DRISI
Caltrans Division of Research, Innovation and System Information

Research Results

Potential Erroneous Degradation of High Occupancy Vehicle (HOV) Facilities

Determine erroneous degradation magnitude of HOV facilities due to general-purpose mainline detectors misconfigured as HOV detectors.

Traffic Operations

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Project Title:
Statewide Managed Lanes (HOV/HOT) System Analysis Tools)

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WHAT WAS THE NEED?

According to the Federal Highway Administration (FHWA) and California Department of Transportation(Caltrans) guidelines, reports on the degradation status of high-occupancy vehicle (HOV) lanes is required annually. In California, these reports depend on data gathered through the Performance Measurement System (PeMS). According to the April 2018 Report to the Legislature, 65 percent (864 out of 1331 total lane-miles) were degraded in the first half of 2016.

However, recent studies at UC Berkeley show that general-purpose mainline detectors may be commonly misconfigured as HOV detectors. In the facilities studied, this misconfiguration corresponded to about 8% to 9% of HOV detectors, or about one wrong configuration every 5-6 HOV lane-miles. It is possible that this level of erroneous data may potentially cause HOV facilities to be wrongly evaluated as degraded.

In 2016, one study investigated 32-lane miles of HOV lanes along I-210 through Pasadena. Along that corridor, 5 HOV detectors were found to have been wrongly configured. Two years after the configuration was corrected, there was an IP conversion project along the same facilities. Immediately following the project, 6 HOV detectors were found to have been wrongly configured by the contractor. In most cases, HOV detectors are misclassified as general-purpose mainline detectors.

Erroneous degradation of HOV facilities skews performance metrics and investment priorities. In addition, it limits Caltrans' ability to fashion policy to address multimodal transportation needs. The research was to assess the extent of this problem.

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WHAT WAS OUR GOAL?

There is no definitive protocol for Caltrans maintenance to check whether detectors are connected to the correct physical terminals in the controller. In addition, there are no data analysis tools to check flow patterns and automatically flag this kind of misconfiguration error. Therefore, the goal of this project was to create a method to detect likely HOV misconfiguration errors and to reveal the magnitude of the problem.

WHAT DID WE DO?

The research team at the University of California at Berkeley (UCB) performed research that explores the application of data science to improve the accuracy of performance measures and therefore directly improve the quality of management decisions. They developed automated means to identify configuration errors of HOV lanes, leveraging the latest research in data science.

The researchers surveyed data-mining methods to assemble clusters of similar patterns and identified anomalies in HOV data. These methods were compared for their accuracy in identifying HOV misconfiguration.

The best method was selected to determine the HOV sensors that are likely misconfigured over a larger region, such as one Caltrans district. These HOV sensors were compared with their mainline neighbors to see if they were wrongly degraded. A report was produced summarizing findings and assess the extent and seriousness of the problem.

WHAT WAS THE OUTCOME?

The researchers successfully completed the primary objective of developing a machine learning algorithm which can detect erroneous HOV sensors for the purpose of minimizing erroneous HOV degradation reporting. Under this primary objective are three goals: Firstly, review existing methods in machine learning to achieve a clear understanding of algorithms that are likely to work for the task of identifying HOV misconfigurations. Secondly, test the effectiveness of the methods identified in the literature survey for the purpose of erroneous HOV sensor detection. Lastly, evaluate HOV degradation results for any misconfigured sensors detected using selected machine learning algorithms over an entire Caltrans district.

Findings for these three goals have been described within the final report. An additional byproduct of this project is a functioning computer program which performs three tasks:

1. Uses machine learning algorithms to detect potential erroneous HOV sensors using 5-minute traffic sensor counts.
2. Calculates percent degradation for HOV sensors in conformance with FHWA guidelines using hourly traffic sensor counts.
3. Compares degradation between erroneous HOV sensors and their corrected values to assess magnitude of change.

WHAT IS THE BENEFIT?

Automated detection of misconfiguration errors provide a more efficient and timely way of finding problems with PeMS data and field elements. In addition, it improves the efficiency and reliability of every future project that uses HOV data from PeMS for any type of analysis, because the initial step of checking that the data are trustworthy will have been completed.

Honest and accurate assessment of HOV-lane facilities performance show that the reported degradation is greater than actual degradation. This will obviate the need to bring a wrongly degraded facility into compliance under FHWA guidelines thus enabling Caltrans to provide more flexible operating policies for HOV-lane facilities.

Increasing the quality of information available to Caltrans management directly improves investment decisions related to the operations of HOV-lane facilities. Better decisions translate into better environmental outcomes and save money by preventing unnecessary projects.

