Data collection and modeling for APTS and ATIS under Indian conditions - Challenges and Solutions

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Outline

- Introduction
- Automated Traffic Data Collection
  - Evaluation of Traffic Sensors for Indian Conditions
  - Development of a Traffic Detector for Indian Conditions
- Mathematical Modeling of Traffic Flow
  - Estimation of Traffic Density - ATIS
  - Bus Arrival Prediction - APTS

Introduction

- **Traffic Congestion**

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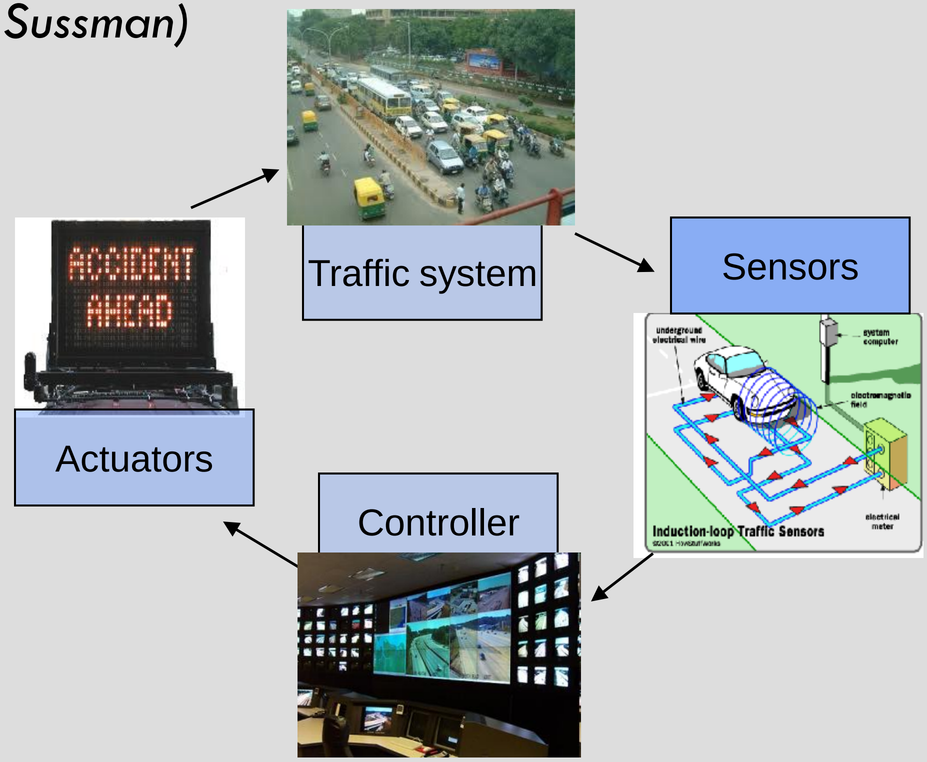
Adding more capacity

Operating existing capacity more efficiently

- ✓ Demand management
- ✓ Congestion management
- ✓ **Advance technology for better management of traffic (ITS)**

ITS

- **Intelligent transportation systems (ITS)** apply well-established technologies in communications, control, electronics, and computer hardware and software to improve surface transportation system performance. *(Source: Perspectives on ITS, J. M. Sussman)*



Main Components

Automated **Data collection**

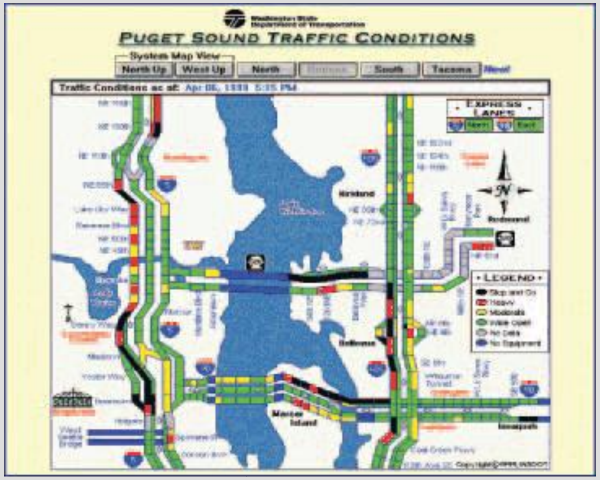
Data/Information transfer

Data analysis and modeling

Information Display

Functional areas

1. Advanced Traffic Management Systems (ATMS),
2. **Advanced Traveller Information Systems (ATIS),**
3. Advanced Vehicle Control Systems (AVCS),
4. Commercial Vehicle Operations (CVO),
5. **Advanced Public Transportation Systems (APTS),** and
6. Advanced Rural Transportation Systems (ARTS).



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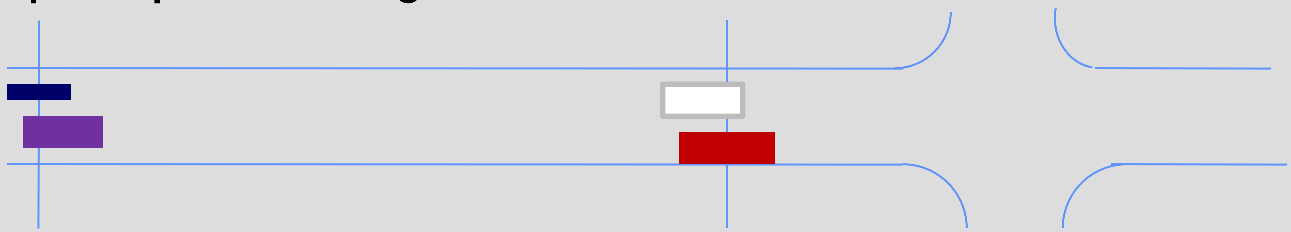
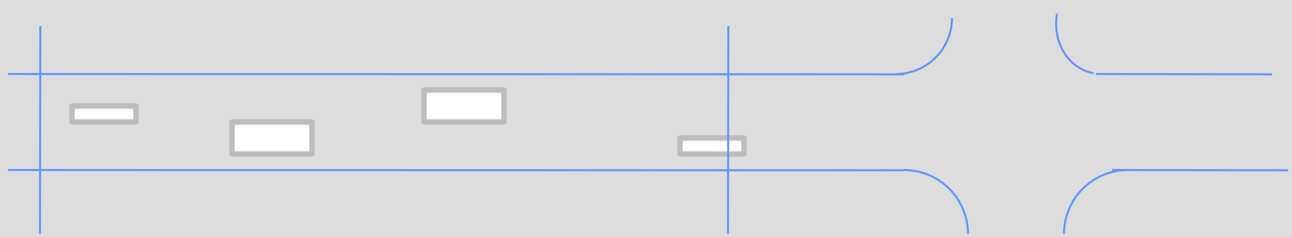
Traffic Data Collection

