Automatic Generation of Timing Plans with High-Resolution Data

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Abstract

A high-resolution (HR) data system for an intersection collects the location (lane), speed, and turn movement of every vehicle as it enters an intersection, together with the signal phase. The system operates 24×7. The data are available in real time and archived. The archived data are used in a three-step automated procedure to optimize timing plans. In the first step, the data are clustered by day-of-week. In the second step an intra-day segmentation is derived for each cluster. In the third step the optimum green split is determined for each intra-day segment to minimize the delay or to equalize VC ratios. Various intersection performance measures may also be derived. The procedure is illustrated for an intersection in Beaufort, SC. HR systems can also be used to evaluate safety, e.g. red-light and right-turn-on-red violations.

Keywords. High-resolution data, arterial data, timing plans, vehicle counts, turn ratios, red light violations

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1 Introduction

Poor management of intersections causes excessive delay and more frequent crashes. Conditions are worse in cities experiencing rapid growth in automobile ownership, but mature cities also face challenges as road capacity is taken away from vehicles to accommodate increasing bicycle and pedestrian traffic. Management today is handicapped by insufficient data. It can be more effective if it is based on high-resolution (HR) real-time and archived data about the movement of vehicles, bicycles, and pedestrians. "If you don't know what's happening on your roads, don't expect to manage them well" is a truism.

A basic HR system measures the location (lane) and speed of every vehicle as it approaches and enters the intersection, together with the signal phase. The system operates 24×7 and the measurements are archived in a database. The database generates reports providing continuous monitoring of the intersection performance in terms of delay, VC ratios and LOS, cycle failures, etc. This paper presents a three-step automated procedure that uses the database to generate optimal timing plans whenever needed. The agency can thus determine when the performance has degraded sufficiently to change the existing timing plans.

Continuous performance monitoring combined with automatic re-timing represents a paradigm shift in intersection management. Urban traffic in the U.S. today is regulated by 300,000 signalized intersections, whose performance is determined by their signal control algorithms. The performance is poor: the 2012 National Transportation Operations Coalition (NTOC) assessment of traffic signal control gives an overall grade of D+ (National Traffic Operations Coalition (2012)). Ninety percent of the signalized intersections use fixed time of day (TOD) plans, which are re-timed once in five years, based on three days of manual data collection. These traffic snapshots and the timing plans based on them completely miss the variability in the traffic to which the plans should adapt. Moreover, the infrequent snapshots do not permit the operating agencies or the public to determine whether the road network is performing well or poorly.

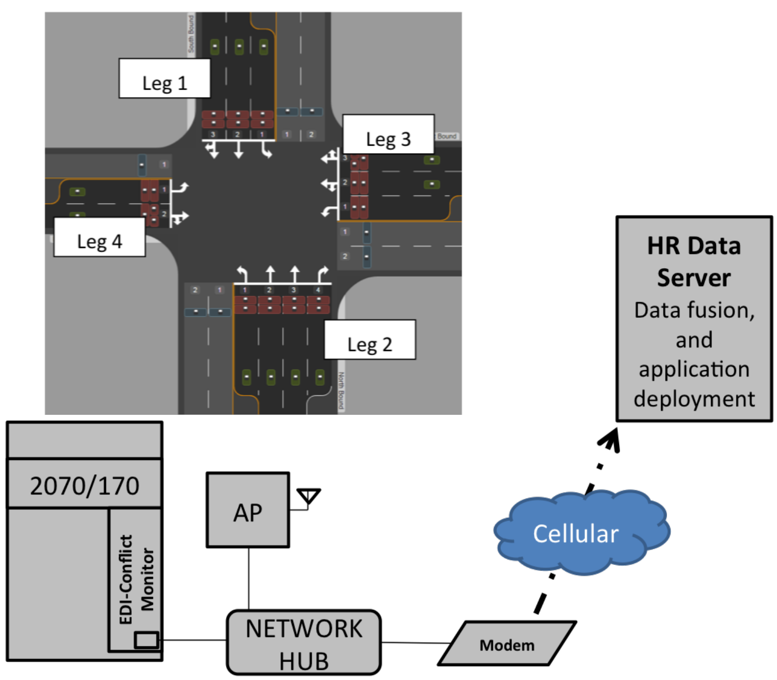


Figure 1: Schematic for HR system at intersection in Beaufort, SC: each small white dot is vehicle detector.

