Application of a Regional Multi-Modal Transportation System Performance Monitoring Framework

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Abstract

Comprehensive archives of regional real-time transportation system data, drawn from public agency fixed and moving detectors and integrated across travel modes, can provide unprecedented opportunities for precise and reliable system performance analysis at relatively low costs. Our access to the state-of-the-art Archived Data Management System (ADMS), a large transportation data archive in Los Angeles, has made possible new research aimed at developing strategies to improve the efficiency and productivity of urban transportation systems. This project, an application of the ADMS, presents a flexible framework to examine the characteristics and explanatory factors associated with intra-metropolitan variation in highway system performance in Los Angeles County. Using one year of highway data and employing three different performance measures that capture network traffic congestion, flow and reliability, we analyze the effects of systematic, random and land use factors on performance variation. We find that performance differs across different types of highway segments, and that population density and accidents are significant factors in explaining these differences. Our study sheds new light on spatiotemporal variations in highway system performance within a large and congested metropolitan area. We underscore the need for investing in regional data archives, and applying them for research and analysis in order to improve planning and system management.

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1. INTRODUCTION

The increasing availability of archived real-time transportation system data provides new opportunities for transportation system performance analysis across highly disaggregate units of space and time, and for developing tools and strategies to improve the efficiency and productivity of urban transportation systems. In this research we demonstrate an application of the Archived Data Management System (ADMS), a comprehensive archive of real-time multi-modal transportation system data in the Los Angeles region, to examine the characteristics and determinants of intra-metropolitan variation in highway system performance in Los Angeles County. Better understanding of performance variation supports more effective transportation system management.

The ADMS program (2010-) funded by the Los Angeles County Metropolitan Transportation Authority (Metro) has two objectives: 1) to develop a comprehensive historical archive of real-time (and near real-time) as well as periodically updated transportation network and system performance data from a variety of sources and modes (in the Los Angeles metropolitan region), with the archive structured as a geo-referenced relational scalable-queryable database, and 2) to demonstrate how the archive can be used for improving transportation planning, operations, and management. The program resulted in the creation of a multi-modal data archive that has few parallels[1] in the US in terms of variety (number of modes and data items), granularity (both spatial and temporal), and database architecture (e.g. for efficient streaming data cleaning, and for big data storage, processing, and querying). The ADMS currently includes historical real-time data (starting October 2011) from over 5,000 highway sensors, 10,000 arterial sensors, ramp meters, video cameras, bus and rail vehicles

[1] Comparable projects include the California PeMS (http://pems.dot.ca.gov/), RITIS (http://www.cattlab.umd.edu/?portfolio=ritis), and PORTAL (http://portal.its.pdx.edu/home/); links accessed on October 20, 2016.

(GPS), and event/incident feeds derived from RIITS (Regional Integration of Intelligent Transportation Systems (RIITS; https://www.riits.net/; link accessed on October 20, 2016), that integrates ITS data produced by several state and local agencies. RIITS-based data is supplemented with transit service supply, demand, and performance data, and multi-modal network configuration data. The ADMS has built-in data cleaning and processing techniques for both streaming and static data to improve the quality and integrity of the archive.

The ADMS employs new methods for high-rate streaming data retrieval, processing, storage, querying, analysis and visualization using Microsoft StreamInsight, Oracle database, and hierarchical multi-dimensional Data Cubes. Transportation applications include integrated corridor monitoring (Giuliano et al., 2016), regional monitoring (Giuliano et al., 2014), transit performance analysis (Chakrabarti and Giuliano, 2015; Chakrabarti, 2015), etc. This project is an extension of our regional traffic performance monitoring research. In the past, we developed a flexible method for monitoring regional and sub-regional highway and arterial traffic system performance across different time periods and locations, taking into account the spatial heterogeneity of sensor locations and data unavailability due to failed sensors or poor data quality. In this project, we leverage the ADMS to better understand variation in performance across and within functionally comparable highway sections across different time periods and locations.

The limitations of traditional agency traffic counts (e.g. archives of average daily or peak-period vehicle counts or spot-speeds at select locations derived from periodic short-duration surveys) as well as third-party probe data (e.g. archives of traffic parameters derived actively or passively from personal GPS device traces using proprietary – “black box” – methods) are well established. Our study demonstrates how archived real-time data from public agency owned fixed highway traffic sensors (infrastructure already available or being installed in most US cities) can help analyze system performance (e.g. recurrent and non-recurrent congestion, travel time reliability, etc.) better, and thereby advance urban transportation planning in addition to real-time information dissemination (via CMS) or incident detection and management applications.

Our analysis consists of four parts: 1) classify the highway system into functionally similar clusters or groups, and analyze variation in system performance across the groups; 2) investigate whether significant performance variation exists across roadway sections within the groups, and also compare within-variations across the groups; 3) analyze the characteristics and sources of performance variations (within each group, and regionally) by exploring systematic, idiosyncratic/random and land use factors; and 4) consider how our study could be used to help regional planners in their system performance improvement efforts.

We use traffic speed, flow (or volume) and buffer index (a measure of travel time unreliability) as test performance measures. We conduct our analysis using one year (January 1 to December 31, 2014) of highway traffic data for Los Angeles County from the ADMS, over five different weekday time periods (AM peak, PM peak, and three off-peaks). Our research provides new information to transportation agencies for monitoring and managing their systems effectively, for evaluating expected performance changes in response to interventions and external changes, and for making better informed investment decisions.

The remainder of this report is organized as follows. We first present a brief review of the state-of-the-art and state-of-practice of highway performance measurement, monitoring, and analysis approaches in the US. Next, we introduce our data and performance measures. We then present our analysis with discussion on findings. Finally, we conclude the report with takeaways for practice and future directions of research.

2. LITERATURE REVIEW

Regional, sub-regional and corridor-level traffic system performance measurement and analysis, across modes, are critical for effective day-to-day operations as well as long-term planning and system management (Shaw, 2003). Performance analysis, across suitable units of space and time, help agencies explore, implement and evaluate strategies aimed at increasing throughput, minimizing delays and improving travel time reliability. For the highway system, fixed roadway sensors (e.g. loop detectors) can serve as a good data source if they are available and provide satisfactory spatial coverage, and if a system for archiving historical data exists. Sometimes agencies conduct periodic manual or automatic traffic surveys to supplement sensor data for achieving better spatial coverage and quality, particularly for short-duration and special-needs programs (FHWA, 2013). Surveys, in fact, are regularly used as the sole basis for performance analyses by agencies in poorly instrumented areas, and by those that do not have the capacity to store and process large volumes of sensor data. The recent phenomenon of probe-based crowd-sourced data from global positioning systems (GPS) and smart phones have led to new data via third-party service providers (e.g. INRIX, HERE, etc.) and hence new opportunities for performance measurement and analysis (Pu and Meese, 2013). Such data, however, has problems. Private parties in the increasingly competitive traffic data marketplace typically do not disclose the sources from which they derive raw traffic data; they also consider their data fusion and processing techniques to be proprietary. Comparison of INRIX speed data, for example, against loop detector data reveal issues such as repeated reporting of same speeds (e.g. see Kim and Coifman, 2014).

Data availability and quality determines performance measurement and hence comprehensive analysis. Review of the highway traffic performance measurement literature reveals a disconnect between theory (and small-scale test applications) and practice. Researchers continue to identify various dimensions of corridor-level and regional highway performance (particularly capturing recurrent and non-recurrent congestion), propose many innovative measures, and suggest new data and infrastructure requirements (Meyer, 1995; Pratt and Lomax, 1996; Turner et al., 1996; Lomax et al., 1997; Cambridge Systematics et al., 1998; Jackson et al., 2000; Margiotta et al., 2006; Cambridge Systematics et al., 2008; Cambridge Systematics, 2014; Yang et al., 2015; Zhang et al., 2015; Brennan et al., 2015). And new regional analysis research is made possible by new data sources (e.g. Sweet et al., 2015). The current state of practice in performance measurement (and monitoring) and analysis in the US, however, is highly aggregate with respect to both space and time, particularly because gathering sufficient (and appropriate) traffic data and then archiving the data have proved to be costly and technically challenging for government agencies (e.g. see SCAG, 2007; 2015 TTI Urban Mobility Scorecard; National Transportation Statistics, etc.). Government-mandated regular performance monitoring tends to happen monthly or annually over large geographies (e.g. state-wide or city-wide) using traditional measures (e.g. vehicle miles traveled derived from sample survey data). The lack of precision or spatiotemporal resolution of the underlying data, and hence the system performance measures, often limits the analyses required for making critical investment or management decisions.