- **Location Based** – At a location – temporal variation
  - Flow, spot speeds - Eg. Video



- **Spatial** – Variation over space and time
  - Density, travel time – Eg. GPS
  - Aerial photo (difficult) or vehicle tracking (participation issue)



Location Based Sensors

- No participation – video, radar/infrared, inductive etc.
- Derive spatial parameters from location based data
- Lane based, for homogeneous traffic
- No proven solution for Indian traffic conditions

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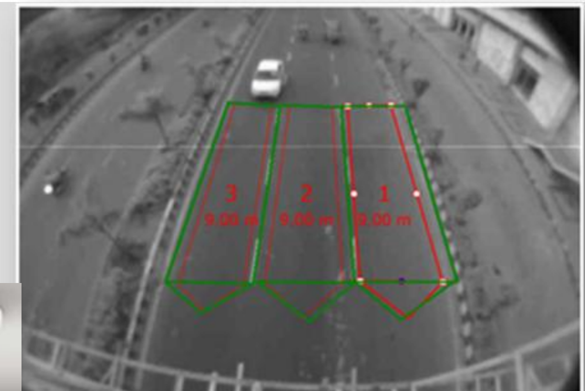
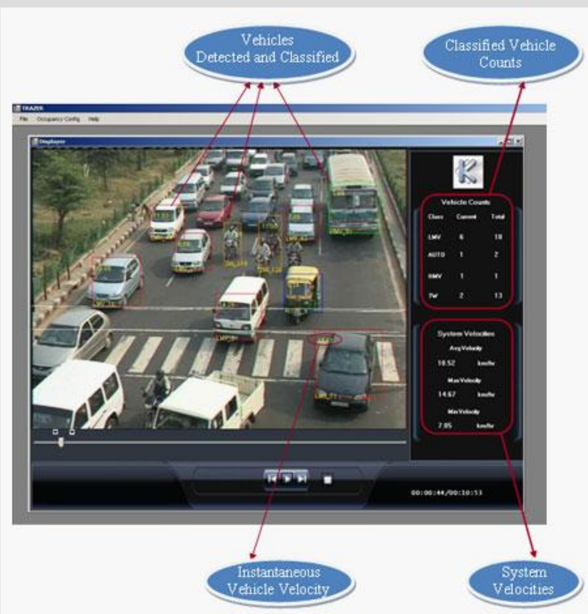
Modification/Calibration of Existing Sensors (Funded by the Ministry of Urban Development, GoI)

- Radar Detector – Smart sensor
- Infrared Detector - TIRTL
- Video Sensor – Collect-R
- Image processing –Trazer





Development - Inductive Loop Detector (ILD)

(Funded by the Ministry of Urban Development, GoI)

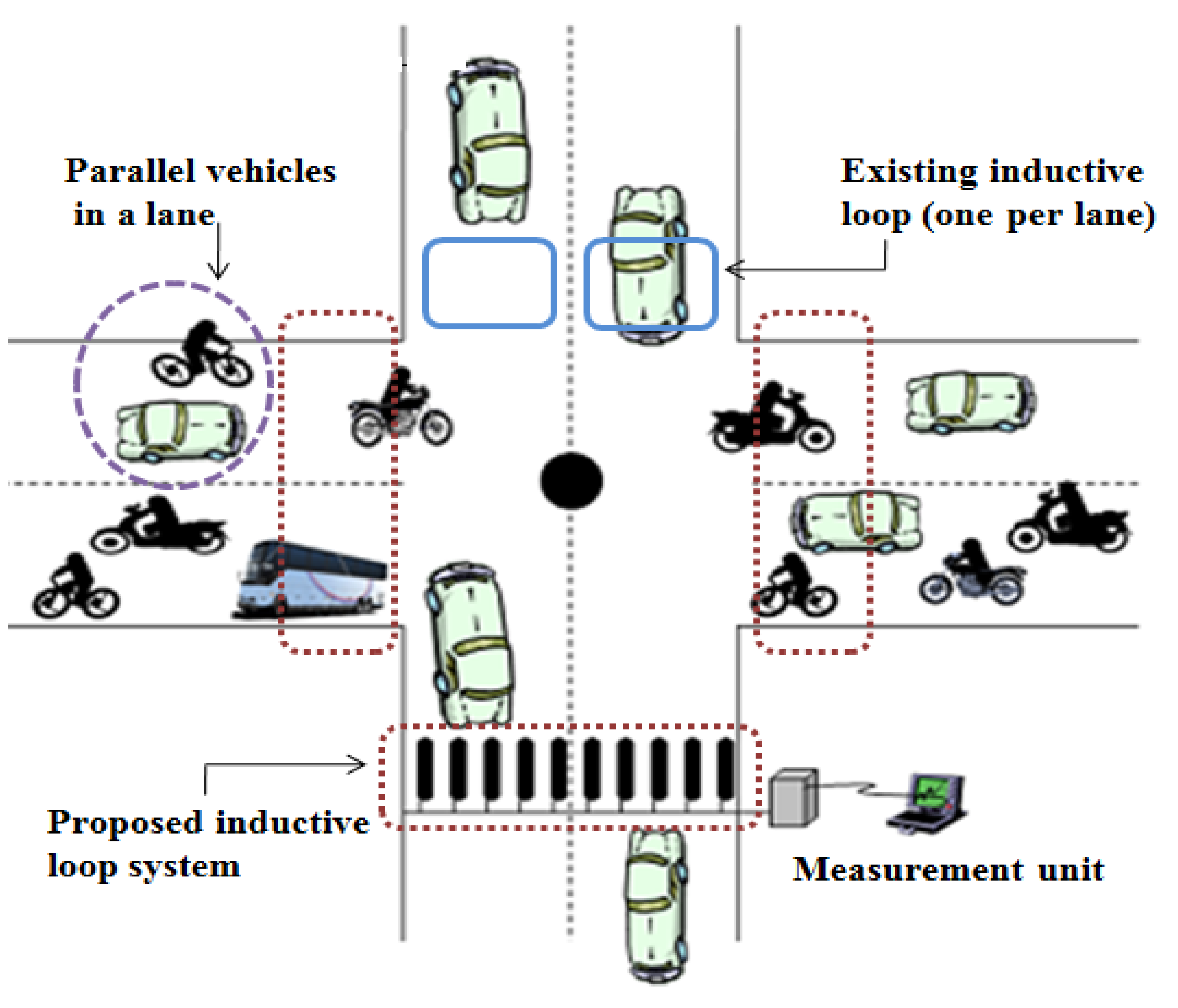
One of the most popular automated Traffic data sources