The applications discussed below use data from an HR system at an intersection in Beaufort, SC, where it has been operating for two years. We briefly describe the hardware architecture of the HR system. The system components are from Sensys Networks, Inc. The Beaufort intersection of Figure 1 is a standard fully actuated four-way intersection with stop bar and advanced detectors. The system has in addition one detector in each departure lane to permit accurate evaluation of turn movements. Each detector senses the time when a vehicle crosses it. All detectors are wireless and communicate with the Access Point (AP) located near the 2070/170 controller. Signal phase is obtained from the controller conflict monitoring card. All measurements are time-stamped and synchronous to within 100ms or 0.1s. The data are sent to the HR data server via a cellular modem. The data are organized in a database called APSAMS in Figure 2.

The rest of the paper is organized as follows. §2 discusses the flow chart of the three-step procedure. §3 describes the clustering by day-of-week. §4 describes how the intra-day segmentation and optimal timing plans are calculated. §5 collects some conclusions.

2 Flowchart

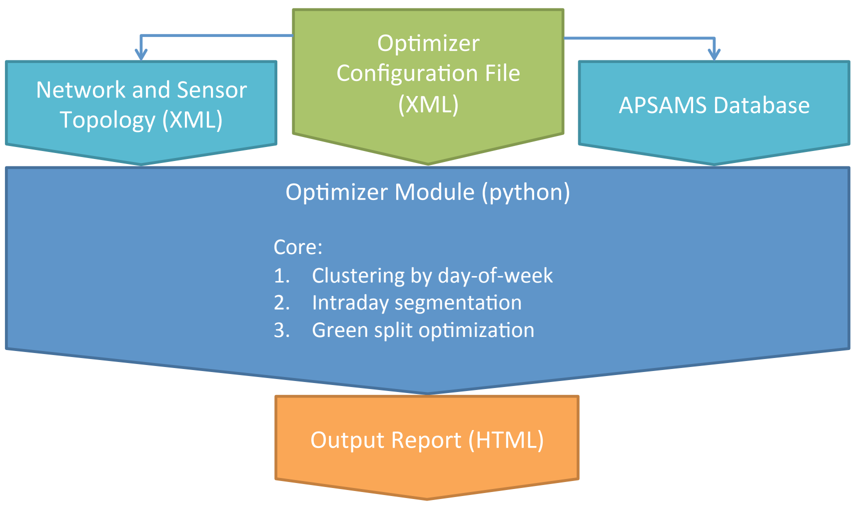


Figure 2: Flowchart for timing plan optimization.

Figure 2 summarizes the steps in the design of the timing plan. The optimization module collects information about the sensor placement in the network. In this illustration the network is a single intersection defined by lanes and turn movements, but more generally there would be a network of intersections. From Figure 1 we see that there are 12 movements in all: left, through and right turn from each of the four legs.

The APSAMS database is part of the HR data server of Figure 1. The optimizer configuration file specifies the range of days for which data is extracted from APSAMS and the parameters used in the optimization algorithms. The raw data consists of detection events for each vehicle. The database aggregates the raw data into 5-minute, 15-minute and hourly intervals.

The optimizer module carries out the three-step procedure: clustering, intra-day segmentation and green split optimization. Each step is described below.

3 Day of week clustering

The standard approach to designing TOD plans begins with manual measurement of counts over three days, selecting days of the week that will have different plans (e.g. weekday and weekend) and, for each day, selecting time intervals with different plans (e.g. AM and PM peak and off-peak periods). The selection of the days and time intervals is based on judgment based on familiarity with the traffic patterns. However, if we have continuous measurements for one year (say), we could cluster the daily data to reveal the days of the week with significantly different traffic patterns, and then cluster the intra-day data to divide the day into periods with significantly different traffic.