The most extensive traffic system performance monitoring takes place as a result of federal policy. Federal laws require states to submit both monthly and yearly traffic data to the FHWA for two different programs: 1) FHWA Traffic Volume Trends, and 2) Highway Performance Monitoring System (HPMS). These data, primarily derived from periodic manual or automatic traffic surveys across a relatively small sample of public roads belonging to various functional classes and published by the US Department of Transportation, are used for assessing highway system performance and to aid federal decision-making regarding future highway investments.

At the metropolitan area level, system performance measurement and monitoring depends on specific needs and how areas are instrumented. Transportation agencies in large metropolitan areas typically use real-time sensor data for real-time monitoring of traffic incidents, current speeds, lane closures and for other short-term needs. Departments of transportation and regional metropolitan planning organizations seldom use real-time traffic sensor data for travel demand modeling or long-range planning, relying instead on imprecise sample survey data aggregated and averaged across relatively large units of space and/or time.

Our access to a historical archive of highly disaggregate highway traffic data with good quality and spatial coverage from the Los Angeles region made it possible to conduct regional system performance analysis in a comprehensive way. Specifically, the data made possible the measurement and comparison of performance across any times of day, days of week, or seasons, or across road segments, corridors, or cities. The possible space/time combinations are almost limitless. Our research demonstrates how metropolitan planning agencies can utilize their assets more effectively for conducting performance analysis by investing in and using comprehensive data archives.

3. DATA AND MEASURES

In this study, we analyze highway traffic within Los Angeles County – our study area. We derive highway network configuration data from three different sources. We use mainline highway sections from the 2012-HPMS shapefile (available from https://www.fhwa.dot.gov/policyinformation/hpms/shapefiles.cfm; link last accessed on October 20, 2016). We then add on/off ramps and interchanges from the 2012-SCAG (Southern California Association of Governments) network file. Finally, we add HOV/HOT lane information from the Caltrans GIS data portal (http://www.dot.ca.gov/hq/tsip/gis/datalibrary/; link last accessed on October 20, 2016). The three data sources complement each other and help compile the complete set of fixed network attributes (configuration) required for this analysis. Our mainline sections (one- or two-way facilities) fall under the following HPMS-defined functional systems: Interstate; Principal Arterial - Other Freeways and Expressways; Principal Arterial – Other; and Minor Arterial. There are a total of 4597 mainline sections (each section is a single polyline representing all lanes across both directions) of varying lengths. Section length is defined arbitrarily in the HPMS, and is of no importance in the context of this analysis.

Traffic data for the LA County highway system is available from 1776 Caltrans (District 7) traffic sensor stations. A sensor station provides average speed (mph; capped at 70), occupancy (percent of time a sensor is covered, partly or fully, by a vehicle) and flow (vehicles per hour per lane) updates, aggregated across all lanes in a given direction, every 30 seconds to the ADMS via the RIITS network. We cleaned the raw data, and aggregated speed and volume records to 15-min intervals. More than 42 million 15-minute aggregated records are used as the basis for this analysis.

We downloaded geocoded highway traffic accident (collision) data for 2014 from California-SWITRS (Statewide Integrated Traffic Records System). The data is collected from accident scenes by California Highway Patrol staff. 34,027 accidents are used in this analysis.

Census tract level population density data is derived from the American Community Survey 2010-14 5-year estimates; average population density of underlying census tracts (in persons per sq. mi.) is attached to each highway section.

We use average (year 2014) speed, volume and buffer index as our performance measures for five different time periods of weekday: Early AM (midnight to 6 AM), AM Peak (6 AM to 9 AM), Midday (9 AM to 3 PM), PM Peak (3 PM to 7 PM) and Night (7 PM to midnight).

Buffer index (defined as the estimated additional time, expressed as percent of the mean travel time, that travelers need to budget in order to ensure on-time arrival) of a given section for a given time period of day, observed over a specified time (year 2014 in the context of this study) is estimated using the following formula:

$$Buffer\ Index = \frac{95th\ percentile\ travel\ time - Mean\ travel\ time}{Mean\ travel\ time} \times 100 \quad (1)$$

4. ANALYSES AND DISCUSSIONS

4.1 Custer analysis

The first step is to classify highway sections within Los Angeles County into functionally similar clusters or groups. We select a series of attributes to define a particular highway section, and then conduct a cluster analysis on the attributes to group the sections. The attributes include measures of demand or use and roadway configuration or geometry, based on the fundamentals of traffic flow and our previous research on regional multi-modal transportation system monitoring (Giuliano et al., 2014). See **Table 1**.

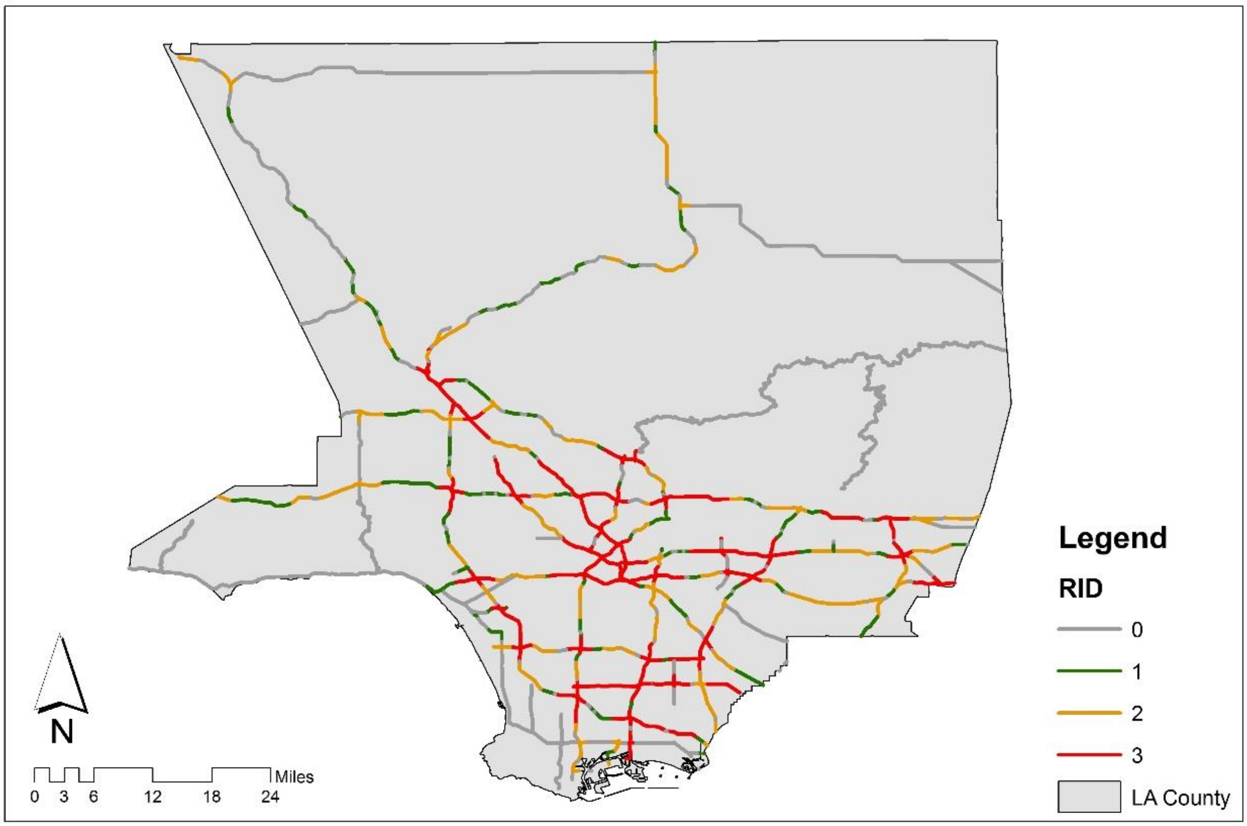
Table 1: Summary of section attributes

Variable (continuous)	**Count**	**Mean**	**Std. Dev.**	**Min**	**Max**
Annual Average Daily Traffic (AADT)	4,597	164880	94094	185	348000
Through lanes	4,597	8	3	2	16
Per-lane AADT	4,597	20261	11004	93	92667
Variable (binary/categorical)	**Count (and %) of sections**				
HOV/HOT lanes					
No	2270 (49.38%)				
Yes	2327 (50.62%)				
Ramp/intersection density (RID)					
0 (none)	1241 (27.00%)				
1 (low)	573 (12.46%)				
2 (med)	1144 (24.89%)				
3 (high)	1639 (35.65%)				

While section level AADT (annual average daily traffic), no. of through lanes, and presence of HOV/HOT lanes are available from agency datasets, information on the presence (and density) of ramps and interchanges required additional data processing.

