Evaluation and Selection of Operational Parameters for Travel Time prediction for Real-time Information Systems

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Abstract— **This paper presents an empirical case study of the Real-time travel time prediction strategies in a prototype Advanced Traveller Information System (ATIS) deployed in Chennai, India. The modules discussed in paper use GPS information of the probe vehicles in real-time to extract travel information and to make short-term predictions of path travel times. In the prediction procedure employed, four major factors are identified which affect the prediction accuracy: information source, spatial resolution, training period, and day of the week. The effect of these factors at various levels is quantified and compared. Evaluation of multiple prediction methodologies is performed in this paper. From the simulated scenarios, it is observed that utilizing short-term historic path level observations provides reliable travel time predictions when the system does not undergo significant overhauls.**

I. Introduction

The fast-growing economies in the developing world have been experiencing a rise in traffic volume over the past decade. This growth in demand is not being met by an equivalent growth in infrastructure, nor is it deemed feasible in most situations. Efficient utilization of the existing facilities is one of the ways to partially address this problem, and Real-time Traveller Information Systems (RTIS) play a major role in it. RTIS are beneficial to commuters, freight operators, and traffic operators in making informed departure time and route choice decisions. In this light, a prototype project titled "Real-time Traveller Information Systems for Indian Cities" was launched in the city of Chennai, India.

Large data sets produced by continual tracking of probe vehicles with GPS open up several methodologies for estimation and prediction of travel times in traveler information and route choice modeling frameworks. Among several information provision strategies, a combination of different levels of various factors such as information classes, fusion methodology and historic training periods can be utilized. The objective of this study is to simulate these strategies and determine important factors and their levels from the set of simulated parameters.

From this, we are able to identify the most suitable information strategy to compute travel time information for Indian conditions. After a review of common information strategies (Section 2), the paper provides a description of the prototype RTIS in Chennai (Section 3), which serves as the data source for analysis. We focus on the information-processing module of the system and provide a brief overview of the remainder of the system. After this, in Section 4, we introduce the methodology used to simulate different information strategies across the different factors that can be calibrated towards information provision. In Section 5, we define common performance metrics for each simulation and discuss their efficiency based on these metrics. Section 6 provides a conclusion of the learning drawn from the overall analysis.

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II. Literature Review

Short-term travel time prediction using Historic archives, Kalman filters and information fusion methodologies have widely been discussed in literature.

The Advanced Driver and Vehicle Advisory Navigation Concept (ADVANCE) project in the Chicago metropolitan area used a combination of historical and instantaneous data for their travel time prediction model *(1,2)*. Seki *(3)* used historical data after correcting them by type of day for prediction of travel time. Manfredi *et al. (4)* developed a prediction system as part of the DACCORD project, where prediction was based on historical and instantaneous data. Zhang and Rice *(5)* used varying coefficients linear model with past instantaneous travel time to predict the future travel time. Rice and Zwet *(6)* investigated the combined instantaneous and historical travel time data, using statistical methods such as principle component analysis and windowed nearest neighbor. Chien and Kuchipudi *(7)* explored the travel time prediction problem using travel time data directly collected through roadside terminals and found that using aggregated historical data in the same weekday (up to four weekdays) combined with real-time data have comparable results with using real-time data from previous time intervals.

Chen and Chien *(8)*, Chien and Kuchipudi, and Nanthawichit *et al. (9)* used Kalman filtering for travel time prediction.

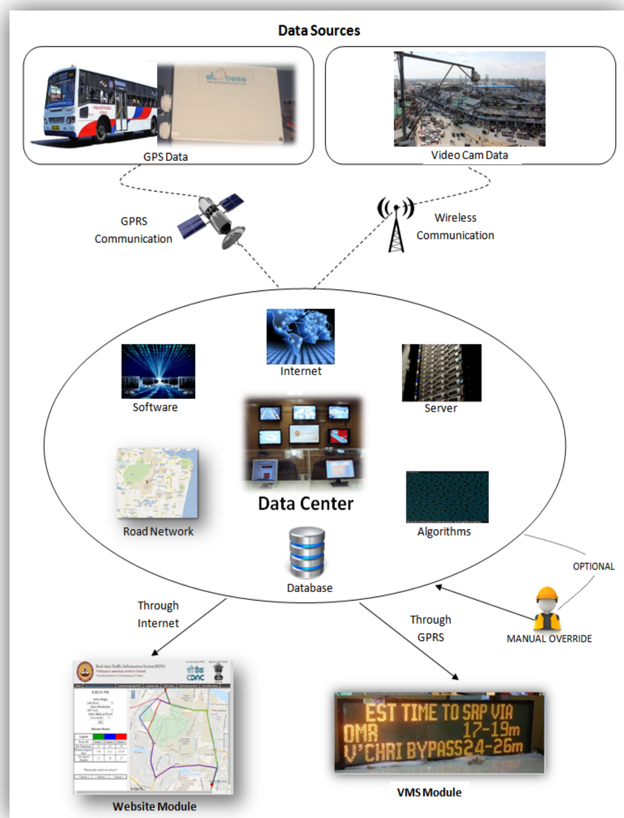
Chien and Kuchipudi developed a travel time prediction model for vehicles with real- time data and historic data. Kalman Filter algorithm was employed for travel time prediction because of its ability to continuously update the state variable with changing observation. Their study, concentrated on a comparison of the path-based and link-based travel time values. Results showed that during peak hours, the historic path based data used for travel time prediction were better than link based data due to smaller travel time variance and larger sample size.