We illustrate the procedure using hourly data for the Beaufort intersection in Beaufort, S.C. for counts of the 12 movements for 164 days, Dec 2014 to May 2015. The data represents each day's traffic by a 24×12 vector of hourly counts, giving 164 (24×12)-dimensional vectors. Before describing the clusters, we indicate the variability of traffic in Figure 3, which displays the measured percentile flows for each movement,using 15-min counts.

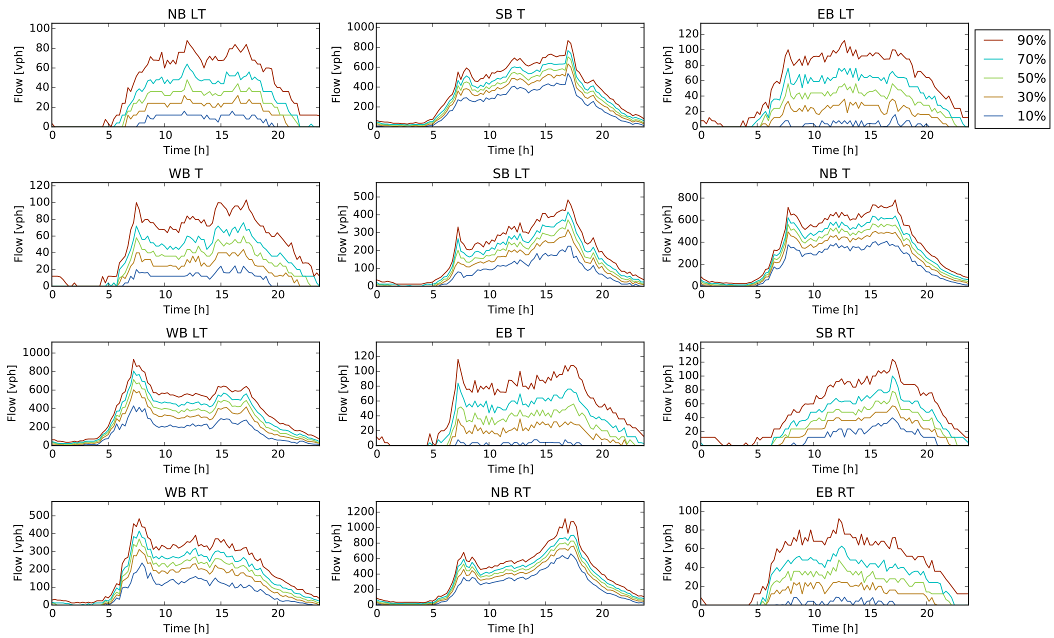


Figure 3: Empirically measured percentile flow for all 12 movements during 164 days.

The large variability suggests that there is a day-of-week structure that may be revealed by cluster analysis. We take the 164 vectors of hourly counts and group them into clusters using a standard k-means clustering of the 164 vectors. The result for $k = 4$ is displayed in Figure 4. The procedure divides the 164 vectors into four groups, G_1, G_2, G_3, G_4. The four plots display the average of these groups. Each average is a 24×12 vector, displayed as 12 separate movements over 24 hours. There is a pronounced day-of-week effect: the four clusters correspond to Mon-Th, Fri, Sat and Sun. The actual traffic plan in the intersection also groups the days of the week into these four classes. So the automatic clustering procedure agrees with experience-based judgment.