Clusters of ramps and interchanges are identified by first defining 100 m buffers around individual on/off ramps and interchange sections, and then by aggregating/merging the buffer polygons based on their spatial location (distance between polygons<100 m → combine). The operation produces 256 distinct ramp/interchange clusters. Based on the sizes of the cluster polygons, the ramp/interchange clusters are classified into large (area>90th percentile), medium (area>median but <90th percentile), and small (area<median). The mainline highway sections are each assigned a "ramp/interchange density" (RID) attribute (categorical variable) based on the cluster that they intersect with. Section RID=3, 2, or 1 when an intersecting cluster polygon is large, medium, or small respectively. If a section intersects with two or more clusters falling into two or more classes, the larger cluster is considered for determining RID. If a section does not intersect any cluster, then RID=0. A map of RID values assigned to highways sections within LA County is given in **Figure 1**. Observe, for example, the high RID values of sections near freeway interchanges, and low (or zero) RID values of sections in relatively low-density outlying areas.

Figure 1: Ramp/intersection density (RID) by highway section



Although per-lane AADT is a useful measure of density of demand, we do not include the variable in our cluster analysis because it is highly correlated (correlation coefficient of 0.80) with the AADT variable across the 4597 highway sections. We tested various clustering approaches, and finally used the K-means cluster analysis approach with Gower dissimilarity measure (suitable for mixed – continuous and binary – data) and five groups. This method produces practical results, and the generated groups are sufficiently distinct from each other in terms of demand and geometry. The output is meaningful and helps understand the structure of the highway network in LA County effectively. **Table 2** presents a summary of section attributes by group.

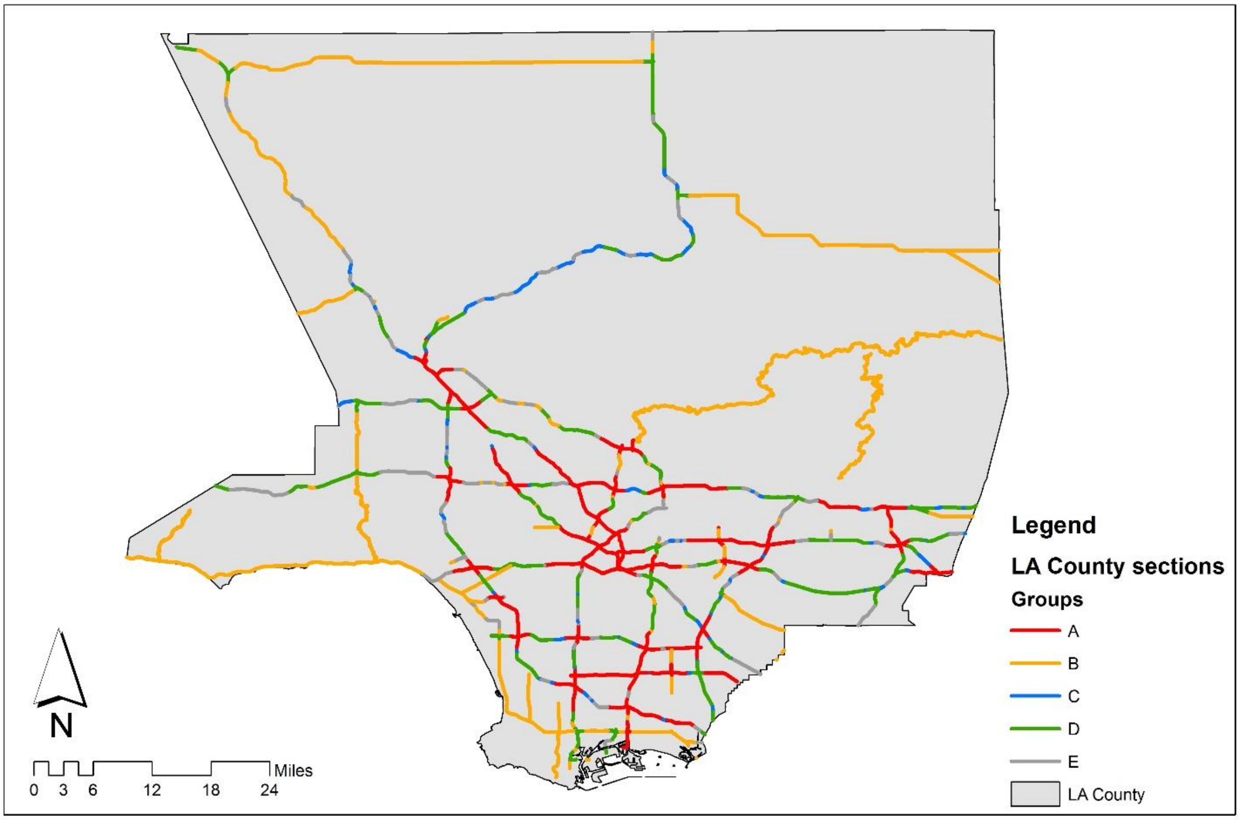
Table 2: Summary of attributes by group

Attributes	**Group**				
	A	**B**	**C**	**D**	**E**
No. of sections	1639	966	275	1144	573
% of total sections	35.65	21.01	5.98	24.89	12.46
% of total highway lane miles	31.97	23.49	5.44	25.11	13.98
Avg. AADT	216,273	42,900	181,530	181,900	181,542
Avg. through lanes	8.68	4.34	8.54	8.28	8.24
Avg. per lane AADT	26,242	7,914	20,885	21,473	21,245
HOV/HOT lanes (% sections in group)					
No	39	100	0	37	43
Yes	61	0	100	63	57
RID (% sections in group)					
0 (none)	0	100	100	0	0
1 (low)	0	0	0	0	100
2 (med)	0	0	0	100	0
3 (high)	100	0	0	0	0
HPMS highway functional system (% sections in group)					
Interstate	57.17	10.56	51.27	53.85	58.12
Principal Arterial - Other Fwy. and Exp.	40.51	5.80	32.36	36.45	30.54
Principal Arterial - Other	2.32	63.15	16.36	9.70	11.34
Minor Arterial	0	20.50	0	0	0

Group A, the largest group in terms of both number of sections and lane-miles, includes highest-volume sections with about nine lanes (both directions), mostly containing HOV/HOT lanes and located around interchanges or areas with high density of on/off ramps. On average, sections in Group B have low daily volumes, four lanes (two in each direction), no HOV/HOT lanes, and no ramps. While sections in Groups C, D and E are comparable in terms of their average daily volumes (which is lower than Group A, but higher than Group B sections) and number of lanes, they are different in terms of their configuration and location. All Group C sections (small fraction of the LA County highway system) include HOV/HOT lanes but no ramps; around 60% of sections in Groups D and E include HOV/HOT lanes, but while all Group D sections are located in areas with medium ramp/intersection density, all Group E sections are located in areas with low ramp/intersection density.

Although the shares of interstates and other freeways and expressways, per HPMS classification, are comparable across the groups (except Group B, which is an outlier), the groups are significantly different from each other in terms of our selected demand and geometric attributes. All parts or segments of a freeway (e.g. I-110) or a state highway (e.g. CA-60) are not functionally similar, and therefore cannot be expected to have similar performance. Our clustering or classification scheme captures the variation within the LA County highway network more effectively than the HPMS, and is better suited for system performance analysis. **Figure 2** shows the groups on a map.

Figure 2: Groups of highway sections



4.2 The data problem

There are several considerations in analyzing system performance variation across the region and within highway groups. First, instrumentation is not ubiquitous across the network. Portions of the network with higher traffic volumes are generally better instrumented (e.g. more sensors per mile) than portions with lower volumes, because of the original purpose of the detector system to support real-time traffic management. Second, freeway portions on viaducts are not instrumented, and older parts of the system have fewer working sensors. Finally, there is a substantial amount of "bad" or missing data due to malfunctioning detectors that tend to be randomly distributed across space. **Table 3** gives the number of functional sensors by group that are used in this analysis.