Vanajakshi *et al.* (10) developed an algorithm based on Kalman Filter algorithm under heterogeneous traffic conditions on the urban roadways of Chennai. Their study was different from the others as most of the studies used data collected from homogeneous lane-disciplined traffic, either directly from the field or indirectly through simulation models. The unique feature of their algorithm is that the discretization had been performed over space rather than over time unlike the previously mentioned KF models. Their algorithm outperformed the average approach on 7 days out of 10 days.

Other than these, regression models, time series models and Neural Networks have also been used for travel time predictions.

III. Description of RTIS System

The prototype traveler information system constructed in Chennai (*11*) has four main components: data input, travel data extraction, traffic prediction and information dissemination. All these components operate and interact in real-time. The system is depicted in the Figure 1. Each of the components is briefly described below.



A. Data Input

The dominant source of information to the RTIS is GPS data from probe vehicles, which are buses of the Metropolitan Transport Corporation. The frequency of capturing vehicle location data is 10 seconds. 115 probe vehicles have been fitted with GPS devices. GPS data are written into a database at the server, which is accessed by the other modules in the system.

The other important input to the system is the test network, which is modeled as a directed graph. The important physical network characteristics needed are the GPS location of the nodes and the bearings of the links leaving and entering a node.

B. Extraction Module

The objective of the extraction module is to utilize the real time GPS readings of the vehicles and extract travel information. The module calculates different travel parameters and generates real-time information database using consecutive location coordinates and the corresponding timestamps of each vehicle.

The network and its physical characteristics are an input to the model along with the real-time GPS data of the probe vehicles. The module tracks vehicles as they move on the network. Travel information for any link is written into the database immediately after a vehicle traverses the link. The travel information extracted includes travel time, stopped time, average speed, variability in speed, signal delays etc.

C. Prediction Module

The prediction module uses real-time travel information from the database populated by the extraction module. It predicts journey times over selected paths on the network. The prediction algorithm runs for each path.

On every path, the link with latest observation is identified and Kalman prediction is performed on all downstream links of the given path. Estimates for the link travel times are stored. On the links upstream of the link with the latest observation, the estimates of the link travel times are taken to be the actual observations in the last 15 minutes. This is repeated for all the selected paths on the network, at the end of which the link travel time estimates can be based on Kalman procedure, actual observations, or both. If there exist links for which these two estimates are not available, historic travel time values are taken as the estimate.

The link historic travel time estimates are built and stored offline in three tables, each of which contains different estimates.

1. 3-minute window: Link travel time estimates are calculated by averaging observations over a three-minute interval. The table contains voids where travel time data is not available in 3 consecutive minutes.

2. 1-minute window: Link travel time estimates are calculated by averaging observations over a one-minute interval. If the voids in the table are filled by linear interpolation of the estimates that are no further than 10 minutes.

3. Free flow: The table is populated by free flow link travel time estimates.

The values in three table have a decreasing order of preference, i.e., the historic estimates of link travel time at a particular time is taken from the first table if available, else from the second table if available, or else the third.

At the end of the prediction procedure, each link can have multiple estimates of travel time, which can be of any three categories, namely Kalman estimates, observation estimates, or Historic estimates. The means of estimates in each category are calculated, and the final forecast of the link travel time is taken to be the mean of Kalman estimates if available, or the mean of observation estimates if available, or the historic estimate.

Estimates for path travel times are calculated by adding the final estimates of the travel times on the links in it. The prediction procedure is implemented every two minutes, and the path travel time forecasts are updated after each run.