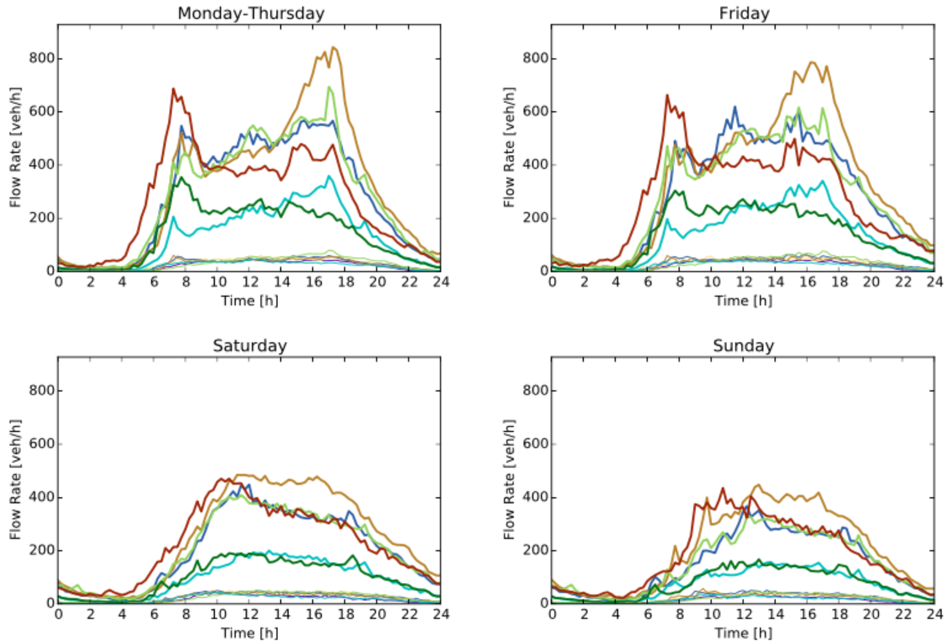


Figure 4: The 4-means cluster for all 12 movements during 164 days.

4 Intra-day segmentation and optimum splits

The next step is to take each of the four 'day' clusters $G_1, \cdots, G_4$ and divide each 24-hour day into a number of disjoint time intervals, $T_1, \cdots, T_m$. The parameter m is the number of intra-day timing plans we want to consider. Since we want a finer time resolution, we now take 15-minute rather than hourly count data. For each m we select the intervals to minimize the sum of squares,

$$\sum_{i=1}^{m} \sum_{t \in T_i} |\mu_i(t) - \bar{\mu}_i|^2.$$

Here $\mu_i(t)$ is the mean of a day cluster G_k for the 15-min period t and $\bar{\mu}_i$ is its average in the interval T_i. Figure 5 shows the result of this procedure for the Mon-Th cluster. A good design is to select 7 TOD (time of day) plans for M-Th (beginning at 0:00, 5:15, 6:45, 8:45, 14:30, 18:00 and 20:15). The figure shows the corresponding time intervals, for each of which we must design an individual timing plan (splits and cycle time). Applied to the other clusters this procedure suggests 8 plans for Fri, 4 plans for Sa, and 3 for Su. These are not shown here.

We design the timing plan for interval T_i taking $\bar{\mu}_i$ to be the 12-dimensional vector of average volumes of the 12 movements. We calculate the 'optimum' splits and cycle time. Two options are available in the optimization.

In the first option the splits and cycle time are determined by solving a quadratic programming problem that seeks to equalize the VC ratio for all 12 movements, constrained by a specified maximum VC ratio and min and max green.

In the second option the splits and cycle time are determined by solving a convex programming problem that minimizes the delay expressed by the HCM formula. We give the results of this minimization. In order to obtain a robust design we take for the demand the 90th percentile (instead of the average) of all 12 flows (see