17 out of 1776 working sensor stations within LA County available in the ADMS could not be assigned to sections, because they are not part of the HPMS highway network used in this analysis. Observe the variation in sensor station density (no. per route mile) across groups. Low density in Group B is due to low traffic volumes across constituent sections. The majority of sections in Group B are not interstates or principal arterials. Density in Group C is low (relative to Groups D and E that have comparable traffic volumes) because of the absence of ramps and interchanges.

Table 3: Sensor stations by group

Attributes	**Group**				
	A	**B**	**C**	**D**	**E**
No. of sensor stations	798	36	64	560	301
Sensor stations per route-mile (avg.)	3.70	0.11	1.72	3.15	3.03

Note: Total route-mile = total length of the centerline of the highway network used in this study

4.3 Performance variation across groups

This analysis reveals the differences in average speed, volume and buffer index, across the five highway groups for five weekday time periods, observed over 2014. See **Table 4**. For a given time period, while group-level mean speeds and volumes are directly calculated from the raw 15-minute aggregated averaged sensor station records, average buffer index is calculated in two steps: first at the section level from sensor station data, and then averaged across all sections for a given group.

Analyses of variance (ANOVAs) reveal that mean speeds, mean volumes, and buffer indices across the five groups are statistically different (at the 95% confidence level or better) for all five time periods. The statistical significance of differences having small magnitudes is expected because of the large volumes of data from which the measures are derived. In general, and as expected, speeds are lower, volumes are higher, and buffer indices are greater during peaks relative to off-peaks. Traffic across Group A highways is slower and more unreliable compared to others on average during peak periods. On average, Group B sections operate at relatively higher speeds during peak periods, significantly lower volumes during all time periods, and significantly lower buffer indices at all times except Early AM. Although statistically different, performance of Group C, D, and E highways seem to be comparable. However, buffer index of Group D highways during the weekday PM peak period is higher. Also, Group C, with 100% sections with HOV/HOT lanes, accommodates higher volume compared to the other groups with same number of lanes on average.

Our analysis demonstrates the intra-metropolitan variation in highway system performance, and lays out a flexible framework for analysis using data over any time span, and by aggregating measures across any time of day and day of week.

Table 4: Mean speed and volume, and average buffer index by group (Weekday)

Time period		**Group A**	**Group B**	**Group C**	**Group D**	**Group E**
Early AM	Speed	60.35	59.28	60.39	60.26	59.47
	Volume	375.87	158.92	444.64	403.94	361.14
	BI (%)	20.99	30.87	44.92	27.48	24.84
	N	3,468,339	162,998	261,364	2,319,928	1,378,123
AM Peak	Speed	52.17	56.09	54.23	53.62	54.99
	Volume	1299.22	742.46	1468.58	1386.73	1307.12
	BI (%)	97.40	50.49	85.95	81.90	74.19
	N	1,718,411	79,852	129,820	1,150,727	683,352
Midday	Speed	55.58	55.78	58.42	56.76	57.38
	Volume	1268.75	681.74	1416.43	1339.73	1262.72
	BI (%)	67.01	32.82	43.81	59.31	52.23
	N	3,408,623	154,226	255,028	2,260,541	1,346,734
PM Peak	Speed	49.15	54.81	54.13	49.93	51.53
	Volume	1326.38	820.48	1542.22	1434.67	1349.98
	BI (%)	114.24	71.41	76.72	104.99	88.84
	N	2,303,644	104,332	172,058	1,528,086	905,639
Night	Speed	61.20	58.42	62.41	61.42	61.57
	Volume	864.95	446.75	957.27	915.36	833.97
	BI (%)	67.01	32.82	43.81	59.31	52.23
	N	2,925,925	132,679	219,409	1,947,260	1,156,632

Speed is in mph; volume is in vehicles/lane/hour; buffer index (BI) is in %
N=15-minute aggregated average records at the sensor station level

4.4 Intra-group performance variation

Next, we analyze performance variation across sections within each of the five groups for the same five weekday time periods. If P_{igt} be the average performance measure (speed, or volume, or buffer index) of section *i* belonging to group *g* corresponding to time period *t* observed over year 2014, we determine the coefficient of variation (CV) of P_{igt} values across all *i* for a given *g* and a given *t*, and then compare the CV's across all *g* and over all *t*.

We do not use the more straightforward metric, standard deviation (SD), to measure intra-group performance variation. This is because SD cannot be meaningfully interpreted independent of the mean. For example, let's say Group M and Group N both have SD of speed (across constituent sections) of 10 mph in the weekday AM peak. Do they have the same level of intra-group performance variation? In order to answer this question, we require additional information on mean speeds (across all constituent sections) of the two groups. If mean speed of Group M and N are 50 mph and 25 mph respectively, it becomes clear that the level of internal variation is more in Group N than in Group M.

Coefficient of variation (CV) = SD/mean is a useful measure for comparing within-group variation across groups. **Table 5** presents the CV of speed, volume and buffer index across sections by group, by time period. For a given *g* and *t* combination, and where *i* represents a section within group *g*, CV is computed as $\frac{Mean(P_{igt})}{SD(P_{igt})}$.

Speed variation across sections is highest in the PM peak period for all groups. Groups B and D have comparatively higher internal variations in traffic volume. The level of intra-group variation in travel time unreliability (measured in terms of buffer index), for all groups and across all time periods, is significantly higher compared to speed and volume. This demonstrates that the level of variability in day-to-day travel conditions vary significantly across space, and even within groups. Similar to **Table 4**, **Table 5** also lays out a flexible framework for performance analysis. The values can serve as a baseline for system managers. Reduction in CV over time can indicate improvement in travel conditions, all else equal.

Table 5: CV of speed, volume and buffer index across sections by group (Weekday)

Time period		Group A	Group B	Group C	Group D	Group E
Early AM	CV of section speed	8.80	12.76	11.64	10.94	9.92
	CV of section volume	34.24	82.85	32.37	112.17	38.68
	CV of section BI	204.00	175.28	266.37	242.53	198.12
	N	418	19	29	303	167
AM Peak	CV of section speed	19.35	14.22	16.46	21.04	16.72
	CV of section volume	42.00	75.33	40.48	75.43	37.19
	CV of section BI	110.07	150.08	86.04	105.40	105.58
	N	463	20	33	326	180
Midday	CV of section speed	13.95	15.05	11.28	14.22	11.66
	CV of section volume	42.37	73.54	42.71	81.77	37.71
	CV of section BI	114.28	124.76	93.53	121.38	105.35
	N	463	20	33	326	180
PM Peak	CV of section speed	25.17	21.88	16.59	26.21	21.38
	CV of section volume	24.90	63.06	12.73	71.87	20.06
	CV of section BI	92.38	196.26	75.06	240.29	104.48
	N	423	20	29	305	167
Night	CV of section speed	8.50	13.68	9.95	8.72	7.13
	CV of section volume	30.30	72.17	24.01	90.43	29.96
	CV of section BI	161.25	187.83	116.92	126.37	123.10
	N	420	20	29	302	167

Coefficient of variation (CV) is expressed as %
Speed is in mph; volume is in vehicles/lane/hour; buffer index (BI) is in %
N=No. of sections considered in analysis

Distributions of performance measures across constituent sections within a group for a particular time period can be illustrated, and visually compared, using density plots. **Figures 3 and 4** present kernel density plots of the distributions of speed, volume and buffer index across sections by group for the weekday AM and PM peak periods respectively. The X-axis represents performance, and the Y-axis represents the probability *P(x)* that a randomly chosen section of a given group in a given time period has performance value *x*. The Y-axis can also be interpreted as the proportion of sections of a given group in a given time period having performance value *x*. The area under the curve between $x=x_1$ and $x=x_2$ gives the total proportion of sections having performance value between x_1 and x_2. Total area under any curve is 1. Observe that while the spreads (i.e. ranges), shapes (e.g. skewness) and peaks of the various distributions across groups, time periods and performance measures are different, Group B is certainly an outlier. Inspection of these plots over time can help monitor system performance changes.

