Detection and Correction of Inductive Loop Detector Sensitivity Errors by Using Gaussian Mixture Models

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Inductive loop detectors (ILDs) form the backbone of many traffic detection networks by providing vehicle detection for freeway and arterial monitoring as well as signal control. Unfortunately, ILD technology generally has limited the available sensitivity settings. Changing roadway conditions and aging equipment can cause ILD settings that had been correct to become under- or oversensitive. ILDs with incorrect sensitivities may result in severe errors in occupancy and volume measurements. Therefore, sensitivity error identification and correction are important for quality data collection from ILDs. In this study, the Gaussian mixture model (GMM) is used to identify ILDs with sensitivity problems. If the sensitivity problem is correctible at the software level, a correction factor is then calculated for the occupancy measurements of the ILD. The correction methodology developed in this study was found effective in correcting occupancy errors caused by the ILD sensitivity problems. Single-loop speed calculation with the corrected occupancy increases the accuracy by 12%. Since this GMM-based approach does not require hardware changes, it is cost-effective and has great potential for easy improvement of archived loop data quality.

The inductive loop detector (ILD) is one of the primary traffic detectors in use today (*1*). ILDs are commonly used for both intersection detection and freeway monitoring and data collection. ILDs have been used for years at the operations and planning levels to identify areas in need of improvement with regard to congestion and capacity. More recently, intelligent transportation systems applications have begun using ILD data. An example is the Washington State Department of Transportation (DOT) flow map, which displays current traffic conditions. Other applications, such as tolling, also use ILDs.

As uses have increased, so has concern over data quality. This concern has led to increased interest in research focused on improving ILD data quality, particularly for future applications such as active traffic management and monetarily sensitive applications such as tolling. Satisfying the higher data quality demanded by these applications may require either replacing or tuning up existing detectors. Replacement costs time, money, and labor, whereas tune-up may

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save some replacement costs; there are also labor costs in visiting the sites and diagnosing errors.

Both solutions may face a problem. Most ILD amplifier cards currently available do not have continuous sensitivity-level settings. Instead, ILD sensitivity settings are generally in powers of 2. For example, Sensitivity Level 3 might detect an inductance change of 0.16%, and Sensitivity Level 4 would detect a change of 0.08% and Level 5 a change of 0.04% (*2, 3*). Sensitivity levels may also be expressed in absolute inductance change rather than percentage of change, depending on the ILD amplifier manufacturer and its detection algorithms. This sensitivity level configuration virtually guarantees some level of sensitivity error because the ideal sensitivity setting may be unattainable. Zhang et al. (*4*) found that approximately 80% of the ILDs in the Puget Sound region have noticeable sensitivity problems.

To diagnose and fix the sensitivity-level errors requires a different course of action. In this study, the Gaussian mixture model (GMM) is used to address the ILD sensitivity problems in two steps. The first step is to fit the on-time (OT) data from an ILD with a GMM. The properties of the fit model will then be used in the second step to identify errors and to generate correction factors to improve the ILD's output data. The GMM fits the data and can be used to identify outlying data. This ability is self-supporting to some degree because each detector is fit with its own GMM and the statistical nature of the GMM allows for identification of those outlying points. This method is in direct contrast to the simple threshold methods, which draw an arbitrary threshold and discard all data beyond the threshold as invalid. Meanwhile, this GMM methodology can reduce the labor costs for diagnosing errors. For cases with mild sensitivity-level errors, this method can also correct the ILD's sensitivity so that hardware repair or replacement may not be necessary.

REVIEW OF LITERATURE

ILD error detection research is decades old, with most modern research split into two broad categories: hardware-based methods and software-based methods. Hardware correction research is largely based on work by Chen and May, which focused on analyzing the output signals from the amplifier card to identify errors affecting data quality (*5*). Before the work by Chen and May, hardware-based methods largely focused on diagnosing electrical problems in wiring or used specialized tools (*1, 6*). Recently, hardware-based research has grown to include event-level data diagnostics, in which equipment is used to directly read an ILD's output signals instead of reliance on data that have been aggregated by the cabinet's controller (*7–10*). This research has generally studied errors such as crosstalk, pulse breakup,

chatter, and hanging. Although these studies have also checked ILD sensitivity levels, they have only corrected sensitivity errors at the hardware level.

To aid in diagnosing ILD errors, Cheevarunothai et al. created a new hardware-based system called the advanced loop event data analyzer (ALEDA) to collect event-level data for ILD error analysis without interfering with the normal operations of the traffic controller connected to the ILD (11). The system details are described by Nihan et al. (12). Further research has expanded the system's capabilities, particularly with regard to dual-loop detectors (9, 10, 13). Dual-loop detectors, or speed traps, use the arrival time of a vehicle at each loop to determine speed and thus are particularly vulnerable to sensitivity errors, which can distort the size of the ILD detection zones. One feature of the ALEDA system is the ability to compare the relative differences in sensitivity between the two ILDs and guide the users to fix the sensitivity problem if possible.