D. *Information Dissemination*

The information is finally disseminated through the variable message signs (VMS) and the web. The VMS display travel time information along fixed paths to the destination. The web displays a richer quantity of information and decision support systems, which include, route-planning interface, speed and delay maps, level of service maps, and other related traffic news.

IV. Methodology

As indicated in section 2, different studies have adopted varying approaches for travel time evaluation even while employing the same techniques for computation. Under such conditions, it is important to evaluate the performance of different strategies. Since we are interested in real-time evaluation of travel time, our analysis focuses on historic archives, forecasting methodologies (Kalman Filters) and real-time observations along with information fusion from these three sources of information.

While developing historic path level travel time archives, analysts can utilize different levels of spatial resolutions and temporal extents for training sets.

In terms of spatial resolution, we could rely on historic link level observations and aggregate them into path level predictions. Or, we could utilize historic runs spanning the entire path, though the occurrence of such observations is sparser and these do not allow the incorporation of alternative information sources into the prediction model.

Training sets can be drawn from different training periods. Though expanding the training period increases the number of observations, unrestricted widening can incorporate non-representative samples.

Even, within a particular training period, training sets are usually chosen from particular days. For example, in the present implementation of the system, weekday predictions are based on only the 10 weekdays from the 14-day training period; weekend predictions are based on the 4 weekdays from the 14-day period.

Each combination of levels for these factors opens up a different prediction strategy and each strategy provides different estimates for travel time. Different levels of accuracy might be observed with each strategy under different conditions.

We have therefore empirically identified four important factors that can be varied to produce different travel time information strategies. In summary, they are:

1. Information sources: We aim to evaluate whether the incorporation of real-time information from a small number of probe vehicles, either directly or using a forecasting methodology, contributes positively to the quality of travel time information provided to travelers.
2. Spatial resolution: When generating path level travel time information, data might be available on certain links of the path from probe vehicles tracing a different path, which shares an overlapping link. We can either confine training historic archives over exactly overlapping paths or combine link level learning from multiple paths. We shall analyze which of the two approaches performs better for paths in our sub-network.
3. Training period: In dynamic networks such as transportation networks, traffic conditions vary over different times of the day. Hence training is often performed over the same time interval of the day over multiple days. Though the number of days over which training is performed increases the number of data point available, traffic conditions might change significantly over longer training periods. These might sometimes be due to changes in seasons or due to change in network conditions such as construction/road blocks and several other possible reasons. An empirical upper-limit often utilized is a 2-week window. In this analysis, performance over three training periods (5 days, 10 days and 14 days) is compared.
4. Weekday/Weekend segregation vs. aggregation: Traffic conditions can be different for different days of week. Appreciable differences are often observed in patterns observed over weekdays and weekends. For weekdays, by training first over weekdays alone and later over both weekdays and weekends, we compare the influence of aggregating and segregating weekdays and weekends. We also present a similar evaluation for weekends.

By analyzing the performance of different strategies drawn from these four factors over a period of two weeks, this paper aims at providing insights into their significance and levels and hence determining the most suitable strategy for Chennai's RTIS.

Performance has been evaluated over eight paths in the ATIS network. The study corridor is approximately 15 km in length and includes parts of Old Mahabalipuram Road (OMR), Velachery Taramani Road, Velachery Main Road, Velachery Bypass Road, Sardar Patel Road, and Taluk Office Road. The paths also incorporate 9 signalized intersections.

The two-week period of analysis spanned from April 28 to May 11 2014. During this period vehicle location from all 115 bus probes were received from 6am to 10pm.

Different combinations of the four factors identified above have been considered. These are listed in Table 1.

TABLE I. SIMULATION PARAMETERS FOR EACH TEST CASE

S.No.	Information Sources			Spatial Resolution		Training Period			Training Days	
	Kalman	*Observed*	*Historic*	*Link based*	*Path*	*5-day*	*10-day*	*14-day*	*WD*	*WE*
1.1*	✓	✓	✓	✓				✓	✓	
1.2	✓	✓	✓	✓			✓		✓	
1.3	✓	✓	✓	✓		✓			✓	
2.1			✓	✓				✓	✓	
2.2			✓	✓			✓		✓	
2.3			✓	✓		✓			✓	
3.1			✓		✓			✓	✓	
3.2			✓		✓		✓		✓	
3.3			✓		✓	✓			✓	
4.1	✓	✓	✓	✓				✓	✓	✓
4.2			✓	✓				✓	✓	✓

The 11 simulation cases can be broadly looked at as falling into 4 categories.

