PERFORMANCE MEASURES FOR TRAFFIC SIGNAL PEDESTRIAN BUTTON and DETECTOR MAINTENANCE

by

Corresponding Author
Jay Grossman
Elkhart County Highway Department
610 Steury Ave.
Goshen, IN 46528
Phone 574-534-9394
Fax 574-533-7103
jgrossman@elkcohwy.org

Charles McKenzie
Trine University
54821 Kristi Lane
Osceola, IN 46561
Phone 574-210-5164
cpmckenzie@my.trine.edu

Darcy M. Bullock
Purdue University
West Lafayette, IN 47097-1284
Phone 765-494-2226
darcy@purdue.edu

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ABSTRACT

The use of high-resolution data collected by traffic signal controllers has been developed and used for engineering related performance measures over the past ten years. This data can also be used to develop maintenance related performance measures to help signal system operators find and correct faulty or misconfigured equipment in a timely manner, returning the system to optimal operation and efficiency. This research looked specifically at pedestrian buttons and vehicle detectors. Pedestrian button performance measures were developed to identify abnormal output from them. Determination of vehicle detector faults was also performed using an algorithm that compares current operation of a detector, based on the number of calls placed, to a historic baseline for the same detector. The length of the window of historic data needed to create a useful baseline was evaluated, as well as the standard deviation threshold used to indicate errors. A system of only identifying errors after three consecutive values above the threshold was implemented to reduce the number of false errors reported. The methodologies described were shown to be effective in detecting both complete detector failures as well as intermittent failures.
INTRODUCTION

Performance measures relying on high-resolution data are increasingly used within the industry to evaluate and optimize the operation of traffic signals [1]. These performance measures have generally been used for engineering functions – analysis of split failures, arrivals on green, amount of green time, and coordination. The log files downloaded from traffic signal controllers that enable performance measures also allow for uses that are more closely aligned with maintenance functions. The log files contain information about all detector calls placed, phases serviced, pedestrian activations, etc. Using this data, useful details about the operation of a traffic signal can be derived. Detection failures, abnormalities and other errors can be identified, alerting the system operator and allowing the problems to be corrected in a timely manner. Examples presented include: verification that pedestrian call buttons are operational, detection of abnormal call button activity, and detection of abnormal vehicle detection. Parameters for developing the historical baseline for comparison are developed, as well as recommendations for identifying errors versus this time line.

MOTIVATION

Finding intermittent errors and abnormal behavior in signal system detectors is a difficult task. Currently, agency staff typically only look for these types of errors in response to obvious operational problems and/or complaints from the public. Developing scalable longitudinal techniques to examine the behavior of each detector (pedestrian or vehicle) in a system, over a number of days, is needed to pro-actively manage modern traffic signal infrastructure. The goal of this research is to develop a method that can be automated and completed on a recurring basis by a central signal system. Potential detection errors can then be identified by the central system, and a manageable list of potential problems can be created for agency staff to then investigate.

Detection errors in signal systems can create large losses in operational efficiency. For instance, if a pedestrian call button malfunctions and places a constant call for a walk phase, the signal may be continually forced out of coordination, and user delay will increase dramatically. Malfunctioning vehicle detectors may have similar effects on the system efficiency, or, if not detecting vehicles at all in a phase, create unsafe conditions as drivers decide to proceed illegally on red after waiting through a number of cycles.
Another motivation for this research is to better identify detector errors. While some tools for identifying detection failures already exist [2, 3, 4], notably for inductive loop systems, developing a tool that can use any type of system detector and identify abnormal behavior is becoming increasingly important as detection at signals is becoming more diverse and moving beyond inductive loops. Video systems, thermal sensors and radar detectors do not lend themselves as easily to the classic detection failure tools that look at the change in electrical properties of the circuit. Misalignment or atmospheric effects can cause detection problems in these newer systems that are difficult to detect. The detector may still be working and placing calls, but not at a ‘normal’ rate.

LITERATURE REVIEW

Audelo, et al., [2] proposed using event log (high-resolution) data to determine detector errors. Their approach focused on calculating the cumulative duration that detectors are ‘on’ or ‘off’ and comparing these values to 90th, 95th, and 99th percentile values. These thresholds were then used to determine if a detector was in error mode or not. Stop bar and advanced detector thresholds were calculated separately. Recommendations for detector fault thresholds were determined.