Software-based research has generally been conducted with aggregated data as part of data cleaning for other research. Many of the methods used to clean aggregated data also derive from the work by Chen and May (5), which connected hardware errors with the aggregated data's characteristics. Further studies have expanded the available techniques and application conditions (14–17). This software-based aggregated data branch of research has generally focused on deriving various thresholds to indicate bad data. Examples include thresholds for the percentage of time a given ILD can report as completely occupied or above a given occupancy threshold (16). For example, even in the heaviest-flowing traffic it is unreasonable to see 100% occupancy for extended periods. Other examples include limits on volume derived from traffic flow theory, in which an upper limit is placed on the number of vehicles that can plausibly pass a given point in a given period (16). For example, even at peak flow rates it is difficult to see vehicle volume at higher than one per second passing over an ILD. Aggregated methods have generally drawn a boundary and discarded all data beyond the boundary as being flawed. Software-based ILD event data analyses have almost exclusively been undertaken by the same researchers conducting hardware-based research as an extension of the programming required to collect the event data and perform the hardware diagnostics.

From this review, this research proposes using GMM to model the OT data collected to detect and correct the ILD sensitivity-level error. GMM is popular in many fields and has been used for machine learning. In the field of robotics, GMM has been used to control hand grasping strength (18). Speech recognition has used GMM to identify specific speakers (19). The GMM is a simple model that is useful for clustering operations that are time-variation insensitive (20). The GMM methodology used in this research may be applied to hardware-level data or to aggregated data.

OT MODELING

ILD Detection Zone and OT Calculation

ILDs are composed of a coil or wire, or loop, embedded in a roadway; a loop amplifier card; and a signal controller. ILDs detect a passing vehicle through decreases in the loop coil's inductance caused by eddy currents in the vehicle's metal body induced as it passes through an electromagnetic field generated by the loop. Numerous factors influence the ease of vehicle detection by an ILD, including operating frequency, sensitivity-level setting, depth of loop coil in the pavement, height of the vehicle being detected, metal content and shape in the vehicle, and many more. Isolating the effects of each of these factors would require extensive research, but the sum total effect is to increase or decrease the detection zone size of the ILD as seen in Figure 1a. Figure 1b shows the extension for dual-loop detectors.

The length of the loop coil is defined as L_L. The difference between the loop coil length and the actual detection zone length is $2d$ as seen in Figure 1a. It should be noted that d will be positive for oversensitive loops and negative for undersensitive loops. The actual detection zone width is L'_L. For dual-loop detectors, the Washington State DOT nomenclature calls the upstream loop the M loop and the downstream loop the S loop. Dual-loop detectors add parameters describing the distance from leading edge to leading edge between loop coils (L) and the leading-edge distance between the M and S loop detection zones (L'). Washington State DOT standards call for a loop width L_L of 6 ft and a distance between the M and S loops (L) of 17 ft.

OT refers to the time that an ILD is occupied by vehicles and can be obtained from the Athol algorithms (21). OT is proportional to the vehicle's length (L_V) and the length of the loop detector coil (L_L) and inversely proportional to vehicle speed (v):

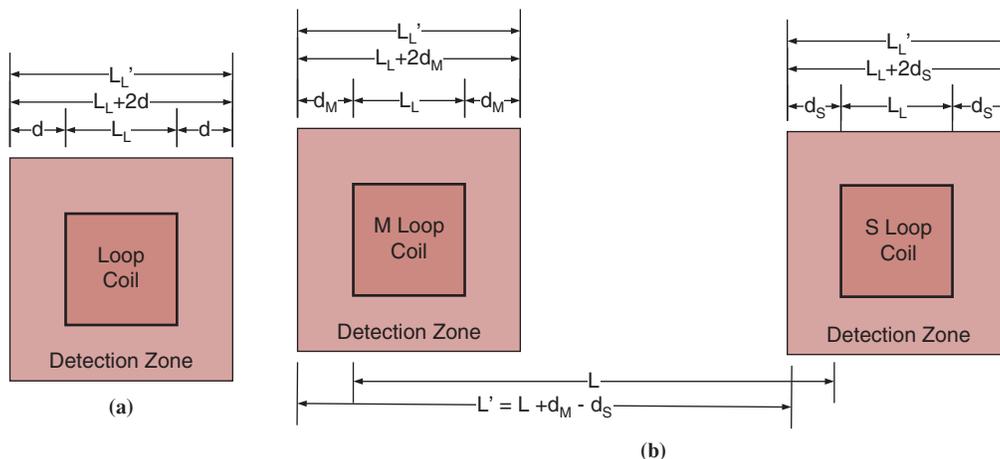$$OT = \frac{L_V + L_L + 2d}{v} \tag{1}$$

FIGURE 1 ILD detection zones for (a) single-loop detectors and (b) dual-loop detectors.

