improving the data quality, which should improve the travel time estimate accuracy. Below is a detailed analysis of each route.

I-80

There are 135 Vehicle Detector Stations (VDS) in the two directions on I-80, where a VDS contains one detector per lane at that location. There is one VDS for each direction at the same location. There are a total of 690 detectors, of which only 284 provided good data. These detectors are double loops which measured speed directly. Probe travel times were measured with tach vehicles, which are equipped with wheel counters to record the number of revolutions of the wheel every second. After calibrating for the wheel size, this gives us the total travel time as well as a detailed trajectory of the vehicle. We made about 74 probe trips between Monday, April 21 and Friday, April 25, 2003.

Using loop detector data from the same period, we computed the travel time estimates for each five minute period. Table 3 shows the probe measurements and estimated travel times for the same departure times. The errors are large on 4/22 and 4/23 AM and 4/22 PM, but they are good on other dates such as 4/24 AM. An examination of the data quality revealed many missing samples, especially during Tuesday and Wednesday. The cause of the missing data has since been found and the problem corrected, but the missing data from the test period cannot be recovered. The summary statistics of the travel time errors are shown in Table 5. After the trips with many missing samples are removed, the root-mean-squared error is 10%.

I-5

The route on I-5 has 120 VDS in both directions. The data quality here is much better than on I-80. However, we did not have access to tach vehicles for this route, so probe measurements were performed manually with an ordinary vehicle. The driver phoned in the times at which he crossed certain designated checkpoints, and the times were recorded by his partner in the office. Fourteen such probe runs were made. Table 4 shows the comparison between probe travel times and loop travel times. Most of the probe measurements matches detector estimates very well. The exceptions are three trips on 5/14 SB. There was a severe accident in the afternoon of this day which was noted by the driver. This may have caused the large error for the point at 2 PM. The other two points in the morning cannot be similarly explained. They may have been the result of gaps in the data coverage. We have scheduled tach measurements for this route, which will provide more detailed data to allow us to diagnose the exact cause of these discrepancies.

The RMS error is about 14%. See Table 5. It is not clear why the probe travel times are always higher than loop-based estimates in these comparisons.

CONCLUSION

We present an implementation of real time travel time prediction on CMS and analyzed its potential benefits. Changeable message signs are installed in many freeway locations in California. They can be programmed to automatically display dynamic content and effectively deliver traveler information to drivers. We plan to use the CMS's to display travel time predictions based on loop detector measurements. We demonstrate an algorithm that operates on real time data and produces predictions every five minutes. The complete system includes the travel time predictor and a program at the Traffic Management Center which reads the predictions and displays them onto the designated signs.

Analysis on historical data shows that a strategy based on CMS travel times provides significant benefits in both average travel time and buffer time reduction. Using real time information often enables the driver to select the quickest route and avoid non-recurring congestion. Even when only one route is available, real time prediction reduces the 90% buffer time by 18%.

Loop data-based travel time estimates are compared with probe measurements. There is good agreement between the two when the data quality is good. But in many cases, a large number of samples are missing from the data, which results in large errors. This is due to a software error and has since been corrected, although more probe measurements will be performed to verify that the data quality is good enough for deployment.

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Route	Length	Detector Stations	Daily Volume
I-5 SB	14.61	12	90,174
I-805 to I-163	14.05	13	86,129/67,769

TABLE 1 Description of routes, San Diego test case. Volumes are daily averages in August, 2003.

Origin and destination	Number of routes	Peak avg. travel time	Travel time reduction	Peak 90% buffer time	Buffer time reduction
I-10 WB at White Ave. to downtown LA	3	41.7	2.9%	75.2	18%
I-5 SB at Terra Bella St. to downtown LA	2	29.8	17.1%	47.7	31%
I-15 SB at I-5 to downtown San Diego	2	22.9	8.7%	29.9	20.7%
I-5 NB at El Toro to Buena Park (I-5 & SR-91)	5	32.9	1.7%	41.8	11%
I-5 NB at El Toro to Seal Beach (I-405 & SR-22)	2	34.2	4.7%	43.5	7%

TABLE 2 Benefit summary for five origin-destination pairs.