Provide count, Speed And Occupancy

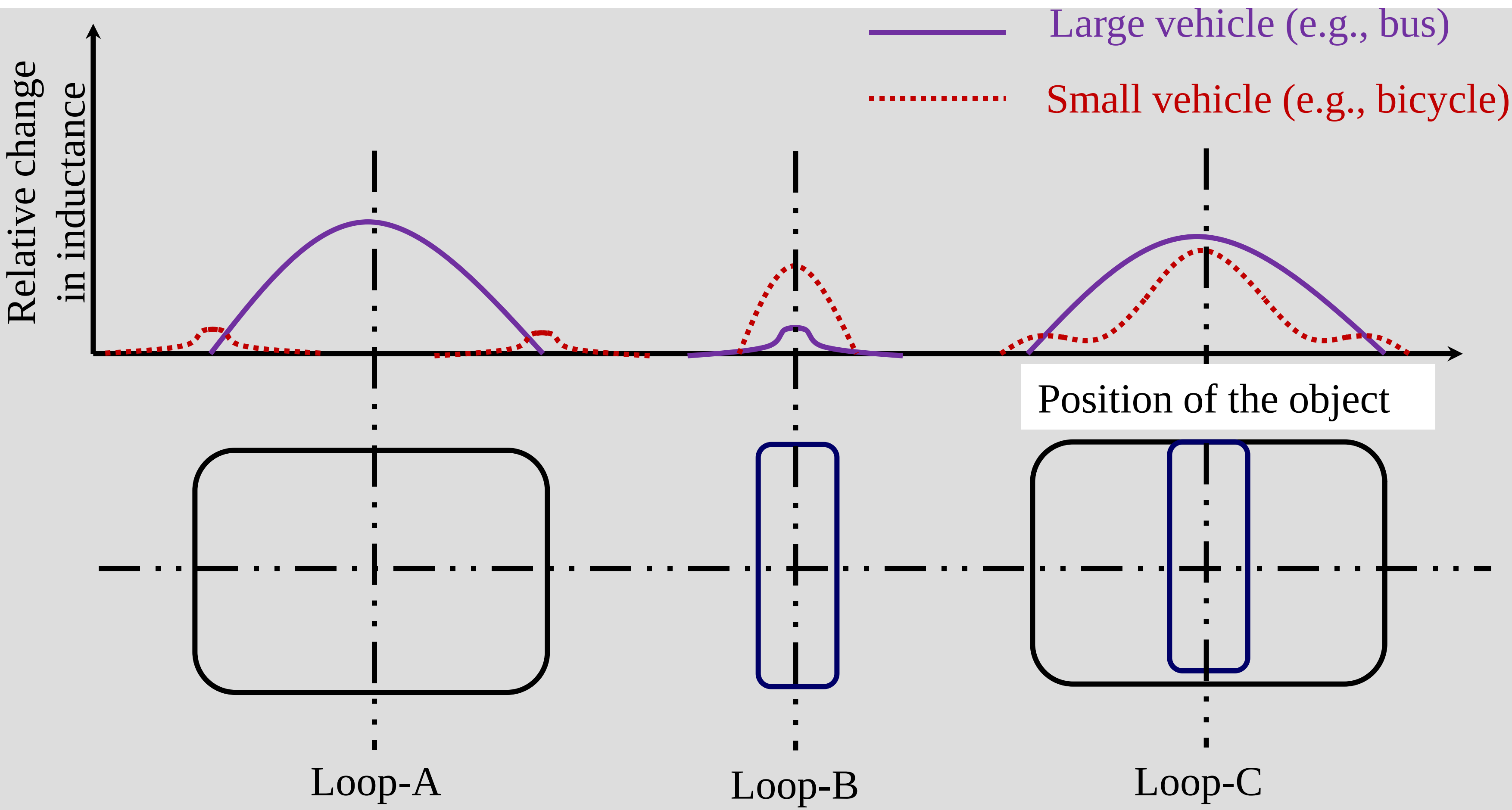
•Lane based- Configuration

•Limited classification –loop structure

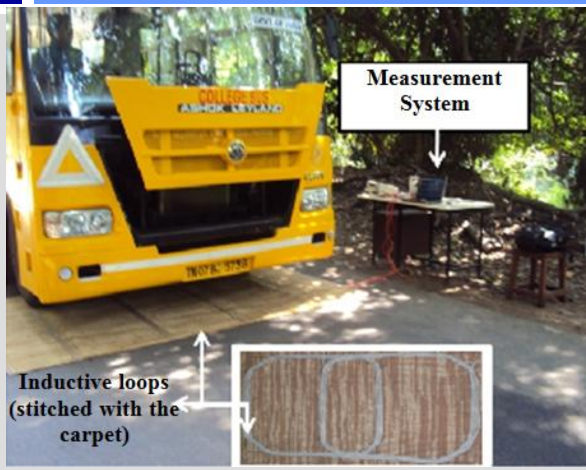
•Intrusive

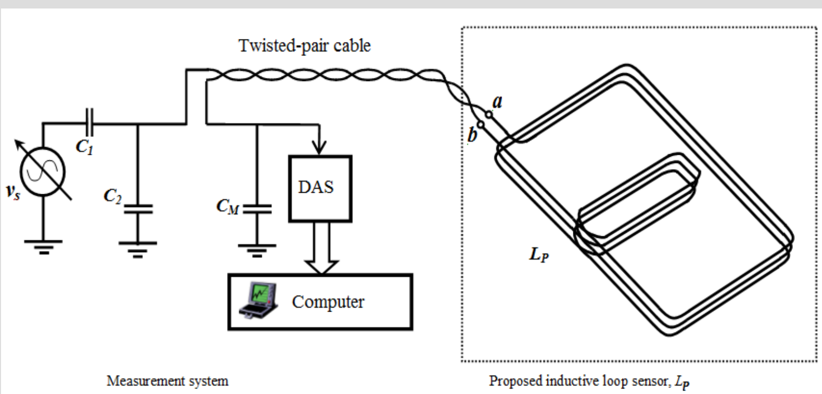


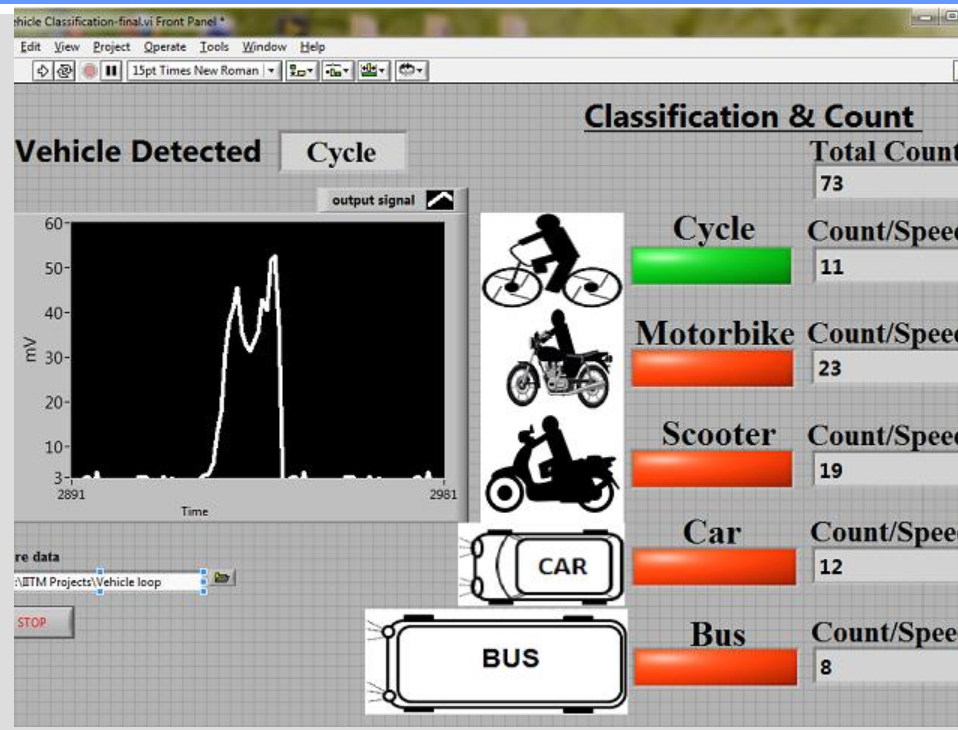
The New Inductive Loop Sensor



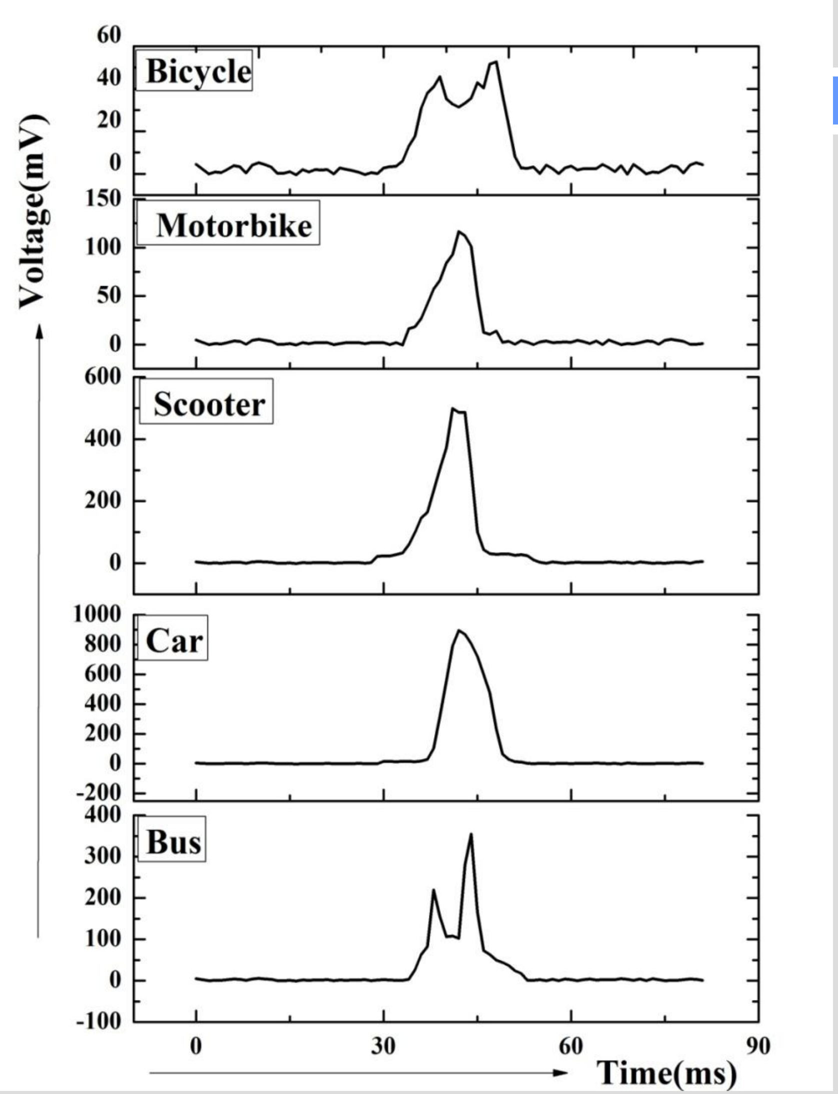
New Inductive Loop Detector

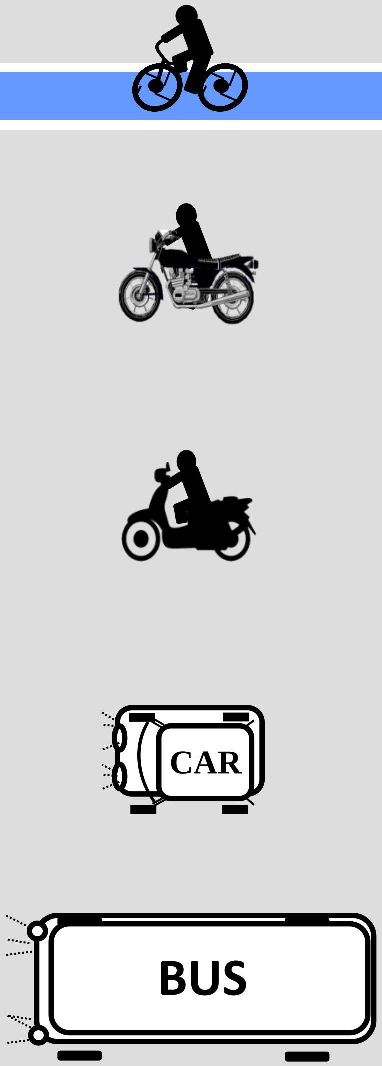






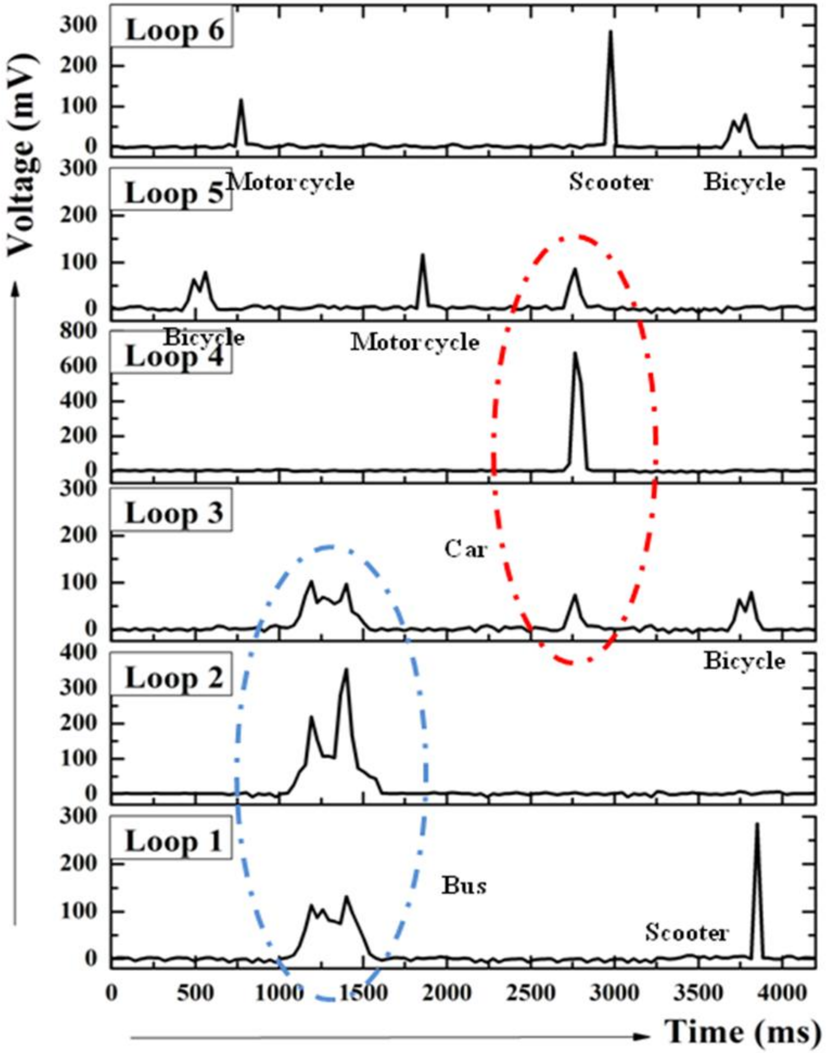
Results from the New Single Loop Detector





Output signal observed for different types of vehicles

Results from the Multiple Loop Detector



Results from the multiple loop detector with six loops (N = 6) recorded when various types of vehicles were moving simultaneously in the road.