OT Modeling with GMM

Traffic is composed of many vehicle types. These vehicles may be short vehicles or any of a variety of sizes of heavy trucks. Previous work, such as that done by May et al. (*7*) and Wang and Nihan (*22*), have indicated that vehicle lengths and free flow OTs show strong peaks corresponding to short vehicles such as passenger cars. Larger vehicles such as heavy trucks are also evident in the study data. The length and OT data for trucks have a much broader distribution than the same data for short vehicles. With these expectations in mind, the current researchers applied a GMM to the OT distribution data in this study (*23*).

The GMM is well known in machine learning but has not been widely used in civil engineering. The GMM consists of fitting K normal distributions with mean, μ_j, and variance, σ_j^2, $j = 1, 2, \ldots, K$, to the data. One additional parameter, ω_j, is added to weight the normal distributions and make the probability sum equal 1. For this research, each normal distribution is numbered from 1 to K by a weight factor, with the first distribution having the highest weight. The probability of a given OT is thus

$$P\left(OT_i\right) = \sum_{j=1}^{K} \omega_j f\left(OT_i, \mu_j, \sigma_j^2\right) \tag{2}$$

where the function $f(OT_i, \mu_j, \sigma_j^2)$ is the one-dimensional Gaussian distribution probability function, as follows:

$$f\left(OT_i, \mu_j, \sigma_j^2\right) = \frac{1}{\sigma_j \sqrt{2\pi}} e^{-(OT_i - \mu_j)^2 / 2\sigma_j^2} \tag{3}$$

OT will never be negative, and the calculated and observed probabilities for the tails of the distributions are unlikely to match without very large sample sizes.

In practice, the fact that short vehicles make up a very large majority of the traffic stream leads the GMM fitting process to regularly assign the first two distributions to better-fitting short vehicles. When three distributions were used, one distribution was fit to trucks specifically, which dramatically improved the means and variances compared with two distributions. To identify the best single number of distributions to apply to the data, the Bayesian information criterion (*24*) values were calculated for each ILD and model distribution number. The best Bayesian information criterion corresponds to the use of three distributions to fit the data. As more distributions are used, the short-vehicle distribution is fit with more distributions of similar weights. Although the overall fit improves with more distributions, the explanatory power of the model does not improve. Therefore, the number of distributions, K, used for this research is 3.

The OT data were fit with the GMM by using the R statistical software package (*25*) with the MCLUST package (*26, 27*). The k-means technique was used to provide the initial groups that the GMM fitting process used (*28*). The final grouping and fitting process used the expectation–maximization methodology internal to R.

ERROR DETECTION AND CORRECTION WITH GMM

Error Detection

These tests are all executed on the highest-weighted distribution, which will be called the primary distribution hereafter. The primary distribution is assumed to represent short vehicles, which are generally the dominant vehicle group. To determine whether an ILD is working correctly, three constraints can be applied to the primary distribution in Equation 2. The first test involves checking whether the primary distribution mean is a reasonable value compared with the vehicle speeds observed in the area. The second test checks the integrity of the reported distributions to filter out ILDs for which the correction methodology cannot generate a unified solution. The final test checks whether the ILD data indicate that the sensitivity level is not correct. These three tests correspond with three commonly observed types of error.

Type 1 Error

To test whether the primary OT distribution mean is valid, ground-truth vehicle lengths of the detected vehicles are needed. However, a single loop cannot directly measure vehicle length. To overcome this problem, statistical features of OTs and vehicle lengths are utilized:

$$\mu_1 = \frac{\overline{L_{V1}} + L_L + 2d}{v_f} \tag{4}$$

where

μ_1 = mean OT of the primary distribution,
$\overline{L_{V1}}$ = mean short-vehicle length,
d = detection zone offset, and
v_f = maximum free-flow speed in feet per second.

"Short vehicles" refers to those shorter than 26 ft, corresponding to the Bin 1 vehicles in Washington State DOT's dual-loop detection network (*29*). Although a specific short-vehicle length is unknown, the mean of all short vehicles is relatively stable and can be considered known. Wang and Nihan observed that the mean length of short vehicles traveling on Puget Sound area freeways is 15.2 ft (*30*).

Obviously, the detection zone should remain positive in length, which corresponds to $d > -L_L/2$. After $d > -L_L/2$ is substituted in Equation 4, the first constraint condition for the GMM is defined as

$$\mu_1 = \frac{\overline{L_{V1}} + L_L + 2d}{v_f} \geq \frac{\overline{L_{V1}}}{v_f} = \alpha \tag{5}$$

where α is the lower boundary value for the average OT of short vehicles. The α-value can vary according to different roadway environments and loop-detector specifications. When Equation 5 is solved for an average short-vehicle length of 15.2 ft and a free-flow speed of 70 mph, the result is that μ_1 must be at least 0.148 s or 148 ms. Since free-flow speed is normally below 70 mph in Seattle, the threshold of 148 ms was used as the cutoff for this research. When the primary distribution mean is below this threshold, the actual detection zone size ($L_L + 2d$) will be negative in length. This is defined as Type 1 error.