Eastbound					**Westbound**				
Departure Time	Probe (min)	Estimate (min)	Abs Error	Bad data	Departure Time	Probe (min)	Estimate (min)	Abs Error	Bad data
4/21 6:57 AM	15.9	16.5	4%		6:57 AM	26.6	20.3	24%	
7:26 AM	15.8	16.0	1%		7:26 AM	31.7	26.7	16%	
8:09 AM	17.6	16.5	6%		7:55 AM	31.2	23.5	25%	
8:38 AM	16.1	17.7	10%		8:24 AM	28.9	22.2	23%	
2:38 PM	17.4	18.2	4%		9:07 AM	20.0	18.8	6%	
3:07 PM	18.7	18.7	0%		2:52 PM	20.6	20.0	3%	
3:36 PM	31.9	31.8	0%		3:36 PM	17.7	18.7	5%	
4:04 PM	29.1	34.8	20%		4:04 PM	17.3	18.3	6%	
4/22 6:57 AM	16.8	18.5	10%	*	6:57 AM	33.5	18.0	46%	*
7:40 AM	15.4	21.5	40%	*	7:26 AM	43.7	15.3	65%	*
8:09 AM	16.1	22.7	41%	*	7:55 AM	42.0	15.5	63%	*
8:38 AM	15.3	27.0	76%	*	8:38 AM	34.0	31.0	9%	*
2:24 PM	16.1	16.8	5%	*	9:07 AM	26.1	16.0	39%	*
2:52 PM	17.6	16.8	4%	*	2:52 PM	17.9	17.0	5%	*
3:36 PM	19.6	17.2	12%	*	3:36 PM	18.9	16.5	13%	*
4:04 PM	19.6	17.2	12%	*	4:04 PM	27.3	17.3	37%	*
					4:33 PM	25.4	18.8	26%	*
4/23 6:57 AM	16.8	17.5	4%	*	6:57 AM	30.6	17.8	42%	*
7:26 AM	15.5	15.3	1%	*	7:26 AM	38.6	17.7	54%	*
8:09 AM	16.2	27.2	68%	*	7:55 AM	38.8	18.7	52%	*
8:38 AM	15.7	16.0	2%	*	8:38 AM	36.8	32.5	12%	*
2:38 PM	16.4	17.3	6%		8:52 AM	30.8	28.0	9%	*
3:36 PM	20.0	22.8	14%		3:07 PM	18.2	19.5	7%	
					4:04 PM	20.4	21.5	5%	
4/24 6:57 AM	17.6	18.0	2%		7:26 AM	44.5	40.5	9%	
7:12 AM	17.9	18.2	1%		7:40 AM	49.4	44.0	11%	
8:09 AM	17.3	18.0	4%		8:24 AM	51.8	45.3	12%	
8:52 AM	17.2	17.2	0%		8:38 AM	51.2	43.5	15%	
2:38 PM	17.6	18.3	4%		9:07 AM	41.1	35.3	14%	
3:07 PM	18.0	19.3	7%		2:52 PM	16.7	17.8	7%	
3:36 PM	20.5	21.0	2%		3:36 PM	16.7	17.7	6%	
4:04 PM	21.1	21.8	3%		4:04 PM	16.3	17.0	4%	
					4:33 PM	16.9	16.3	3%	
4/25 6:57 AM	16.2	16.2	0%		7:12 AM	20.5	21.3	4%	
7:40 AM	16.1	16.3	1%		7:26 AM	21.3	19.5	8%	
8:09 AM	16.8	16.5	2%		7:55 AM	19.8	18.3	7%	
3:07 PM	21.1	19.0	10%		8:24 AM	18.8	18.8	0%	
4:04 PM	22.3	18.0	19%						

TABLE 3 Tach measurements on I-80.

Date	Dir	Probe	Estimate	Error	Incident
5/13 8:09 AM	S	36.5	30.5	16%	
2:24 PM	S	22.0	21.0	5%	
2:38 PM	S	23.0	21.0	9%	
7:40 AM	N	28.0	24.2	14%	
1:55 PM	N	22.0	21.8	1%	
3:07 PM	N	28.0	23.8	15%	
5/14 6:28 AM	S	31.0	27.7	11%	
7:12 AM	S	40.0	30.0	25%	
2:09 PM	S	38.0	26.7	30%	*
6:43 AM	N	21.5	20.5	5%	
7:12 AM	N	24.5	20.7	16%	
1:55 PM	N	22.5	21.7	4%	
5/15 1:55 PM	S	22.6	20.8	8%	
1:55 PM	N	22.5	21.5	4%	

TABLE 4 Travel time measurements and estimates on I-5.