Addressed heterogeneity and lane discipline issue.

Future work: Possibility of making it non-intrusive

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MATHEMATICAL MODELING OF TRAFFIC FLOW

Mathematical representation of traffic system to characterize and predict its behavior.

- **Microscopic Models** – the behavior of each vehicle and its interaction with other vehicles are modeled. Eg. car following models
  - Need to include the effect of driver behavior - challenging
  - Intensive in terms of data and computation power

- **Macroscopic models** - Aggregate behavior of the traffic stream is modeled

Macroscopic Models

- **Continuum Models** - The flow of traffic is commonly treated as analogous to that of compressible fluids or gaseous flow

  - Number of vehicles does not justify it being modeled as a continuum
  - Two - way propagation of disturbances

- **Non Continuum Models**
  - Macroscopic **lumped parameter dynamic model** - illustrated for the estimation and prediction of traffic density.

Features and Assumptions

- Physical system divided into lumps or segments
- Within each segment spatial variation of traffic variables (such as density, speed, etc.) neglected and assumed to depend only on time
- Results in governing equations of model being ordinary differential equations (in continuous time domain) and ordinary difference equations (in discrete time domain)

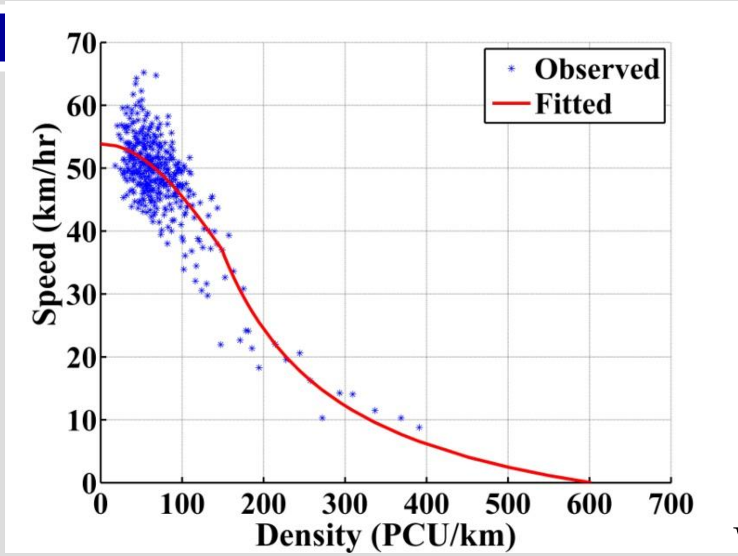
Model Based Estimation

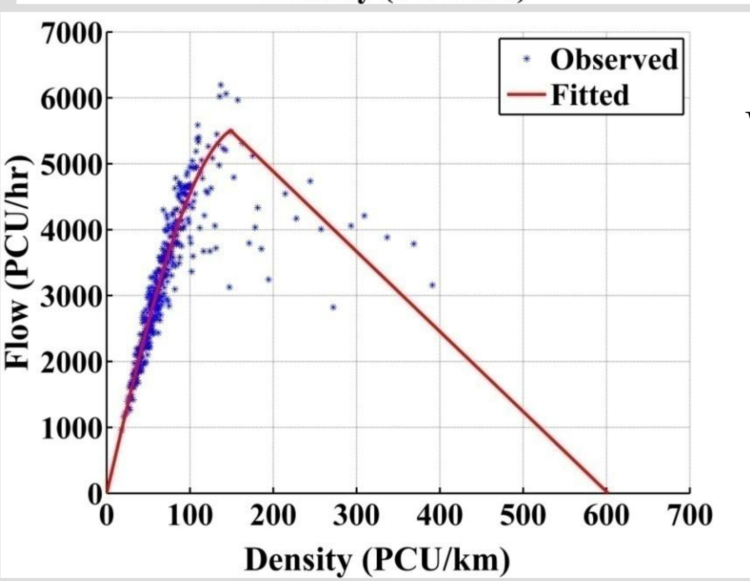
- Requires a base model and an auxiliary set of equations to support the estimation scheme.