Type 1 error occurs because the ILD is detecting only a fraction of the actual vehicle length. By the time an ILD is undersensitive enough to have a primary distribution mean value below this threshold, it has generally stopped detecting trucks altogether and is detecting only a very narrow distribution of short-vehicle on-times. Figure 2*a* shows the on-time distribution for the M loop on northbound Lane 3 of Station 005es15996. This figure is a typical example of Type 1 error. In Figure 2*a,* the ILD data are shown in black and the GMM fit is shown in red. Almost all of the OT values are less than 150 ms.
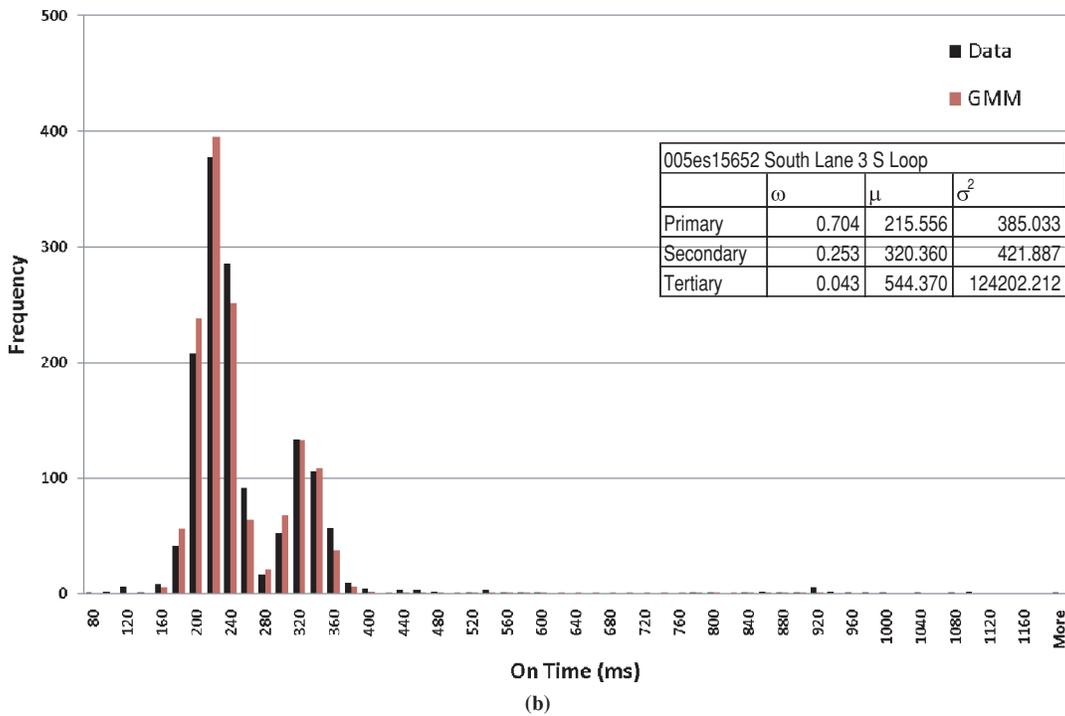
005es15996 North Lane 3 M Loop			
	ω	μ	σ^2
Primary	0.972	119.130	42.949
Secondary	0.024	225.645	16554.258
Tertiary	0.003	269.720	96.623

(a)