Freeway	Mean err.	Mean absolute err.	RMS err.
I-80	-5%	16%	24%
I-80 (removed)	-2%	7%	10%
I-5	-11.5%	11.5%	14.1%

TABLE 5 Summary statistics from probe measurements.

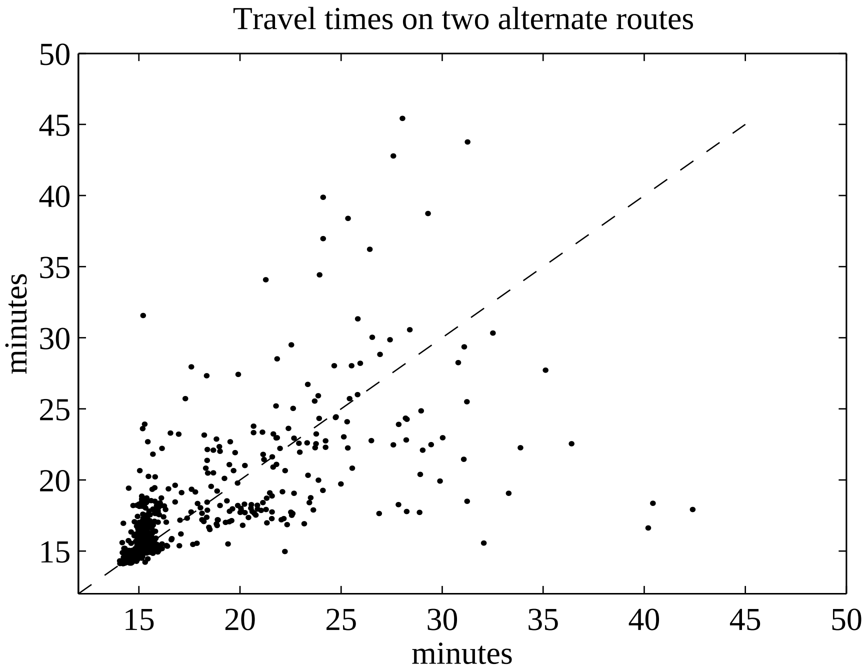

FIGURE 1 Travel times on routes 1 and 2.

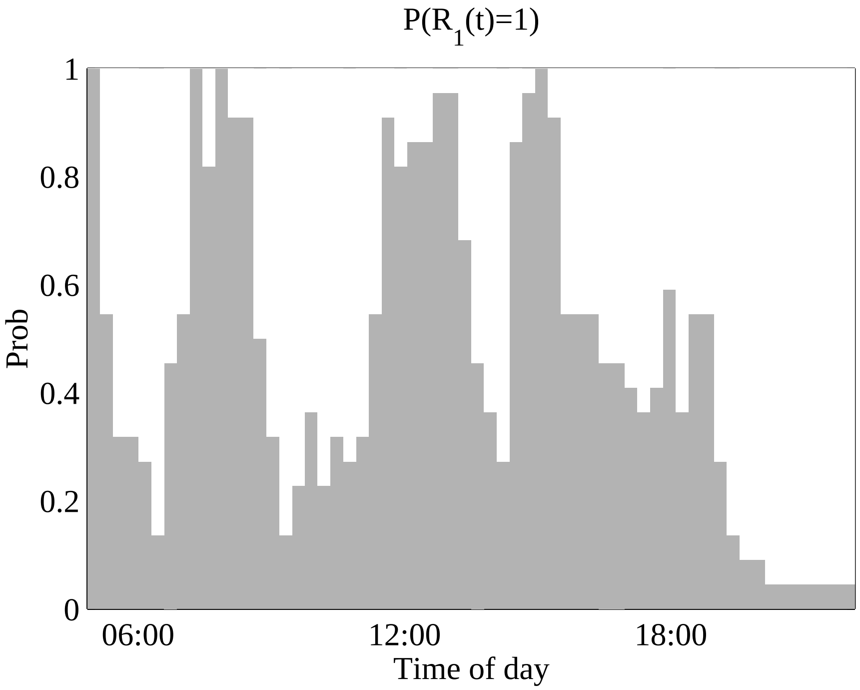

FIGURE 2 Decision based on predicted travel time.