- Base model – Mostly conservation of vehicles equation

- Auxiliary equations commonly used include:
  - Fundamental traffic flow relation
  - **Empirical Traffic stream models**
  - Surrogate measures for SMS and density
  - Constitutive equations relating traffic variables
  - Conservation of momentum.

Stream Model





Data collected using videography

Extracted manually due to lack of automated systems

$$\left.\begin{aligned} v &= 53.86.\exp\left(-0.5\left(\frac{\rho}{172}\right)^2\right) \quad for \quad 0 \le \rho \le 149 \\ v &= 12.146\left(\frac{602}{\rho} - 1\right) \quad for \quad 149 \le \rho \le 602 \end{aligned}\right\}$$

$$\left.\begin{aligned} q &= 53.86.\rho.\exp\left(-0.5\left(\frac{\rho}{172}\right)^2\right) \quad for \quad 0 \le \rho \le 149 \\ q &= 12.146.\rho\left(\frac{602}{\rho} - 1\right) \quad for \quad 149 \le \rho \le 602 \end{aligned}\right\}$$

Proposed Dynamic Model

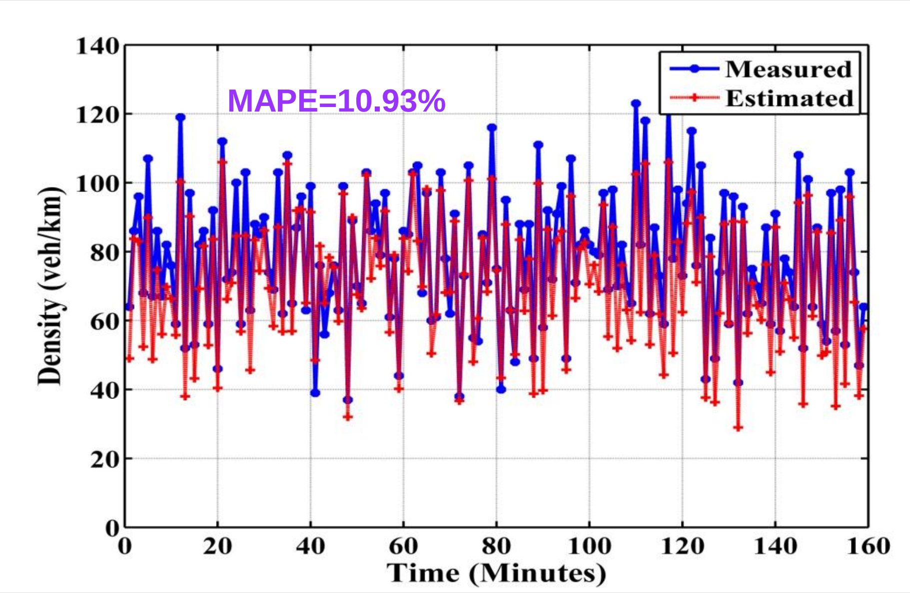
- First governing equation: Density - Conservation of vehicles inside the section

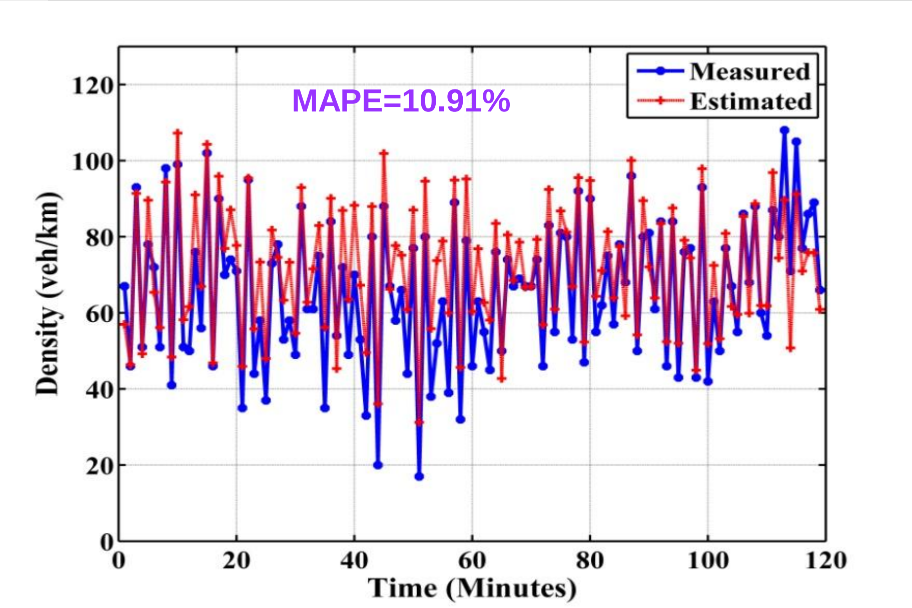
$$\rho(k+1) = \rho(k) + \frac{h}{L}\left[q_{en}(k) - \rho(k).v(k) + q_{side}(k)\right]$$

- Second governing equation: Speed - Dynamic speed equation by incorporating an appropriate stream model

$$v\left[k+1\right] = v\left[k\right] + ah\left[V(\rho) - v(k)\right] + \frac{h}{L}\frac{d\left[V(\rho)\right]}{d\rho}\left[q_{en}(k) - \rho(k).v(k) + q_{side}(k)\right]$$