1. Information fusion with higher preference to real-time information: Prediction is performed by fusing information from all the 3 sources- Kalman Filter predictions, current observations and historic information. If information is unavailable in a particular category, fusion occurs with the latter category. The three variants of training period are evaluated for this category.
2. Provision of information from historic archives with link based aggregation: Different training periods (14 days, 10 days and 5 days) have been evaluated with this approach.
3. Provision of information from historic archives using path level information: Here, we substitute the link level aggregation methodology with utilizing only those records that provide complete coverage over the queried path.

   Note: The first 3 categories have been evaluated over the weekdays of the two weeks under consideration.
4. Incorporating both weekdays and weekends in historic archives: In the scenarios simulated thus far, historic archives for weekdays were generated only weekdays and those for weekends using weekends. Here, we extend the coverage of historic archives to all days of the week. We then simulate information provision through both the fusion methodology as well as solely based on historic archives. The analysis in this category is extended to weekends as well. Since weekends were not analyzed in prior categories, the results for them are provided separately.

Within the first three categories, since we look at 3 different training periods for historic archives, we shall discuss the impact of varying training period on the quality of predicted information. The major focus of the analysis is on comparing performance across categories.

Three performance metrics have been chosen evaluating performance. These include the mean average error (MAE); the mean average percentage error (MAPE) and 3-minute reliability of the provided travel time. The 3-min reliability is defined as the percentage of times that the absolute error of predictions was less than 3 minutes. These are presented for each of the test cases in Section 5.

V. RESULTS AND OBSERVATIONS

Results for the weekdays for the 11 simulations are shown in Table 2. Since analysis for weekends is of special interest is category, it is provided separately in table 3.

TABLE II. PERFORMANCE OF THE 4 SIMULATION CATEGORIES FOR WEEKDAYS

S.No.	MAPE	MAE	3-min Reliability
1.1	14.69	1.35	89.44
1.2	14.96	1.37	89.26
1.3	16.86	1.56	86.39
2.1	15.17	1.41	88.56
2.2	15.57	1.45	87.88
2.3	17.94	1.70	83.87
3.1	3.76	0.36	99.82
3.2	3.05	0.30	99.84
3.3	2.45	0.22	100
4.1	14.91	1.38	89.23
4.2	15.45	1.45	88.38

From table 2, it can be inferred that-

1. Since the MAPE and MAE for information provision via fusion are lower and 3-min reliability is higher than those from only historic archives with the same training period, information fusion is appropriate for traveler information
2. Historic path-based averaging has significantly lower MAPE and MAE, and higher reliability than the first two categories.
3. Within category 4, information fusion again outperforms predictions based on only historical archives.
4. A comparison of 4.1 with 1.1 and 4.2 with 2.1 shows that incorporating weekends while building historic archives for weekdays has a negative influence on the performance of prediction
5. For link based predictions using information fusion and only historic archives, reducing the training period from 14 days to 5 days impacts the performance of prediction negatively.
6. For path based predictions, however, reducing the training period has a positive impact on the quality of prediction

TABLE III. COMPARISON OF PERFORMANCE OF AVERAGING OVER ONLY WEEKENDS OR BOTH WEEKDAYS AND WEEKENDS FOR HISTORIC ARCHIVES OF WEEKENDS (LINK BASED)

S.No.	Description of Simulation	MAPE	MAE	3-min Reliability
1	Information Fusion with 14 day training	15.00	1.36	90.02
2	Historic archives with 14 day training	15.53	1.42	89.17
3	14 day historic archives including weekdays	16.02	1.27	91.05

From table 3, it is seen that for weekends as well, information fusion performs better than predictions derived from only historic archives. Incorporation of weekdays in the historic training period has a negative impact on the quality of prediction.

VI. INFERENCES AND CONCLUSION

The analysis performed suggests that historic path based prediction significantly outperforms both information fusion and link based predictions. Since this is observed to be true over a long period of two weeks, it suggests that this class of predictions substitute predictions real-time models.

It is also observed that while historic link-based prediction perform better with longer training periods, the converse is true for path-based predictions.

Analysis from category 4 suggests that considering weekdays and weekends as disparate entities produces better results for historic archive-based predictions for weekdays. In case of weekends, the converse is observed to be true. This might, however, be due to a significant difference in the count of weekends alone (4) versus all days of week (14) in a 2-week period and therefore warrants further investigation.

While the analysis might be suggestive of switching from real-time methodologies to historic path based techniques, it should be realized that despite their better performance on typical days, historic archives are inherently incapable of capturing exceptional traffic conditions. The author suggests that both estimates be computed for practical purposes. In cases with exceptional discrepancy between travel times indicated by real-time methodologies and historical path-based approach, information systems should rely on real-time indicators.

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