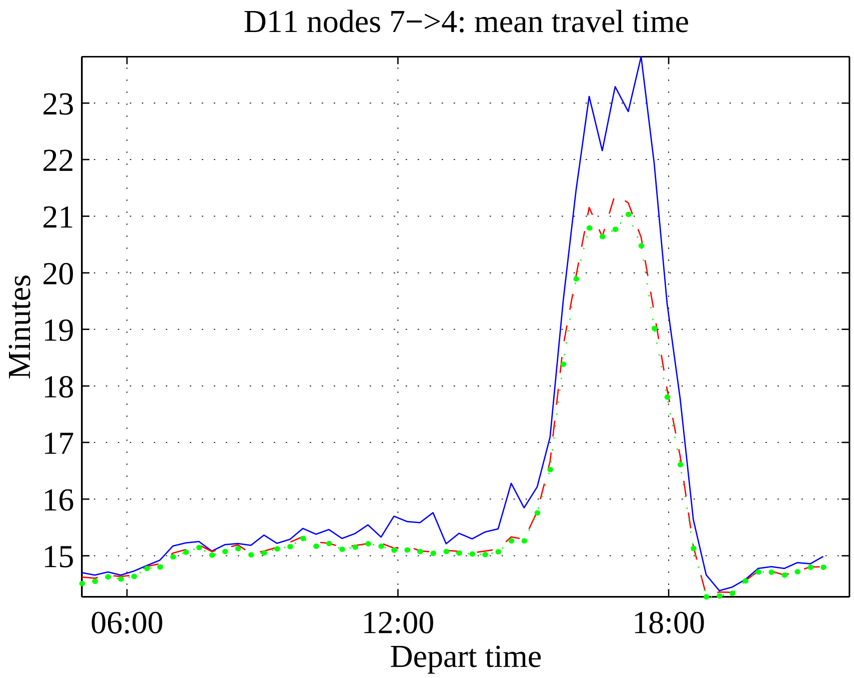

FIGURE 3 Mean travel times using the three strategies. Solid line = T_0, dashed = T_1, dotted = T_2.

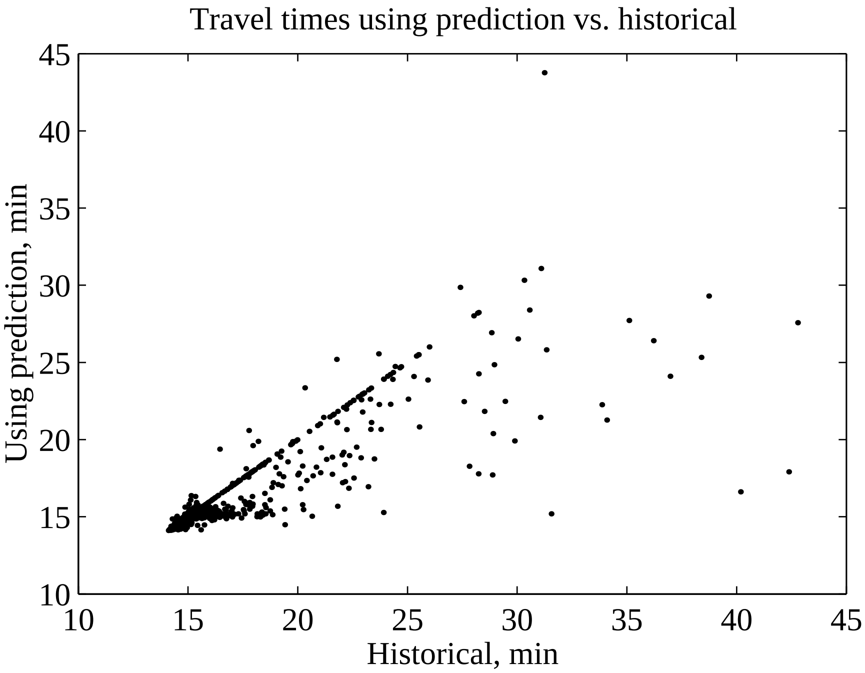

FIGURE 4 Travel time using prediction vs. using historical median only.