Figure 3: Distributions of weekday AM peak speed, volume and buffer index across highway sections by group

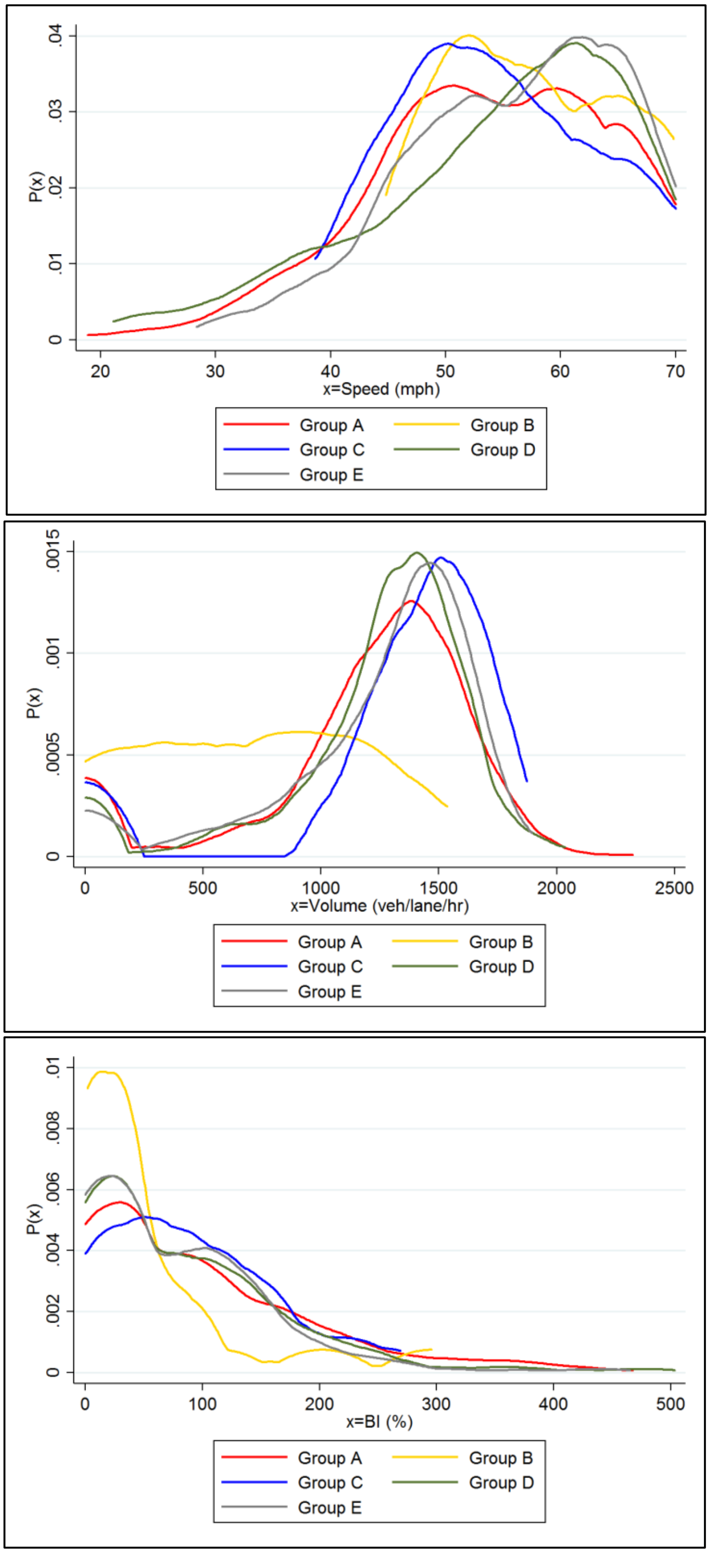
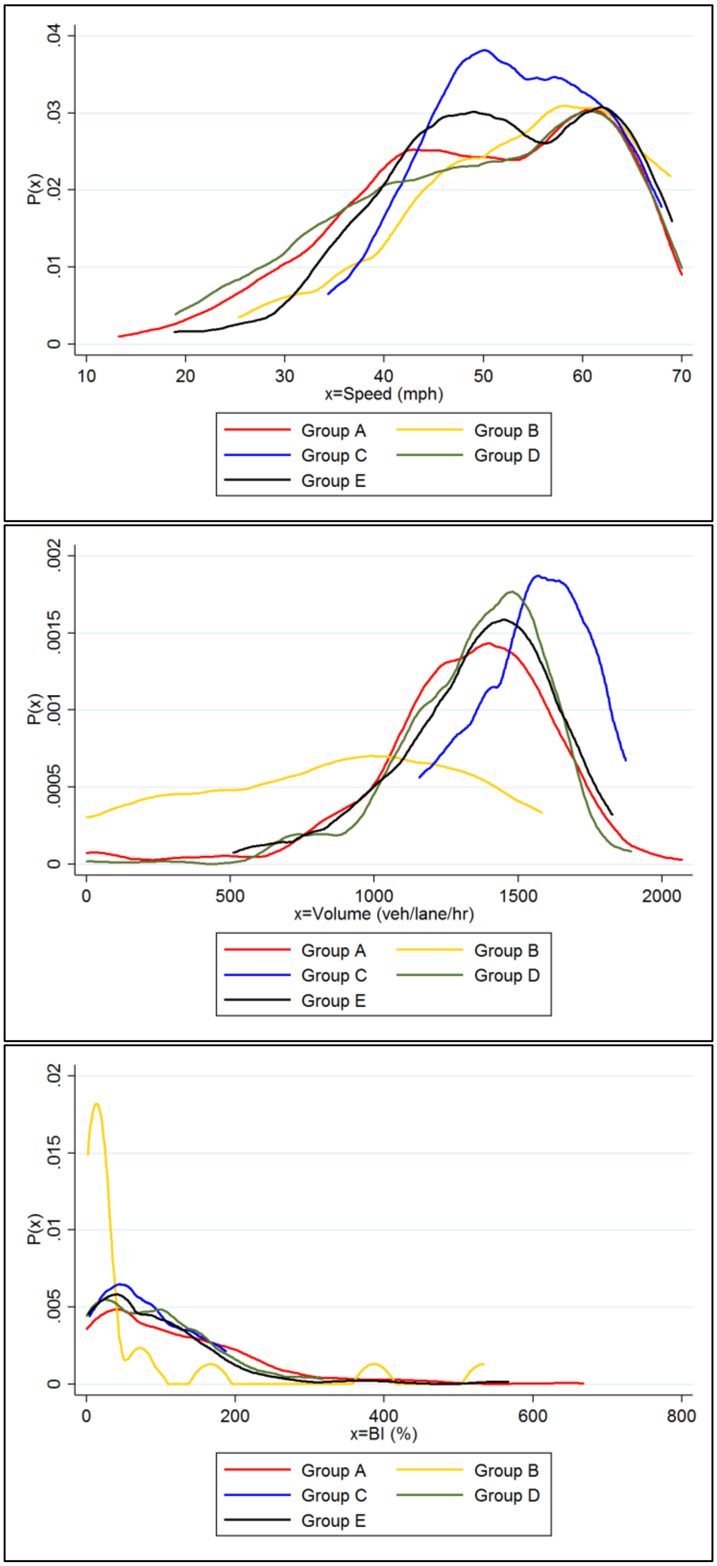


Figure 4: Distributions of weekday PM peak speed, volume and buffer index across highway sections by group



4.5 Regression analysis

In the previous section, we presented a descriptive analysis of traffic performance variation across and within groups. In this section, we analyze the determinants (or sources) of performance variation across sections within each group, and across sections within the entire study region.

We first explore factors associated with the variation in section performance within each group. We know, from traffic theory and empirical evidence, that time periods affect performance. For example, we expect speeds to be lower and buffer indices to be higher on average during peaks relative to off-peaks, particularly in heavily traveled road segments. We run a series of regressions (Model 1), for each group separately, to verify the time period effect on average section performance.

In addition to confirming the time period effect, we test the effects of two exogenous factors – accident occurrence and neighboring population density – on performance variation across otherwise similar (considering group subscription) highway sections. The idea is to investigate the effects of idiosyncratic and local land use factors, and help agencies make spatially targeted investments or traffic management plans to improve system performance across problem sections. We therefore run a second set of regressions (Model 2), for each group separately, where the time period dummy variables are essentially used as controls to measure accident and density effects.

Finally, we estimate pooled regressions (i.e. by pooling sections across all groups) to compare the contributions of deterministic or systematic (group and time period effects), stochastic or idiosyncratic (accident occurrence), and land use (population density) factors to the variation in section performance across the region (Model 3).