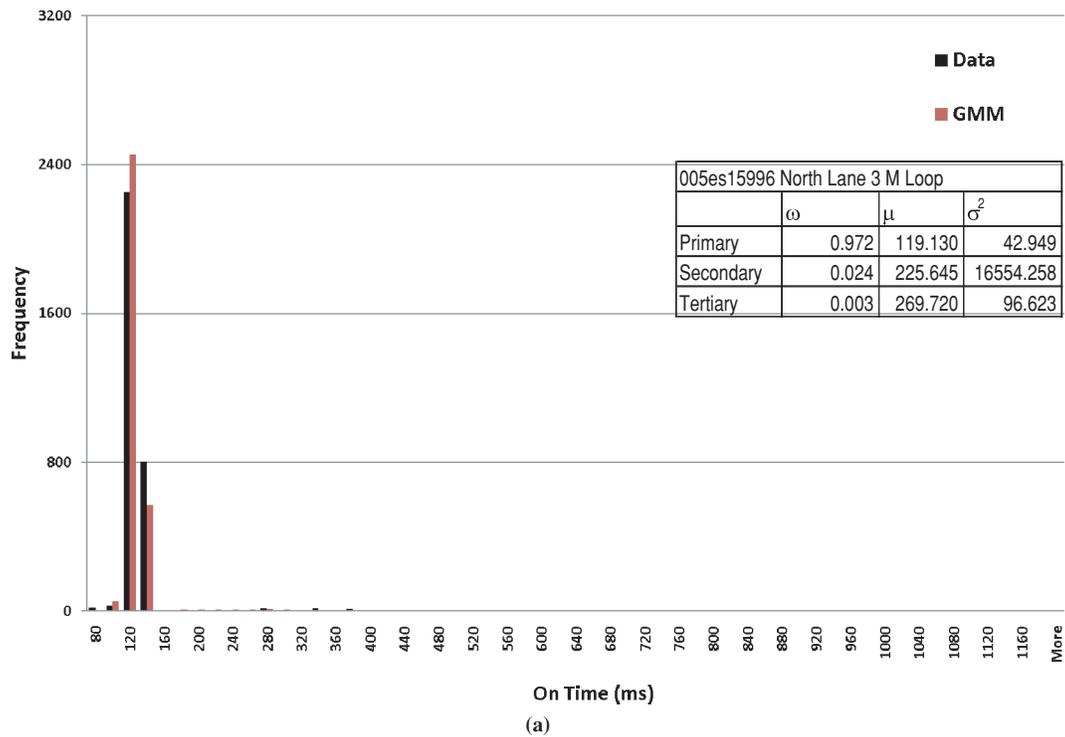| 005es15652 South Lane 3 S Loop			
	ω	μ	σ^2
Primary	0.704	215.556	385.033
Secondary	0.253	320.360	421.887
Tertiary	0.043	544.370	124202.212

(b)

FIGURE 2   Type 1 and Type 2 errors: (*a*) Station 005es15996 northbound Lane 3 M loop and (*b*) Station 005es15652 southbound Lane 3 S loop.

Type 2 Error

The second test is based on studies such as those done by Wang and Nihan (*22*) and May et al. (*7*) that have indicated that short vehicles are narrowly distributed in length. Wang and Nihan found that short vehicles averaged 15.2 ft with a standard deviation of 1.31 ft (*30*). Short vehicles are generally expected to exceed 90% of traffic. The primary distribution of the GMM is expected to correspond to short vehicles and to have the largest weighting factor. The second test condition is

$$\omega_1 > \beta \tag{6}$$

where ω_1 is the weight of the primary distribution and β is the weighting threshold. The β-value can differ according to the roadway environment in different cities. If the second test condition in Equation 6 is not satisfied, the loop is not stable enough to give reliable on-time values. This type of error is defined as Type 2 error. Type 2 errors generally manifest as one distribution that indicates undersensitivity while another distribution indicates oversensitivity. To allow for fitting variation and random effects, the threshold value for the primary distribution weight β was set at 80%. A primary distribution with a weight below this threshold generally corresponds to a fracturing of the primary distribution.

Figure 2*b* shows a typical example of the OT distribution for the S loop of southbound Lane 3, Station 005es15652, which is located on Interstate 5 at Milepost 156.52. In Figure 2*b* the ILD OT data are shown in black and the GMM fit is shown in red. The OT distribution is split into two discontinuous distributions with the weight of the primary distribution less than 80%.

Type 3 Error

The third test checks whether the ILD is producing data that are within acceptable margins of error. If the calculated value of *d* is small enough, the sensitivity of the ILD is at the correct level. Otherwise, sensitivity adjustment is needed. The following equation is used to judge if the sensitivity adjustment is needed:

$$|d| < \gamma \tag{7}$$

where γ is the boundary of allowable ILD sensitivity error in the loop detector system. With Equation 7 substituted into Equation 4, the third constraint condition can be rewritten in terms of the GMM primary distribution mean OT:

$$\frac{\overline{L_{V1}} + L_L - 2\gamma}{v_f} < \mu_1 < \frac{\overline{L_{V1}} + L_L + 2\gamma}{v_f} \tag{8}$$

A ±10% threshold was used for this research. This threshold corresponds to a γ-value of 1.06 ft. The γ-value can vary depending on loop specifications and research goals. If the third test condition (Equation 8) is not satisfied, the loop detector is not producing data within acceptable margins of error. This type of error is defined as Type 3 error. If an ILD is able to pass all three tests, its data are within an acceptable margin of error.

Error Correction

Correcting ILD errors requires that the ILD data be relatively close to correct. Type 1 error is problematic because when an ILD is showing severe undersensitivity, it is completely missing some long vehicles such as trucks and may be missing short vehicles as well. ILDs with Type 1 error cannot be corrected because the monotonic distribution is missing or incorrectly detecting vehicles and the narrow distribution will generate singular speeds and lengths that are not useful.

Similarly, Type 2 error is problematic because there are two distributions where there should be one. The fractured distributions of Type 2 error cannot be corrected with this method because the correction process is based on finding a detection zone offset for the main distribution that corrects the speed and length estimations. When one distribution of a fractured distribution is corrected, the other will be made even more incorrect. Only Type 3 errors are correctible in this manner.