Sample Density Estimates

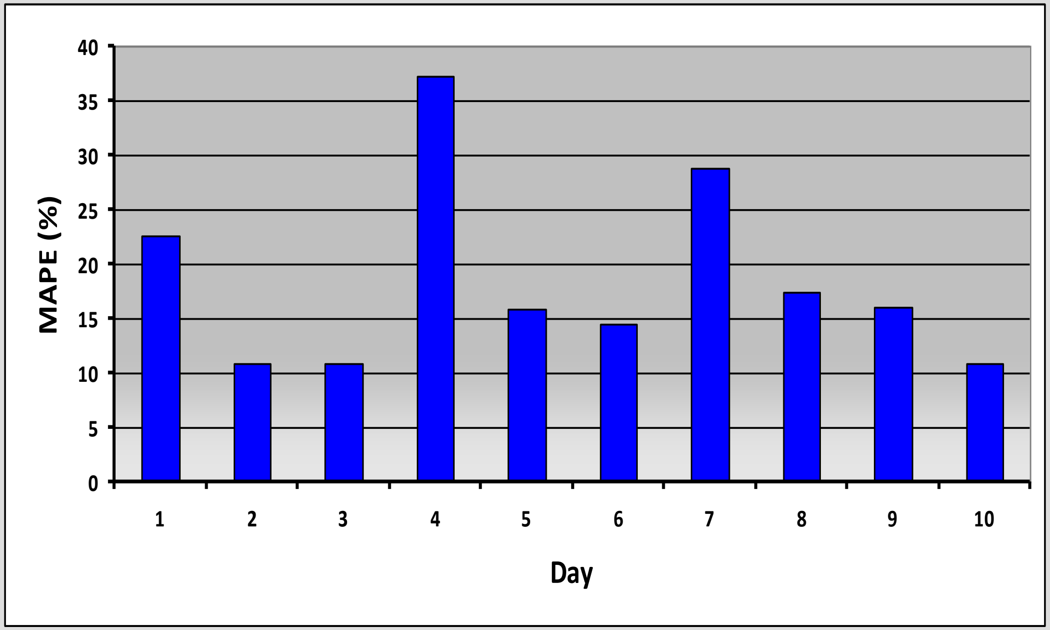




$$MAPE = \left[\frac{1}{N} \sum_{i=1}^{N} \frac{|\, x_{est} - x_{obs}}{x_{obs}} \right] * 100,$$

MAPE for Density Estimates

Section	Day	MAPE (%) Density
I (1 km)	1	22.53
	2	10.93
	3	10.91
II (0.738 km)	4	37.26
	5	15.82
	6	14.54
	7	28.76
	8	17.33
III (1.738 km)	9	16.09
	10	10.91

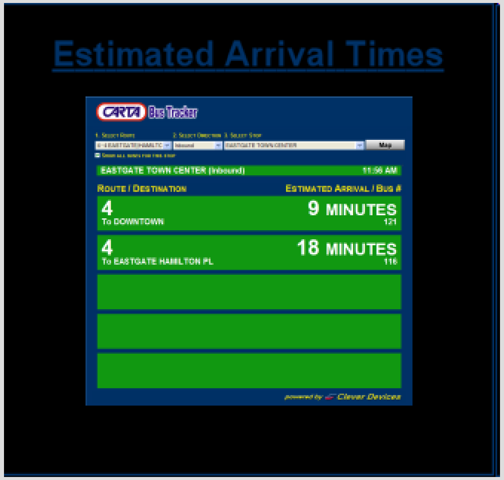


Possible Modifications

- Vehicle conservation – very difficult to satisfy through measurements under Indian conditions – estimate side road entries using statistical distributions with known mean and variance
- Accuracy of flow data – difficult to achieve – especially during congestion
- Accuracy of speed is expected to be better than flow – estimate flow at locations of congestion
- Use data fusion for improved performance
- Use of better estimate of space mean speed (SMS)

APTS

- Advanced Public Transportation Systems – one component is bus arrival prediction
- Automatic Vehicle Locators for data collection – most popular is GPS/GPRS



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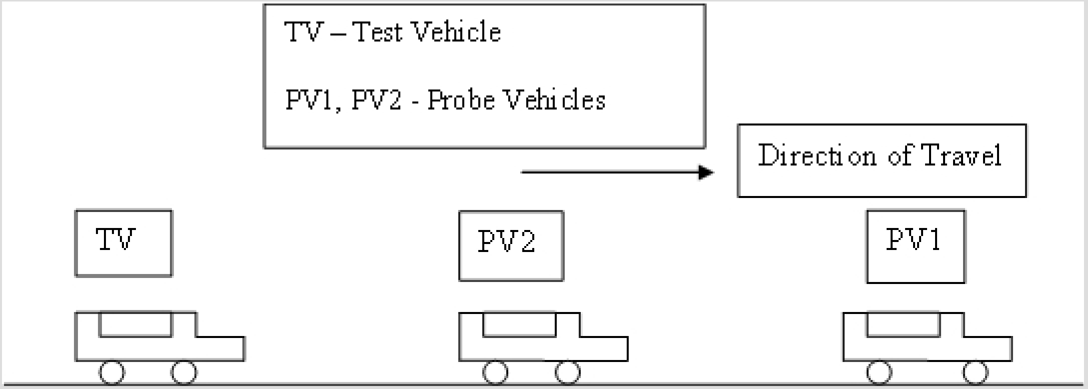
Bus Arrival Prediction - Approaches

- Existing methods - Mainly historic pattern based and data driven approaches – Data intensive OR
- Based on average speed and known distance – Cannot capture the real time variations and randomness

- A model based approach using real time data from previous two buses – captures prevailing traffic conditions.

Case Study

- The GPS data obtained included the GPS units' ID, time, latitude and longitude at every 1 sec/5 sec.
- The overall section was divided into smaller subsections of 100 m length.



Governing Equations

- It was assumed that the evolution of travel time between the various subsections is governed by

$$x(k+1) = a(k)x(k) + w(k).$$

- The measurement process was assumed to be governed by

$$z(k) = x(k) + v(k).$$

- It was further assumed that $w(k)$ and $v(k)$ are zero mean white Gaussian noise signals with $Q(k)$ and $R(k)$ being their corresponding variances.