The functional forms of the models are –

Model 1 (time period effect; by group): $P_{igt} = \alpha + \beta T + \varepsilon$ (2)

Model 2 (exogenous+time effect; by group): $P_{igt} = \alpha + \beta A_{igt} + \gamma D_{ig} + \delta T + \varepsilon$ (3)

Model 3 (regional, pooled): $P_{igt} = \alpha + \beta A_{igt} + \gamma D_{ig} + \delta T + \mu S_{ig} + \varepsilon$ (4)

Where P_{igt} is a performance measure of section *i* belonging to group *g* within time period *t* aggregated over 2014; A_{igt} is the number of accidents per mile of section *i* belonging to group *g* within time period *t* in 2014; D_{ig} is the population density adjacent to section *i* belonging to group g; T denotes a series of time period dummies; S_{ig} denotes a vector of factors (used in cluster analysis) characterizing section *i* belonging to group *g*; and ε is the idiosyncratic error term. Weekdays are considered only. Since the time periods do not contain equal number of hours, average vehicles/lane/hour within a given time period of day is used as the volume measure.

We tested the effect of adjacent employment density in addition to population density. Data was derived from x-y level firm location and employment data from SCAG for 2011. We found that: the employment density variable is not statistically significant in most of the estimated regression models; it does not significantly improve the explanatory powers of the models; and it does not affect the magnitudes and directions of influence of other independent variables. In some cases, however, addition of employment density renders the population density variable insignificant. This is attributable, at least in part, to the correlation between population and employment density across sections used in the regressions. We therefore decided to drop employment density from this analysis.

Figures 5 and 6 present total accidents per mile (in 2014) and adjacent population density, respectively, for the highway sections. **Tables 6-9** summarize regression model results. We report standardized (beta) coefficients that help compare effect sizes across variables.

Although we used AADT in our cluster analysis for classifying sections into groups, we do not include the variable in Model 3 (**Table 9**) because we do not expect average daily traffic volume across a section to determine its performance within a given time period of the day (e.g. peaks and off-peaks). We, however, include average traffic volume within a given time period (measured in terms of volume/lane/hour) as the determinant of system performance in the speed and buffer index models. Parameter estimates suggest, as expected, that traffic volume affects speed and travel time reliability of the highway system.

Figure 5: Accidents per mile by highway section (2014)