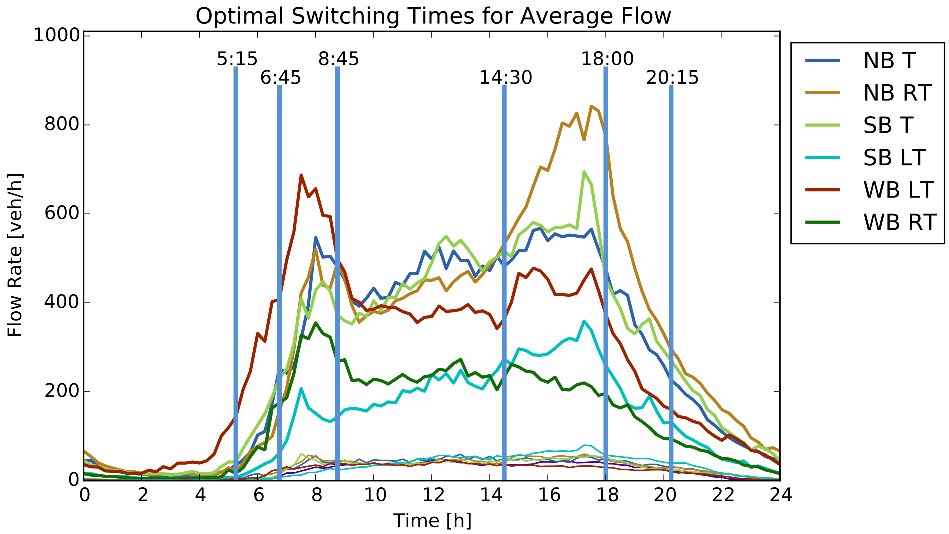
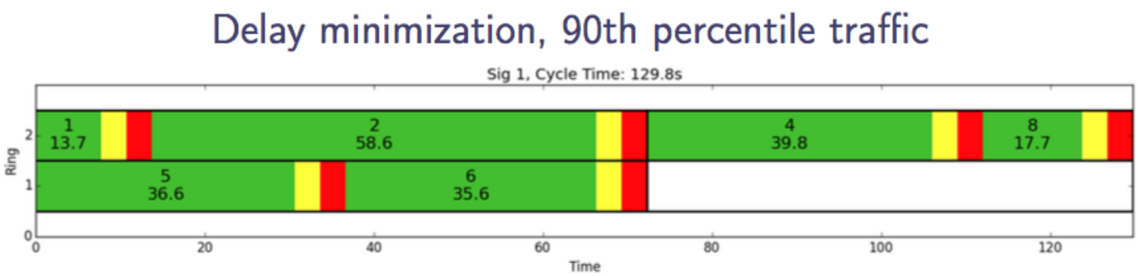


Figure 5: Optimum intra-day segments for the Mon-Th cluster.

Figure 3). Figure 6 shows the minimum delay splits and its predicted performance for the 90th percentile traffic. The predicted performance uses HCM formulas.



	Phase 1	Phase 2	Phase 4	Phase 5	Phase 6	Phase 8	Intersection
Splits (incl. Y and R)	13.7s	58.6s	39.8s	36.6s	35.6s	17.7s	129.8s
Splits (Green only)	7.7s	52.6s	33.8s	30.6s	29.6s	11.7s	105.8s
Splits (%)	6.0%	40.5%	26.0%	23.6%	22.8%	9.0%	81.5%
VC Ratios	65.6%	57.5%	92.1%	95.3%	92.8%	92.9%	93.3%
Avg. Queue Length	1.2veh	5.9veh	15.1veh	5.7veh	12.0veh	4.0veh	43.8veh
Avg. Delay	57.1s	26.7s	36.9s	51.4s	38.9s	57.1s	38.5s

Figure 6: Minimum delay splits with 90th percentile traffic and predicted performance.

Figure 7 compares the existing timing plans with those produced by Synchro and the delay-minimizing plan of Figure 6.

The existing cycle time of 130s is virtually the same as the delay-minimizing cycle time of 128.8s. Synchro gives a cycle time of 60s which is too short. In the plans of Figure 7, Synchro is forced to use a cycle time of 130s. The main difference between the three plans is the green time devoted to phase 4 which carries the west bound left turn traffic (WBLT) which is by far the largest, as seen in Figure 3. The existing plan gives the least green time to phase 4, Synchro gives the most, and the delay-minimizing plan has an intermediate value.