Once an ILD has been selected for correction, the next step is to calculate the detection zone offset *d,* which will account for the shift of the primary distribution. To calculate the offset value requires rearranging Equation 4 to form Equation 9:

$$d = \frac{1}{2}\left(\mu_1 \cdot v_f - \overline{L_{V1}} - L_L\right) \tag{9}$$

Speeds measured by a dual-loop detector are calculated according to Equation 10. The distance between the two ILDs changes according to the detection zone offsets of the component ILDs as seen in Figure 1.

$$v_d = \frac{L}{\Delta t} = \frac{L + d_M - d_S}{\Delta t} \tag{10}$$

where v_d is the measured dual-loop speed and Δt is the difference in arrival times at the two ILD detection zones. Similar detection zone offsets between the M loop and the S loop indicate that the dual-loop speed measurements are not substantially affected. When the detection zone offsets are equal, the dual-loop measured speed will not be affected by the ILD sensitivity errors. Length calculations from dual-loop detectors will still be affected by sensitivity errors because length calculations involve ILD OTs, which will be affected by the sensitivity errors.

GMM APPLICATION

Application Sites

The GMM has been used to detect and classify ILD errors and to develop a correction methodology for application to ILD data. The particular data used to generate the error detection and correction methodology were event data collected with the ALEDA system developed by the Smart Transportation Applications and Research Laboratory at the University of Washington. The ALEDA system directly reads the loop amplifier card's outputs and can collect data from a cabinet without affecting its regular operation. The data used to test the methodology were gathered from 10 dual-loop detectors at three different Washington State DOT highway monitoring cabinets. Dual-loop detectors were chosen to demonstrate both single- and dual-loop correction. Of those 10 dual-loop detectors, 2 were deemed candidates for correction.

The correction process involves actually determining the detection zone offset value *d* that brings the ILD's speed and length measurements into line with expectations. Calculating an expected mean OT is the first step and may be accomplished by using Equation 4 with a detection zone offset equal to zero. For the ILDs in this study segment, a v_f of 64 mph was used. This value was observed

from dual-loop detectors in the area. An ILD was not considered in need of correction unless its primary mean value was beyond the expected value of ±10%. The range of the primary mean value can be calculated by Equation 8: 203 ms < μ_1 < 249 ms for 64 mph. These values change with free-flow speed, loop length, and average short-vehicle length.

Station 005es15652, Southbound Lane 4

The on-time distribution of the M loop on southbound Lane 4 of Station 005es15652 can be found in Figure 3a. The ILD data are shown in black and the GMM fit data are shown in red. This ILD has a primary distribution weight of 88.3% and a primary distribution mean

005es15652 South Lane 4 M Loop			
	ω	μ	σ^2
Primary	0.883	200.215	298.339
Secondary	0.107	258.281	4766.954
Tertiary	0.010	780.269	23092.750

(a)

005es15652 South Lane 4 M Loop			
	ω	μ	σ^2
Primary	0.883	200.215	298.339
Secondary	0.107	258.281	4766.954
Tertiary	0.010	780.269	23092.750