TEST SITES AND INFRASTRUCTURE

This study was conducted using data collected largely from the Elkhart County, Indiana, County Road 17 corridor. This corridor was connected via fiber-optic in 2011, with controller, cabinet and server upgrades allowing high-resolution data from each controller to be uploaded and stored in a central database. Traffic volumes along County Road 17 range from 7,000 vehicles per day to over 30,000 on a ten mile long, four-lane expressway. The County Road 17 Corridor is shown in Figure 1.
Intersections in this corridor have a variety of detection technologies deployed including: inductive loop, video, thermal and radar. The variety of detection provides a useful test bed for detection related research.

Data from the City of Mishawaka, Indiana, was also used for validation of error detection algorithms. Mishawaka gathers and records high-resolution controller data from a large portion of their city’s signals following a system upgrade in 2013. The use of Mishawaka’s data provided a check on the transferability of the methodologies developed on the Elkhart County system.
PEDESTRIAN CALLS

Operational Verification

An ongoing issue for system operators is verification that signal equipment was installed and configured properly. The use of high-resolution data can be used as a type of ‘as-built’ verification that the detectors and other equipment was properly installed during construction and is operational.

Pedestrian call buttons at intersections in suburban locations may be activated infrequently. Elkhart County has two intersections with pedestrian call buttons, and at each location there is little activity on two of the walk phases, as there is no development in those quadrants. If call buttons at these locations were inoperable, it is unlikely the agency would be aware of this until a citizen complaint was received.

As a test of the system, and as a demonstration of the ability of high-resolution data to verify operations, each of the pedestrian call buttons at the intersection of County Road 10 and County Road 17 was activated by a staff member in the same hour of one day. The data log file on the server was then analyzed, and graphs created for that day. Figure 2 shows the number of pedestrian calls recorded on the test day, per hour, and by phase assignment. As can be seen, all of the pedestrian buttons can be verified as being operational. Figures 2b and 2c show that, except for the staff member conducting the test, phase 4 and 6 are seldom used.
Figure 2 Pedestrian calls by hour and phase at the intersection of CR10 and CR17, demonstrating that all call buttons are operational after staff activated each button in the 14:00 hour.

Call Button Error Detection

In suburban situations, traffic signals are often not programmed with the phase time required to accommodate pedestrian walk times. Due to the infrequency of pedestrian calls, it’s more efficient to optimize the phase splits for the vehicular traffic, and allow the signal to exit the coordinated pattern when a pedestrian phase is called, and then transition back into coordination after the call has been served. If a pedestrian call button malfunctions and errantly places numerous (or constant) calls for the pedestrian phase, major losses of efficiency and coordination can occur. Therefore, a check on pedestrian calls at an intersection is thought to be a useful maintenance related performance measure.

As a study of pedestrian call activity, the Elkhart County intersection at County Road 10 and County Road 15 was analyzed. This intersection can be seen in Figure 3.
Figure 3 County Road 10 at County Road 15, Elkhart County, Indiana (Source: Google Maps).

Figure 4 shows the number of pedestrian calls at this intersection, per hour, for a three day period in July. The data from July 15, when compared to the day before and the day after, can be seen to be abnormally high for this period. As seen in Figure 3, this location is not near any businesses or events that might generate late night pedestrian activity, there was no underlying cause found for this behavior. Analysis of this problem revealed that an electrical storm in this area on July 15 had put the call buttons into an erratic pattern, probably due to a voltage surge. This was an equipment error that should be identified so that the agency can correct the problem.

Figure 4 Pedestrian calls, per hour, at the CR10/CR15 intersection for three consecutive days.
Figure 5 shows pedestrian calls per hour at the intersection of Main and Mishawaka Streets, in the City of Mishawaka for July 4th and 5th. The average number of calls per hour for this intersection for the previous two weeks, for the same days of the week, is also plotted. As can be seen, there is an abnormal peak on the evening of July 4th. In Figure 6 it can be seen that this location is urban, and adjacent to a riverside park. Unlike the abnormal activity at County Road 10 and County Road 15, the peak at this location is explainable, due to a fireworks show in the adjacent park that night. While a system should be able to detect abnormalities and alert operators, it will still take judgment to determine if these abnormalities are equipment errors.

Figure 5 Pedestrian Calls, by hour, at Main/Mishawaka on July 4 and 5 with two week historic baseline, by day of week, plotted.
VEHICLE DETECTOR ANALYSIS

Methodology

Developing a methodology for identifying potential errors in vehicle detectors is also important. A central system can then analyze the data for detectors system-wide and alert operators to any potential problems that need to be reviewed.