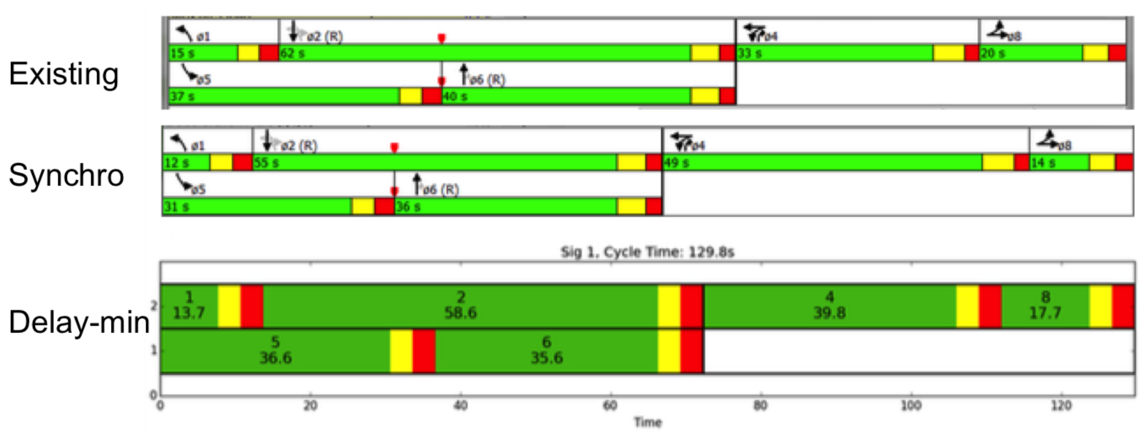


Figure 7: Splits from existing timing plans, Synchro and delay-minimizing plans.

We offer an educated guess as to why Synchro gives the most green time to phase 4. Synchro calculates the 90th percentile traffic for WBLT by inflating the average rate λ vph to the 90th percentile, assuming the arrivals are Poisson. By making a Gaussian approximation to the Poisson distribution, the 90th percentile is $\lambda + 1.6\sqrt{\lambda}$. Because we have event-by-event data we can actually obtain the inter-arrival distribution. Figure 8 shows histograms of inter-arrival times for 11 out of 12 movements (the missing movement from leg 3, lane 1 does not have an advanced detector and is not considered). Superimposed on each histogram is the exponential distribution in red. The numbers below the *x*-axis is the average inter-arrival time λ^{-1} in seconds. The histogram is close to the exponential for small values of λ, which is not surprising. However, for the right-turn movement from lane 4 of leg 2 , which has the largest rate, the exponential is a poor fit and suggests a much larger variance than what the data indicate. Hence for this movement the empirical 90th percentile is much smaller than Synchro's estimate of $\lambda + 1.6\sqrt{\lambda}$. This is the reason we believe that Synchro assigns a larger split to this movement (as well as a larger cycle length) than what the actual data indicate is required.

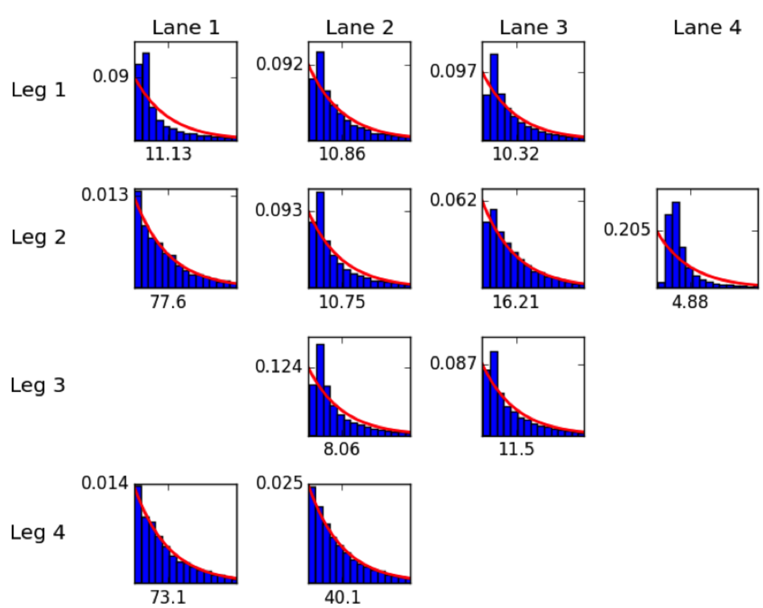


Figure 8: Histogram of inter-arrival times.