Prediction Scheme

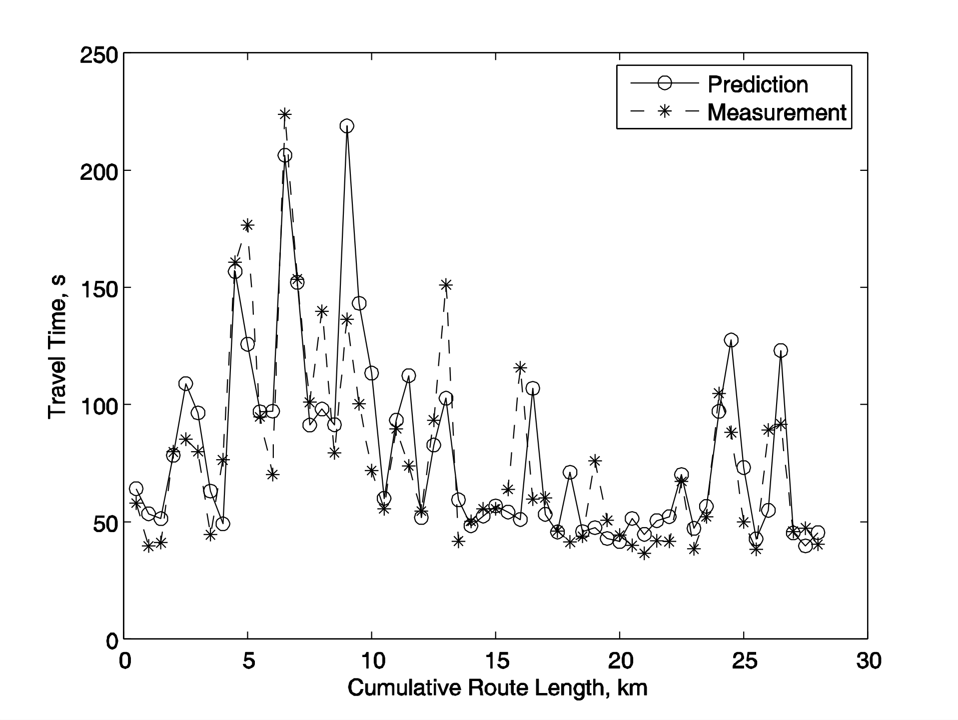
- The prediction scheme based on the Kalman filter.
- Data from PV1 used to obtain the value of *a(k)*
- The value of a(k) was obtained using

$$a(k) = \frac{x_{PV1}(k+1)}{x_{PV1}(k)}, k = 1, \ldots, (N-1).$$

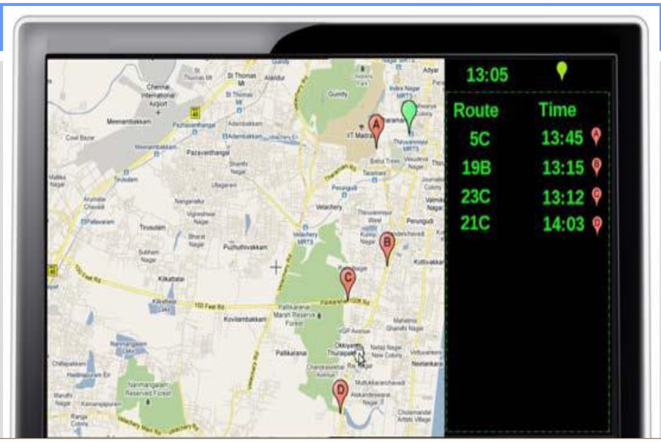
- Data from PV2 used to obtain the a posteriori estimate.

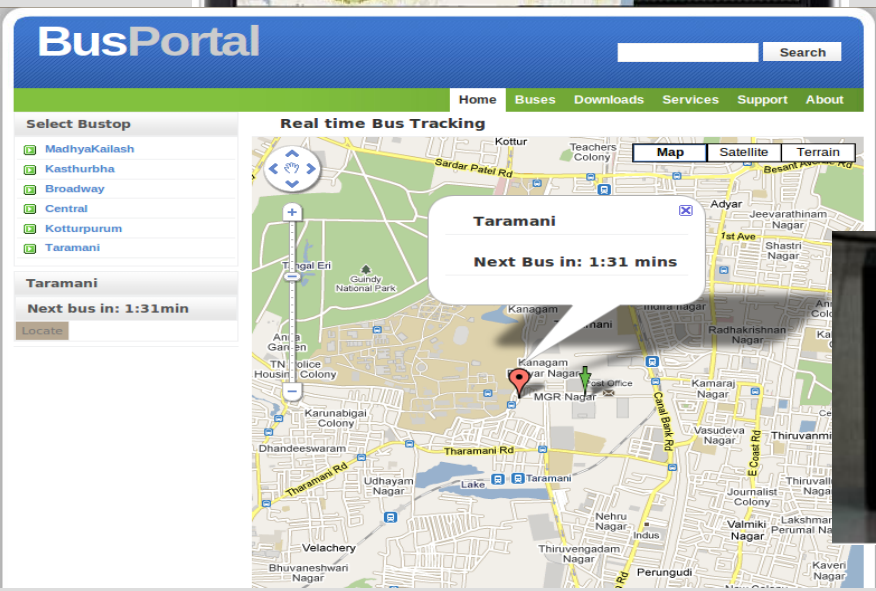
Corroboration

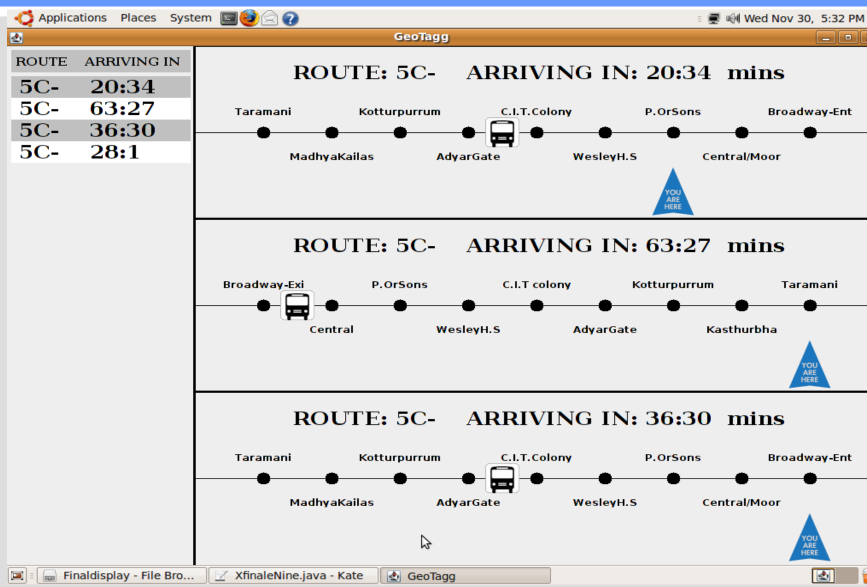
S.NO	APE (Model based approach)	APE (Average speed method)
1	10.4	37.5
2	8.6	6
3	13.9	34.8
4	19.5	66.2
5	16.9	47.5
6	13.6	30.3
7	10.5	38.9
8	11.4	40.1
9	20.6	35.5
10	23.3	65.4



Field Implementations







Possible Extensions

- Incorporate dwell time separately into the prediction scheme.
- Adaptive prediction scheme to take into account variations in disturbances and noise characteristics.
- With more data base, possibility of identifying most influencing inputs based on pattern analysis.
- Use of public transit GPS data alone to characterize the traffic stream as a whole.

Thank you

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