The major components in this task are: creation of an appropriate historical baseline from which comparisons can be made, determination of a threshold for what defines a probable error, and a means of reducing false error identifications.

High-resolution log data being communicated to a central database and stored provides a good platform from which to build a baseline of historic data for a detector. This provides a range in timeframe or data types that can be incorporated in a baseline.

In the initial creation of a baseline for a detector it was determined that the best baseline for comparison would use only historical data from the same detector. Given the large variation in detector types, functions and traffic, this may seem obvious. A second determination was to develop a baseline that would compare detector functions for a given day of the week only to data from the same day of
the week. There are large differences in traffic volumes, peak times, etc., by day of week. Detector data
for a Monday is thereby only compared to other Monday data. The final point in creating a baseline is
determining how many previous weeks of data are needed. A long analysis period will require more
computational resources, while a short period may not build an adequate representation of ‘normal’
operation. Determination of this period is explored in the examples that follow.

This study used binned hourly detector calls to form the baseline. As will be shown in the following
examples, hourly bins provided enough resolution to detect even intermittent errors. Again, smaller
bins may provide more resolution but at a cost of computational time. These bins were then averaged
by hour of the day and day of the week. Standard deviations were then calculated for each hourly bin
over the study period. A detector’s current call volume, per hour, was then compared to this baseline,
and a range of standard deviation thresholds was used to generate potential error flags. Trial and error
determined that a standard deviation range of 1.5 to 2.0 produced meaningful results. This is explored
in more depth in the following examples.

The final step in this study’s methodology was to try and reduce the number of isolated potential errors
identified, reporting just those most likely to be indicative of true errors. As with any real-world system,
there is some randomness and inherit variability in the data from a detector. Instead of reporting every
individual instance of an hourly detector count being outside of the standard deviation threshold, a
system was put in place that only reported an event as an error if it was the third hourly count in a row
that was outside the threshold. Again, this will be shown in detail in the following examples.

**County Road 17 and Beck**

Figure 7 looks at a single day’s data for a detector at the intersection of County Road 17 and Beck Drive.
The historical baseline for this detector is shown as a dashed line, with the current day’s counts shown
as a solid line. Figure 7a plots the historical average for just one prior day, the week before. It then
identifies any event above a standard deviation of 1.5 as a potential error. This is an example of a short
historical comparison window, with no cleaning of isolated potential error identifications.
Figure 7 Comparison of error analysis for detector 18 at CR17/Beck for March 12, 2014, highlighting error periods based on a single hour above standard deviation threshold of 1.5 (Figures a, c, e, f) and three error hours in a series above threshold (Figures b, d, h) with one through four weeks of historical data used to create the baseline for comparison.
Figure 7g shows the same detector analysis, but using four prior days of data to create the baseline for comparison. As can be seen, the number of events flagged does not change much from the case of Figure 7a with only one day of prior data for comparison. Figures 7c and 7e do the same analysis with two and three weeks of prior data respectively. Each of these figures do not try to remove isolated events.

Figures 7b, 7d, 7f, and 7h show the same detector analysis, but with events being flagged only if they are the third consecutive event above the threshold of 1.5 times the standard deviation. As can be seen, applying this requirement reduces the number of events identified, and helps identify events more likely to be true errors versus random variations.

The amount of prior weeks of data needed to create a good baseline for comparison can also be seen in this data. One week of prior data, as in Figures 7a and 7b, demonstrates a number of isolated events identified as potential errors. With two weeks of prior data, as in Figures 7c and 7d, the error analysis is already noticeably improved, with fewer random or isolated identified events. Adding three and four weeks of prior data makes some minor improvement over two weeks of data, but not a considerable improvement. There is little change between the graphs using three and four weeks of data, suggesting that using four weeks of data is probably not required for accurate error identification.