5 Discussion

The paper presented a procedure for automatically generating optimal TOD plans based on high-resolution (HR) data. The procedure requires several months of 24×7 detector data to cluster days of week, to select optimum intra-day intervals and to determine delay-minimizing splits. This way of automatic TOD plan generation is a paradigm shift from the current practice of designing plans based on manual traffic counts for three days once every few years. Using HR data to automatically produce timing plans is just one instance of the dramatic impact that an HR system will have on intersection management. We briefly describe other applications, grouping them into mobility and multi-modal traffic.

Mobility From individual event data we can determine such performance measures as cycle and split failures, wasted green, queue estimation and waiting times, and progression quality (Muralidharan et al. (2016)). The procedure described above to design the splits for time interval T_i uses only the average counts $\bar{\mu}_i$ in that interval. But the HR system provides *real time* counts, which one could use to *predict* future volume. These predictions could be used to adapt the splits to take the predicted traffic into account. This leads to proactive timing plans that anticipate changes in traffic (Coogan (2015)). Queue estimation permits implementation of sophisticated adaptive traffic control that maximize throughput in a network (Varaiya (2013)). Data for a network of intersections can be used to optimize offsets (Coogan et al. (2015)).

Knowledge of the time and lane location when a vehicle enters the intersection can be combined with the phase information to determine whether the vehicle is running a red light or whether it is making a right turn on red. The HR system can automatically detect such hazardous events and one can analyze the frequency of these event by phase movements and time periods to determine if corrective measures are needed to reduce these hazards.

Multi-modal traffic In addition to vehicle detectors an HR system may have sensors that detect pedestrians and bicycles and parked vehicles (Muralidharan et al. (2016)). As vehicles, bicycles and pedestrians compete for the same roadway surface, conflicts are inevitable since these different modes of traffic move with different speeds and occupy space with different shapes. The conflicts will be most severe in intersections and so managing the movement of this multi-modal traffic will be of growing importance. We can see an evolution in the way space is shared. Fixed time controllers provide "walk/don't walk signals" for pedestrians at marked crosswalks; but if crosswalk utilization is low, it may be more efficient to use push-buttons. If the occupancy of parking spaces is sensed, the price for on-street parking may be adapted to keep occupancy at a desired level, e.g. 80 percent (Pierce and Shoup (2013)). Similar to congestion pricing in HOT lanes, such a pricing policy will reduce double-parking and the number of cars looking for an empty spot.

HR systems as described here collect microscopic data on individual vehicles at particular locations. This data is naturally complemented by sensors that collect a sample of vehicle trajectories, e.g. using Bluetooth or WiFi receivers or GPS traces. The trajectory data can be analyzed to reveal O-D patterns and preferred paths. In case of incidents this patterns may be used to suggest alternative paths to drivers. It may be used design incentives for travelers to change their trip times and other behavior in ways that improve traffic (Pluntke and Prabhakar (2013)). The only practical way to accommodate the growing demands on the urban road system is to change behavior, and motivating the appropriate change will require fine-grained and extensive data.

References

S. Coogan. History's principal components repeat themselves: Using data for traffic predictive control. IPAM Workshop on Traffic Control, UCLA, October 2015.

S. Coogan, G. Gomes, E.S. Kim, M. Arcak, and P. Varaiya. Offset optimization for a network of signalized intersections via semidefinite relaxation. In *IEEE 54th Conference on Decision and Control (CDC)*, pages 2187–2192, 2015.

A. Muralidharan, S. Coogan, C. Flores, and P. Varaiya. Management of intersections with multi-modal high-resolution data. *Transportation Research, Part C*, 2016. to appear.

National Traffic Operations Coalition. 2012 National Traffic Report Card, 2012. http://www.ite.org/reportcard/.

G. Pierce and D. Shoup. SFpark: Pricing parking by demand. *Access Magazine*, 43(Fall), 2013.

C. Pluntke and B. Prabhakar. INSINC: A platform for managing peak demand in public transit. *JOURNEYS, Land Transport Authority Academy of Singapore, Journeys*, pages 31–39, September 2013.

P. Varaiya. Max pressure control of a network of signalized intersections. *Transportation Research, Part C*, 36:177–195, 2013.