LEARN MORE

The final report will be posted to this website when available:

https://dot.ca.gov/programs/research-innovation-system-information/research-final-reports

IMAGES

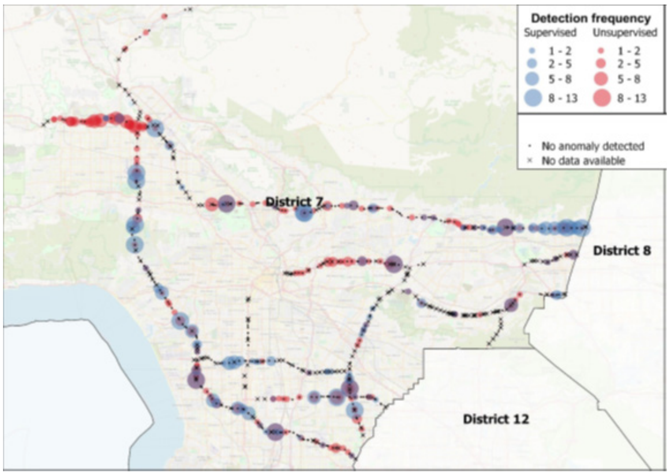

Image 1: Map of misconfiguration detection frequency in District 7 by unsupervised learning (red dots) and supervised learning (blue dots) where larger dots indicate more detections per sensor

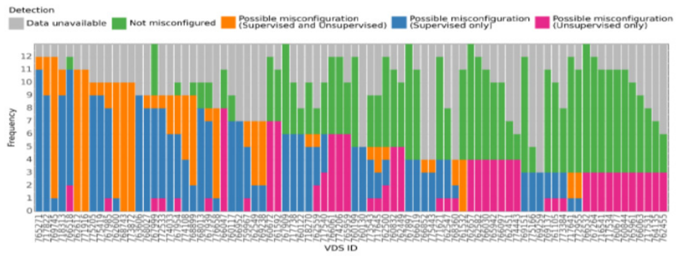

Image 2: Sorted frequency distribution of misconfigured sensor detections for quarterly analyses from 2018-Q1 to 2021-Q1, truncated to only sensors with at least two detections

Table 0-1: AM Degradation change from reassigned misconfigured lanes

			AM (Existing Erroneous)						AM (Corrected)						
Erroneous HOV ID	Correct ID from ML	Correct ML lane #	VMT	VHT	Avg Speed	Days with data	Days <45mph	% degraded	VMT	VHT	Avg Speed	Days with data	Days <45mph	% degraded	Change in % degraded
718313	718312	Lane 1	203,557	8,941	22.8	100	90	90%	236,022	5,306	44.5	100	61	61%	-29%
762549	717742	Lane 1	179,209	7,585	23.6	86	76	88%	139,092	7,008	19.8	86	70	81%	-7%
717822	717821	Lane 1	139,992	8,142	17.2	122	93	76%	116,964	6,717	17.4	122	71	58%	-18%
762500	717121	Lane 2	327,215	8,355	39.2	92	56	61%	158,306	3,339	47.4	103	23	22%	-39%
774055	774053	Lane 1	177,251	4,053	43.7	71	36	51%	17,391	400	43.5	7	4	57%	6%
769745	769744	Lane 3	174,370	4,134	42.2	105	42	40%	74,622	1,737	43	105	25	24%	-16%
718270	764604	Lane 2	63,883	1,250	51.1	86	22	26%	46,891	689	68.1	86	0	0%	-26%
769238	718287	Lane 1	153,222	2,509	61.1	75	3	4%	76,581	1,062	72.1	67	0	0%	-4%
768743	717152	Lane 4	165,147	2,690	61.4	105	1	1%	43,277	696	62.2	104	0	0%	-1%

Table 0-2: PM Degradation change from reassigned misconfigured lanes

			PM (Existing Erroneous)						PM (Corrected)						
Erroneous HOV ID	Correct ID from ML	Correct ML lane #	VMT	VHT	Avg Speed	Days with data	Days <45mph	% degraded	VMT	VHT	Avg Speed	Days with data	Days <45mph	% degraded	Change in % degraded
718313	718312	Lane 1	154,417	7,557	20.4	104	96	92%	268,933	6,573	40.9120903	103	42	41%	-52%
762549	717742	Lane 1	82,329	4,493	18.3	85	75	88%	97,785	5,282	18.5116741	85	75	88%	0%
717822	717821	Lane 1	213,498	5,841	36.6	85	74	87%	141,360	2,479	57.0204894	85	0	0%	-87%
762500	717121	Lane 2	176,747	4,237	41.7	73	46	63%	151,376	2,954	51.2522828	66	4	6%	-57%
774055	774053	Lane 1	187,590	3,375	55.6	104	8	8%	71,018	1241.42545	57.2064156	104	8	8%	0%
769745	769744	Lane 3	125,168	2,250	55.6	72	3	4%	13,727	277	49.547802	7	2	29%	24%
718270	764604	Lane 2	174,707	2,931	59.6	98	4	4%	148,378	2132.96294	69.5641154	98	2	2%	-2%
769238	718287	Lane 1	216,681	3,597	60.2	127	3	2%	93,427	1,290	72.4386819	127	1	1%	-2%
768743	717152	Lane 4	209,766	3,796	55.3	89	0	0%	55,243	787.163298	70.1800886	102	0	0%	0%
Legend:	Not Degraded (≤10%)		Slightly Degraded (10 – 49%)		Slightly Degraded (10 – 49%)		Very Degraded (50 – 74%)								

Image 3: Degradation Calculation Results Table