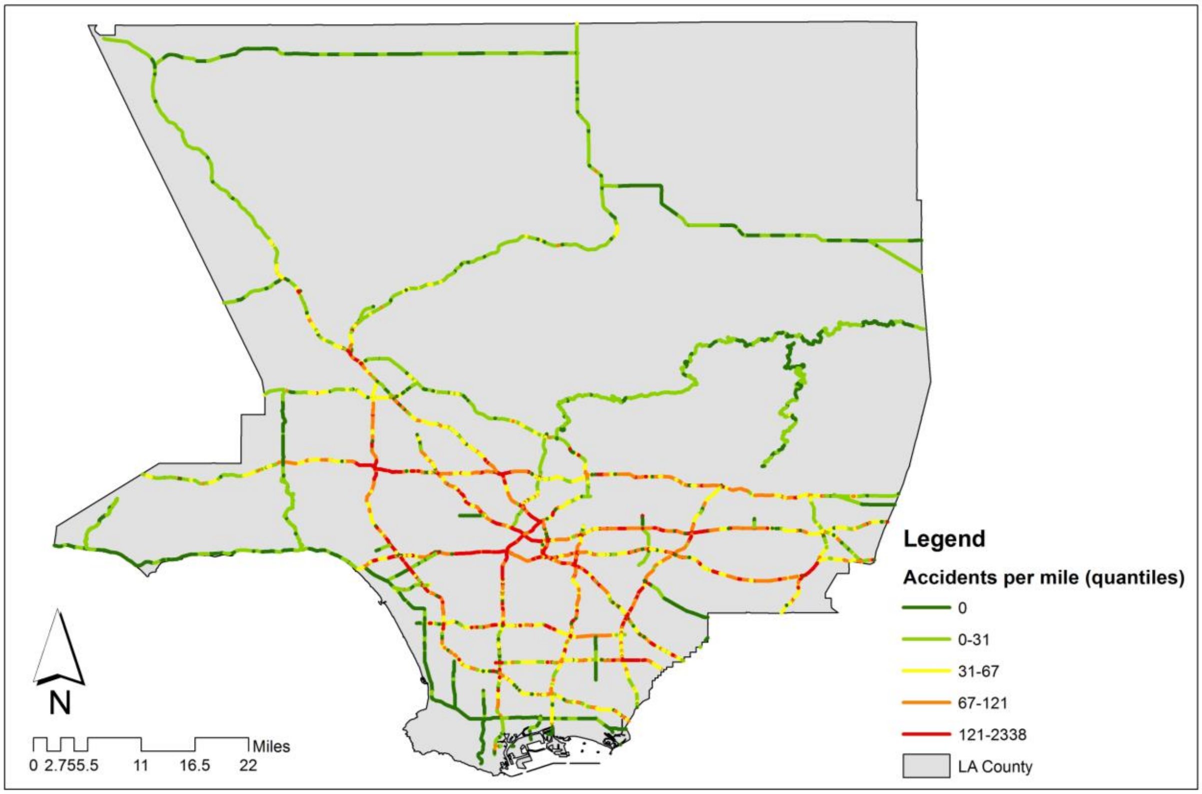


Figure 6: Population density by highway section

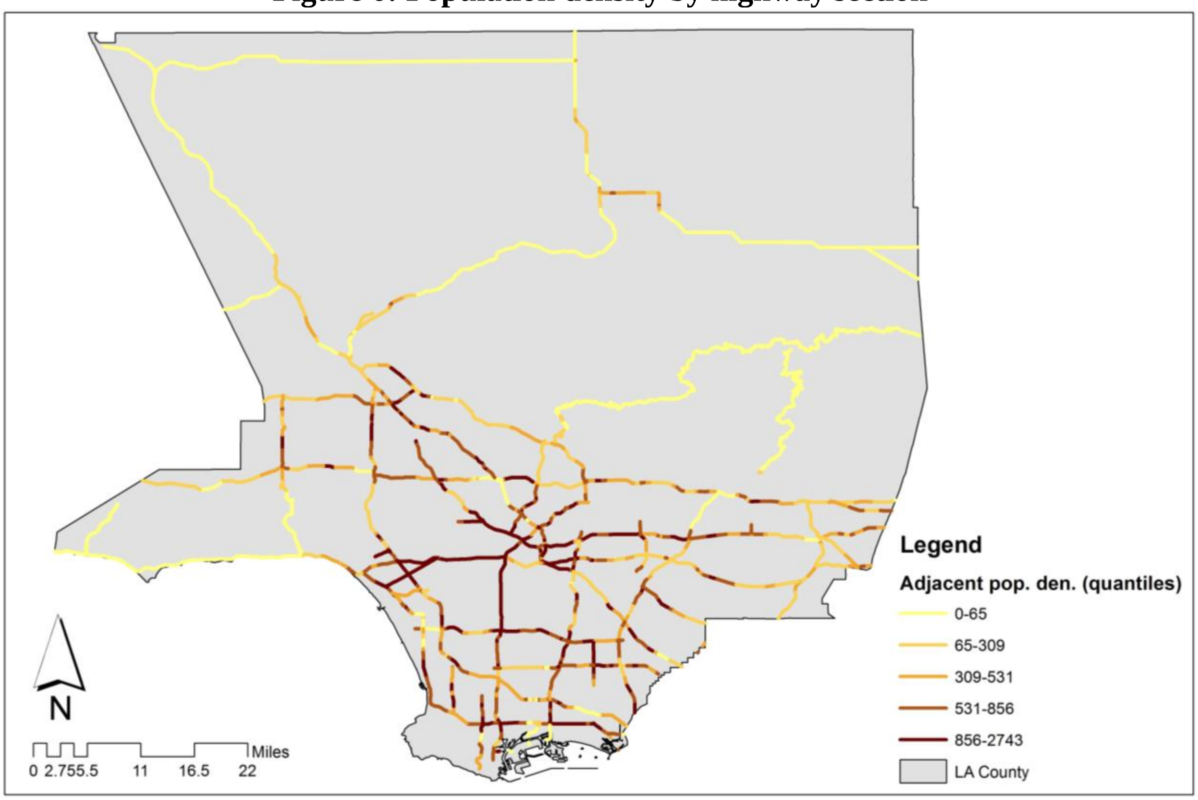


Table 6: Regression models 1 and 2 of mean speed (mph) by group

Model 1										
Variable	Group A		Group B		Group C		Group D		Group E	
	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|
Early AM	-0.036	*0.14*	0.039	*0.76*	-0.106	*0.28*	-0.057	*0.06*	**-0.106**	*0.01*
AM Peak	**-0.286**	*0.00*	-0.023	*0.86*	**-0.307**	*0.00*	**-0.246**	*0.00*	**-0.255**	*0.00*
Midday	**-0.163**	*0.00*	-0.051	*0.69*	-0.111	*0.27*	**-0.140**	*0.00*	**-0.146**	*0.00*
PM Peak	**-0.471**	*0.00*	-0.173	*0.18*	**-0.382**	*0.00*	**-0.454**	*0.00*	**-0.463**	*0.00*
N	2187		99		153		1562		861	
Adj. R-sq.	0.18		0.00		0.10		0.16		0.15	
Model 2										
Variable	Group A		Group B		Group C		Group D		Group E	
	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|
Acc. per mi.	**-0.137**	*0.00*	**-0.207**	*0.04*	-0.107	*0.20*	**-0.175**	*0.00*	**-0.178**	*0.00*
Pop. den	**-0.093**	*0.00*	**0.218**	*0.03*	-0.066	*0.39*	**-0.150**	*0.00*	**-0.063**	*0.04*
Early AM	**-0.051**	*0.04*	0.039	*0.76*	-0.106	*0.28*	**-0.075**	*0.01*	**-0.126**	*0.00*
AM Peak	**-0.276**	*0.00*	-0.015	*0.91*	**-0.290**	*0.00*	**-0.240**	*0.00*	**-0.253**	*0.00*
Midday	**-0.125**	*0.00*	-0.010	*0.93*	-0.077	*0.46*	**-0.098**	*0.00*	**-0.111**	*0.01*
PM Peak	**-0.440**	*0.00*	-0.180	*0.15*	**-0.351**	*0.00*	**-0.416**	*0.00*	**-0.418**	*0.00*
N	2187		99		153		1562		861	
Adj. R-sq.	0.21		0.05		0.10		0.21		0.18	

Night is the reference time period in both models; constant is not reported in the tables of std. (beta) coefficients; coefficients that are statistically significant at the 95% confidence level (corrected up to two decimal places) or better are highlighted in bold text

Table 7: Regression models 1 and 2 of mean volume (veh/lane/hr) by group

Model 1										
Variable	Group A		Group B		Group C		Group D		Group E	
	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|
Early AM	**-0.382**	*0.00*	**-0.221**	*0.05*	**-0.395**	*0.00*	**-0.210**	*0.00*	**-0.384**	*0.00*
AM Peak	**0.264**	*0.00*	**0.232**	*0.04*	**0.246**	*0.00*	**0.152**	*0.00*	**0.319**	*0.00*
Midday	**0.238**	*0.00*	0.200	*0.08*	**0.229**	*0.00*	**0.138**	*0.00*	**0.284**	*0.00*
PM Peak	**0.363**	*0.00*	**0.344**	*0.00*	**0.422**	*0.00*	**0.206**	*0.00*	**0.417**	*0.00*
N	2187		99		153		1562		861	
Adj. R-sq.	0.44		0.21		0.47		0.14		0.52	
Model 2										
Variable	Group A		Group B		Group C		Group D		Group E	
	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|	Beta	*P*>|*t*|
Acc. per mi.	0.016	*0.36*	**0.335**	*0.00*	-0.106	*0.08*	0.023	*0.36*	**0.091**	*0.00*
Pop. den	**0.052**	*0.00*	0.043	*0.61*	**0.207**	*0.00*	**0.111**	*0.00*	**0.124**	*0.00*
Early AM	**-0.381**	*0.00*	**-0.223**	*0.04*	**-0.395**	*0.00*	**-0.207**	*0.00*	**-0.374**	*0.00*
AM Peak	**0.263**	*0.00*	**0.219**	*0.04*	**0.268**	*0.00*	**0.150**	*0.00*	**0.318**	*0.00*
Midday	**0.233**	*0.00*	0.134	*0.21*	**0.268**	*0.00*	**0.132**	*0.00*	**0.267**	*0.00*
PM Peak	**0.359**	*0.00*	**0.355**	*0.00*	**0.453**	*0.00*	**0.201**	*0.00*	**0.394**	*0.00*
N	2187		99		153		1562		861	
Adj. R-sq.	0.44		0.32		0.52		0.15		0.54	

Night is the reference time period in both models; constant is not reported in the tables of std. (beta) coefficients; coefficients that are statistically significant at the 95% confidence level (corrected up to two decimal places) or better are highlighted in bold text

Table 8: Regression models 1 and 2 of buffer index (%) by group

Model 1										
Variable	Group A		Group B		Group C		Group D		Group E	
	Beta	*P>|t|*	Beta	*P>|t|*	Beta	*P>|t|*	Beta	*P>|t|*	Beta	*P>|t|*
Early AM	**-0.082**	*0.00*	-0.015	*0.91*	0.110	*0.27*	-0.052	*0.10*	-0.050	*0.22*
AM Peak	**0.261**	*0.00*	0.081	*0.53*	**0.346**	*0.00*	**0.115**	*0.00*	**0.234**	*0.00*
Midday	**0.123**	*0.00*	-0.005	*0.97*	0.110	*0.28*	0.045	*0.16*	**0.107**	*0.01*
PM Peak	**0.326**	*0.00*	0.183	*0.16*	**0.280**	*0.01*	**0.182**	*0.00*	**0.310**	*0.00*
N	2187		99		153		1562		861	
Adj. R-sq.	0.14		0.00		0.07		0.04		0.11	
Model 2										
Variable	Group A		Group B		Group C		Group D		Group E	
	Beta	*P>|t|*	Beta	*P>|t|*	Beta	*P>|t|*	Beta	*P>|t|*	Beta	*P>|t|*
Acc. per mi.	**0.121**	*0.00*	0.153	*0.14*	0.126	*0.13*	**0.093**	*0.00*	**0.205**	*0.00*
Pop. den	**0.139**	*0.00*	-0.058	*0.57*	0.039	*0.62*	**0.091**	*0.00*	**0.075**	*0.02*
Early AM	**-0.069**	*0.01*	-0.015	*0.91*	0.110	*0.27*	-0.043	*0.18*	-0.027	*0.50*
AM Peak	**0.252**	*0.00*	0.075	*0.56*	**0.325**	*0.00*	**0.111**	*0.00*	**0.232**	*0.00*
Midday	**0.089**	*0.00*	-0.036	*0.78*	0.069	*0.51*	0.023	*0.47*	0.066	*0.10*
PM Peak	**0.298**	*0.00*	0.188	*0.14*	**0.244**	*0.02*	**0.162**	*0.00*	**0.259**	*0.00*
N	2187		99		153		1562		861	
Adj. R-sq.	0.18		0.00		0.08		0.06		0.15	

Night is the reference time period in both models; constant is not reported in the tables of std. (beta) coefficients; coefficients that are statistically significant at the 95% confidence level (corrected up to two decimal places) or better are highlighted in bold text

Table 9: Pooled regression model 3 by performance measure

Variable	Speed (mph)		Volume (veh/lane/hr)		Buffer index (%)	
	Beta	*P>|t|*	Beta	*P>|t|*	Beta	*P>|t|*
Acc. per mi	**-0.152**	*0.00*	**0.025**	*0.05*	**0.117**	*0.00*
Pop. den	**-0.077**	*0.00*	**0.098**	*0.00*	**0.098**	*0.00*
Early AM	**-0.144**	*0.00*	**-0.276**	*0.00*	-0.020	*0.25*
AM Peak	**-0.201**	*0.00*	**0.202**	*0.00*	**0.164**	*0.00*
Midday	**-0.062**	*0.00*	**0.177**	*0.00*	**0.037**	*0.04*
PM Peak	**-0.347**	*0.00*	**0.272**	*0.00*	**0.200**	*0.00*
Through lanes	0.024	*0.07*	**0.049**	*0.00*	**-0.035**	*0.02*
Vehicles/lane/hour	**-0.265**	*0.00*	(omitted)	-	**0.092**	*0.00*
HOV/HOT lane=1	**0.037**	*0.01*	**0.096**	*0.00*	-0.010	*0.50*
RID=0	-0.007	*0.59*	-0.007	*0.59*	-0.014	*0.34*
RID=1	**0.026**	*0.05*	**0.040**	*0.00*	**-0.029**	*0.05*
RID=2	-0.008	*0.53*	**0.086**	*0.00*	-0.011	*0.46*
N	4862		4862		4862	
Adj. R-sq.	0.25		0.27		0.12	

Night is the reference time period; E is the reference group; HOV/HOT lane=0 (or absent) and RID=3 are the reference section configuration categories; constant is not reported in the table of std. (beta) coefficients; coefficients that are statistically significant at the 95% confidence level (corrected up to two decimal places) or better are highlighted in bold text

4.6 Findings with discussion

Model 1 estimates help validate the established effect of time period on highway performance – speed, volume, and buffer index – across all groups. In general, speeds are lower, and volumes and buffer indices are higher, in peaks relative to off-peaks across highway sections within all five groups. PM peak traffic performance is worst; early morning and night time traffic conditions are comparatively better. Speed and buffer index of Group B sections, interestingly, do not vary across time periods; we provide plausible explanations.