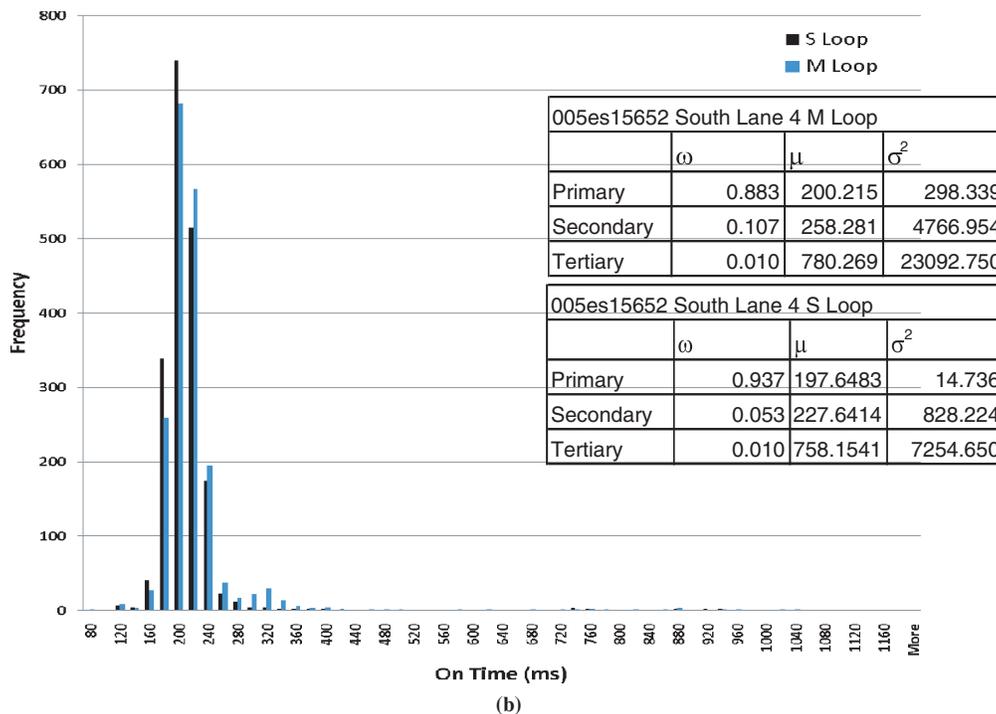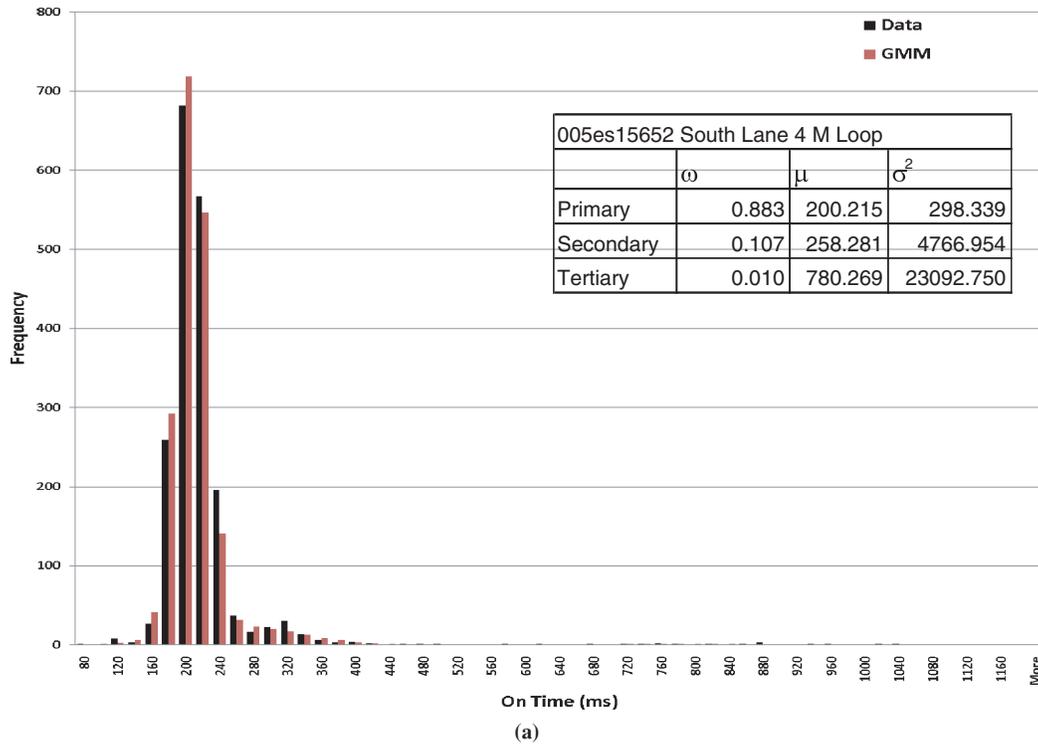| 005es15652 South Lane 4 S Loop			
	ω	μ	σ^2
Primary	0.937	197.6483	14.736
Secondary	0.053	227.6414	828.224
Tertiary	0.010	758.1541	7254.650

(b)

FIGURE 3 Correctible dual-loop detector: (a) OT distribution of Station 005es15652 southbound Lane 4 M loop and (b) detection zone offsets for Station 005es15652 southbound Lane 4 M and S loops.

of 200 ms, which indicates that this loop is suffering from Type 3 error. Similarly, the S loop on this lane also has Type 3 error. There are three features to note:

- The data include a large primary distribution indicative of short vehicles of varying lengths and speeds,
- There is a single primary distribution as opposed to the fractured distribution seen in Figure 2*b,* and
- Although it can be difficult to see in Figure 2*b,* this ILD is clearly detecting long vehicles.

This ILD is part of a dual-loop detector, with the other ILD being similarly undersensitive. The two ILDs together are shown in Figure 3*b,* with the M loop from Figure 3*a* shown in black and the S loop shown in blue. The detection zone offsets, calculated by using Equation 9, for the 005es15652 southbound Lane 4 M and S loops are −1.20 ft and −1.32 ft, respectively. The corrected distance between the two ILD coils is 17.12 ft instead of 17 ft, or less than 1.5 in. of difference. Errors at this scale probably represent similar or less error than the measuring error during installation of the dual-loop detector.