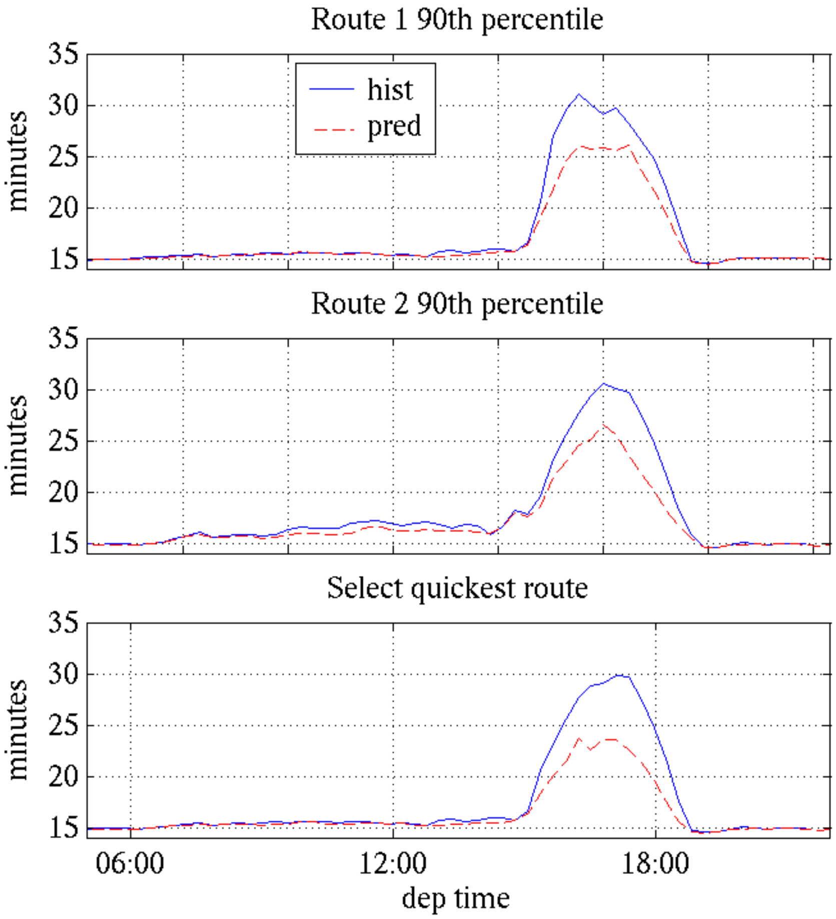

FIGURE 5 Ninety percent buffer times on both routes and using route selection.

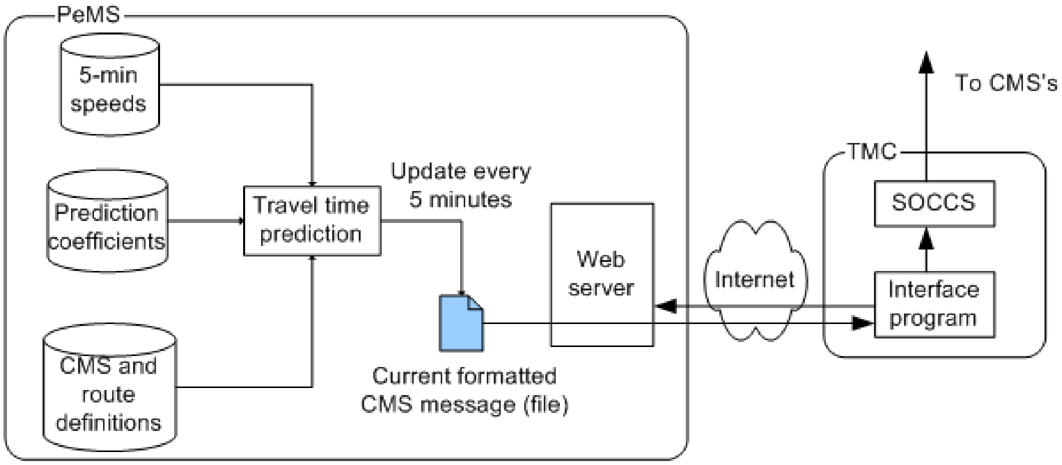

FIGURE 6 CMS application system and networking.