Comparison of Model 1 and 2 results (for speed, volume, and buffer index) shows that addition of accident occurrence and population density variables improves the explanatory powers of the regression models in 12/15 cases (except Group C speed, Group A volume, and Group B buffer index models). Moreover, the time period effects remain largely unchanged in the expanded models. Statistical significance and effect sizes of the accident and population density variables are discussed.

Our observations regarding the variation in system performance across highway sections within LA County, using Model 2 (expanded model) estimates, are summarized below. Parameter estimates with $p \leq 0.05$ are considered to be statistically significant.

> ***Speed:*** Accident occurrence and population density both have statistically significant negative associations with speed, all else equal, in groups A, D and E. Standardized coefficients show that the effect size of accident is bigger than population density. Accident and density effects are not statistically significant in Group C. In Group B, the accident variable is statistically significant and has the expected (negative) sign. The sign of the statistically significant population density variable, however, is positive, suggesting that higher speeds are associated with sections in higher-density locations.

Group B sections are, on average, located in low density outlying areas and have four (two in either direction) lanes with low volumes. The observed effect can be due to higher traffic volumes, more lanes, and consequently higher speeds, in parts of Group B highways that pass through relatively high density neighborhoods. Slower speeds in mountainous segments can also explain the effect.

In Groups A, D, and E, average speed is different across all time periods, and lower during the peaks. In Group C, peak speeds are significantly lower than night, but speeds during other off-peak periods are not different from each other. PM peak traffic is relatively slower than AM peak traffic in the above groups. The time period effect is missing in Group B. This could be due to the small number of sections (or observations) in this group. The effect could also be attributed to the absence of large diurnal variation in speed (refer **Table 4**) due to the characteristics (e.g. low traffic volume, location away from the central city and high-density population/job centers) of Group B sections.

Volume: Accident occurrence is not associated with traffic volumes across sections in Groups A, C and D, but is positively correlated with section volumes in Groups B and E. In general, accidents do not seem to be able to significantly reduce traffic flow or vehicle throughput on average. The positive association in Groups B and E could be due to higher frequency of accidents in high traffic zones. Higher population density–higher traffic volume relationship holds across sections within all groups except B.

Peak volumes are significantly higher than off-peak volumes, and PM peak traffic is heaviest, in all groups. However, there is no difference between midday and night volumes in Group B. In general, volumes are different across time periods as expected.

Buffer Index: In groups A, D and E, more accidents and greater density are associated with higher buffer index (i.e. lower travel time reliability). The effects are not statistically significant in Group C.

Peak-period buffer indices are significantly higher than off-peak in all groups except B. Buffer indices in the three off-peak periods, however, are only statistically different from each other in Group A, with early morning travel time being most stable or predictable.

For Group B, we cannot reliably determine the association of buffer index with any of the independent variables due to poor model fit.

Pooled regression model 3 helps comprehensively investigate factors that are significantly associated with the variation in speed, volume and buffer index across highway sections within LA County by analyzing the full set of variables. That is, we use group attributes rather than the groups themselves. **Table 9** shows, on average, that accident occurrence, population density, time period, and section location-configuration-demand factors have statistically significant effects on performance. Accident and population density variables are negatively associated with speed and travel time reliability, and positively associated with traffic volume. Peak-period speed and travel time reliability is lower, and volume higher, than the off-peaks. All else equal: more number of lanes is associated with higher traffic volume and lower buffer index; higher traffic volume is associated with lower speed and higher buffer index; and presence of HOV/HOT lanes is associated with faster and heavier traffic. The independent effect of ramp/intersection density on traffic performance is mixed. There is indication, however, that speed is higher and buffer index is lower when RID=1 relative to RID=3, which is expected. Volume or flow seems to drop when RID=3, relative to RID=1 or 2, possibly due to bottleneck effects. Comparison of standardized coefficients reveals that peak-period effect on system performance dominates. Overall, our findings highlight the significant roles of deterministic, stochastic and land use factors in explaining the variation in highway system performance across the study area.

5. CONCLUSION

In this report, we proposed a flexible framework for analyzing intra-metropolitan variation in highway system performance using an archive of real-time traffic loop detector data. Using Los Angeles County as the study region, 2014 as the test year, and speed, volume and buffer index as test performance metrics, we empirically demonstrated our approach. By employing descriptive and inferential statistical tools, we analyzed the characteristics and determinants of variation in system performance both within and across groups of functionally comparable highway sections, as well as regionally, for different weekday time periods. Although results and policy takeaways are specific to the Los Angeles region, methods are generalizable. Our study underscores the benefit of archiving traffic sensor data and effectively using it for performance measurement, monitoring, and analysis. If our study is replicated, the research design, including delineation of study area, selection of performance measures and explanatory variables, clustering approach, and the level of space-time disaggregation must be context specific. There is no golden rule.

Better understanding of how and why performance varies can contribute to more efficient system management and hence improved mobility and reliability of travel. Examination of the various dimensions of performance variation – e.g. systematic or caused by fixed (time-invariant) attributes, and idiosyncratic or caused by random fluctuations in demand due to accidents or other incidents – can help make strategic capital investments or implement innovative traffic management strategies targeted at specific parts of the system at specific times in order to not only reduce variation in performance across the system but to improve overall system performance. Our report provides guidance for regional transportation planners.

Improving highway system performance is challenging, and hence an analytical approach, as outlined in this report, is useful. If performance is found to be largely a function of exogenous factors (e.g. population density), the management implications are for overall efficiency or capacity enhancement strategies (e.g. HOT lanes). If accidents and incidents play a major role, strategies that reduce incident duration and impact may be appropriate. In our study of the Los Angeles region, we find evidence to consider both of the above strategies. In general, it is key to analyze the relative importance of different factors and evaluate alternative policy or investment choices.

Although we have solely focused on the highway system, improvement of regional travel conditions requires a multi-modal approach. Highway performance is not independent of arterial traffic, transit and other non-motorized modes, and therefore analysis of the characteristics and determinants of variation in regional transportation system performance is key. Policies targeted at one mode can affect the performance or productivity of another. For example, dedicated bus lanes and transit signal priority can not only help increase average bus speeds, but may also improve arterial traffic flow and person throughput. Investments in ITS and development of regional real-time multi-modal data archives such as ADMS will make such analyses possible.

6. DEPLOYMENT AND IMPLEMENTATION

This research was conducted as part of a larger, long-term effort to work with LA Metro and other stakeholders on developing applications from the ADMS data that could be used in planning and operations practice. Results of this research have been shared with LA Metro. City of Los Angeles, and Caltrans. A journal paper based on this report is in progress, and we have presented our results at two conferences.

Transportation system performance is a critical part of system management, and system operators constantly seek better ways to both monitor and manage the system. This research shows the potential of using ADMS data for far more comprehensive system monitoring.

Better understanding of how and why performance varies can contribute to more efficient system management and hence improved mobility and reliability of travel. Examination of the various dimensions of performance variation – e.g. systematic or caused by fixed (time-invariant) attributes, and idiosyncratic or caused by random fluctuations in demand due to accidents or other incidents – can help make strategic capital investments or implement innovative traffic management strategies targeted at specific parts of the system at specific times in order to not only reduce variation in performance across the system but to improve overall system performance. Better performance results in less congestion, improved energy efficiency, and reduced pollution.

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