Figure 7 clearly indicates there may be an error on this detector on the analyzed day, with detections dropping to zero in the middle part of the day. This is a video detector aimed to the north, and there was a wet, sticky snow event on this day, blowing strongly from the north and coating the north face of traffic equipment with a heavy coating of snow. The effects to a signal head after this event can be seen in Figure 8. The on-board heater in the video detector eventually cleared the snow from the lens and the detector resumed normal operation. The central system’s detector error reporting feature did not identify any problem with this detector during this period.
Figure 8  Coating of snow on traffic signal lenses, March 12, 2014.  (Source: The Elkhart Truth)

County Road 17 at County Road 14, Early January

Figure 9 shows a similar analysis of detector counts at the intersection of County Road 14 and County Road 17. In the interest of brevity, only two evaluation cases are shown. Figure 9a identifies all individual errors (no smoothing) with a baseline using just one week of prior data. Figure 9b indicates only the third potential error in a series, with four weeks of prior data. Figure 9b can be seen to provide a more accurate identification of errors than Figure 9a. It is interesting to note the results of January 8th in both Figures 9a and 9b. The effects of the New Year’s day holiday one week before can be seen in the plotted averages of prior data for both the one week and four week baselines, creating larger than normal standard deviations in the data and causing both analyses to miss what should be identified as potential errors (zero detections). The four-week baseline used in Figure 9b allows the potential zero count errors on January 6th and 7th to be identified, which the one-week baseline of Figure 9a did not.

In this instance, the apparent errors in the detector calls between January 6th and January 9th are the result of a county-wide snow emergency and travel ban. Obviously the ban worked better on January 6th than the subsequent days. This is an example of an operator being able to determine if system identified potential errors are accurate or not.
Figure 9  Error analysis of detector 12 at CR14/CR17 intersection showing indication of errors based on standard deviation greater than 2.0 based on one week and four weeks of prior data.
**County Road 17 at County Road 14, Late January**

Figure 10 shows another example of a potential intermittent detector error, identified through the use of high-resolution data. Figures 10a and 10b show the week of January 19-25 for detector 12 at County Road 14 and County Road 17. Starting about January 23\textsuperscript{rd}, the detector is reporting zero calls in the over-night hours, but operating at near normal levels during the midday. Figures 10c and 10d show the following week of January 26-February 1. The odd night-time detection problem seems to persist, more or less, until January 31. The error threshold used in this example was 2.0 times the standard deviation. Figures 10a and 10c identify all individual errors, Figures 10b and 10d identify the third potential error in a series. Again, Figures 10b and 10d, with smoothing, appear to identify the appropriate errors with fewer random identifications.

Noticing a detection error at this location, a maintenance technician was dispatched to investigate. This detector is a thermal sensor connected to an in-cabinet video processing unit. The technician, while checking the cables between the video feed and the processing units found this unit’s connection had a short in the cable. Being a very cold winter, the cable apparently shortened in the night enough to short out the video feed, but when temperatures increased during the day, the video feed resumed and the detector operated normally. This type of intermittent error is very difficult to detect with traditional means. The central system’s current detector fault reporting mechanism did not identify this as operating improperly.

An interesting result seen in this case is that the baselines used for comparison in the week of January 26-February 1 included the data from the week prior, when the detector began to fail. The earlier week’s data was, therefore, actually better at identifying the problem as it was cleaner. If a detection problem persists for multiple weeks, it is conceivable that using the methodology employed in this study will eventually consider that behavior ‘normal’ and identify no errors. Holiday periods or other abnormal traffic flow periods may also cause false error detections, and suggest that a one or two week period of prior data for comparison may not be as good as three weeks or more.
CONCLUSIONS

High-resolution data collected by a signal system can be used to effectively verify installation and configuration of traffic signal components, ensuring that detectors are mapped to the right channels and phases, and place calls when activated.

This data can also indicate malfunctioning equipment, whether it’s placing too many calls, or too few. By comparing the operation of a detector or pedestrian push button to a historical baseline, and then defining an error threshold based on standard deviation, more difficult transient errors can also be identified.
Results from analysis of data in Elkhart County suggest that a useful error threshold may lie between 1.5 and 2.0 standard deviations. However, it seems useful if this value remains user definable given the variations between intersections and detector traffic patterns.

Analysis also showed that using four weeks of data to develop a comparison baseline yielded the most accurate error determinations. However, there was little improvement in accuracy over using three weeks of data. Using only one week of data was not very accurate, and resulted in a large number of errors identified.

Only identifying errors after three consecutive periods outside the error threshold helped reduce the number of extraneous potential errors identified, while still identifying any real detection problems.

This approach to identifying detector errors appeared well suited to use with newer detection technologies. It was able to identify intermittent errors, and errors where the equipment was technically still functional, but obscured or misaligned.

Incorporation of these algorithms in a commercially produced central system should allow for more efficient use of an agency’s staff time, and maintain a higher level of system maintenance and efficiency. The central system can identify suspect devices, allowing the agency’s staff to then investigate the root cause of any abnormalities, catching detector failures sooner.

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