When the ILD sensitivities are incorrect, the length estimates will also be wrong even if the dual-loop speed measurement is correct. In addition, the Washington State DOT dual-loop algorithms will discard results when the length calculations of the two ILDs differ by 10% or more (*8*). The M and S loop length estimations based on dual-loop speed were averaging short-vehicle lengths at about 12.5 ft and 12.75 ft, respectively. After the detection zones are corrected, the dual-loop length results improved to 15.1 ft. The single-loop speed estimations based on Athol's algorithm (*21*) also improved from average estimates of 72 mph and 73 mph, respectively, to 64 mph.

Station 005es15996, Northbound Lane 4

The dual-loop detector at 005es15996 northbound Lane 4 (Figure 4) represents a different story. The M loop is undersensitive and the S loop is oversensitive, which indicates that the dual-loop speed calculation is very inaccurate. The single-loop speed estimations for the M and S loops are also highly affected by the over- and undersensitivity. Inaccurate speed measurements will affect the length calculations. Figure 4*a* shows the M loop in black and the S loop in blue. The M loop primary distribution mean is 195 ms and the S loop primary distribution mean is 251 ms, which are below and above the 10% threshold, respectively. Both M loop and S loop suffer from Type 3 error.

The dual-loop detector in northbound Lane 4 at Station 005es15996 represents a borderline case for correction of ILD data. The main reason is that the M loop is undersensitive enough to begin missing trucks. Figure 4*b* shows the OTs of each ILD by vehicle. When the two ILDs report the same on-time, the point will be on the 45-degree line. The M loop is missing trucks, and its undersensitivity problem is easily seen. The circled area shows where the M loop is measuring short-vehicle length OTs and the S loop is measuring truck length on-times for the same vehicle. The M loop would seem to be suffering a mild form of extreme undersensitivity error similar to that seen in Figure 2*a.* Missing trucks would also explain why the tertiary distribution has such a low mean and high variance. The S loop appears to be beginning a similar descent into error with what may be the beginning of a fractured distribution. The secondary distribution accounts for 12% of the data.

When *d*-values are calculated for the M and S loops, the results are −1.42 ft and −1.16 ft, respectively. Unsurprisingly, the dual-loop

speed measurements are significantly different from the expected 64 mph. The actual distance between the detection zones is 14.42 ft instead of 17 ft. The resulting speeds average 82.7 mph with a median of 77.3 mph. The median value will be used to assess whether the speeds are corrected because the missed trucks and other skewed vehicle detections are a significant weight on the average. After the detection zone offsets are calculated and applied, the average speed is 69.7 mph and the median speed is 65.1 mph, which appear more reasonable for this site.

The M loop calculated average vehicle lengths change from 12.87 ft to 15.73 ft and average lengths calculated by using the S loop change from 18.32 ft to 15.2 ft. The differences in length between the M and S loops virtually guarantee that this dual-loop detector will not report any data back because the two ILDs are virtually incapable of agreeing on vehicle length. The M loop single-loop speed estimation averages 73.3 mph before correction and 65 mph after. The S loop single-loop speed estimate averages change from 57.1 mph to 64.5 mph. The M loop is missing trucks and generally not reporting correct on-times. Correction improves but cannot completely fix this ILD without hardware intervention.

Aggregated Data Versus Event Data

It is inherently more difficult to collect event data than aggregated data, which may be a barrier to the application of this method for ILD data correction. In addition, there are large databases of historical data that would be either invalidated or rendered useless for comparison purposes once hardware correction was instituted. To account for these potential problems the methodology can also be applied with some limitations to aggregated data. Occupancy can be used to find the OT simply by multiplying the percentage of time occupied by the interval length.

Aggregation poses some specific problems. First, only total occupancy is known, which means that only the average vehicle OT can be known. Second, the precision of the aggregated data limits the ability to determine the on-time of a vehicle. For example, when occupancy is recorded to a single decimal place and the interval is 20 s long, the smallest increment of OT that can be used is 20 ms. Finally, segmentation error can occur (*31*). Segmentation refers to the splitting up of a vehicle's data because it is traversing the ILD at the changing of an aggregation interval. Typically, the volume count goes to the first interval and the occupancy is split between the two intervals (*31*).

The first problem can be solved by selecting intervals with only one vehicle so that the average per-vehicle occupancy is also the individual vehicle's occupancy. The second problem, occupancy precision, is more of a database design and data collection problem and cannot be addressed through selection criteria. The third problem, segmentation, can be overcome only by selecting data with a single vehicle and empty intervals before and after.

Table 1 shows the application of the GMM to 20-s aggregated data obtained from the University of Washington's Smart Transportation Applications and Research Laboratory's Datamart (*32*). These data, from August 2009, were screened for segmentation error and for single-vehicle intervals. Approximately 1,200 rows and 1,900 rows of data were used in the aggregated data calculations for Table 1. The event data calculations used 1,900 and 3,150 rows. More variation should be expected from aggregated data than from event data because of the longer collection period involved. The aggregated data were collected over a month, and the event data were collected
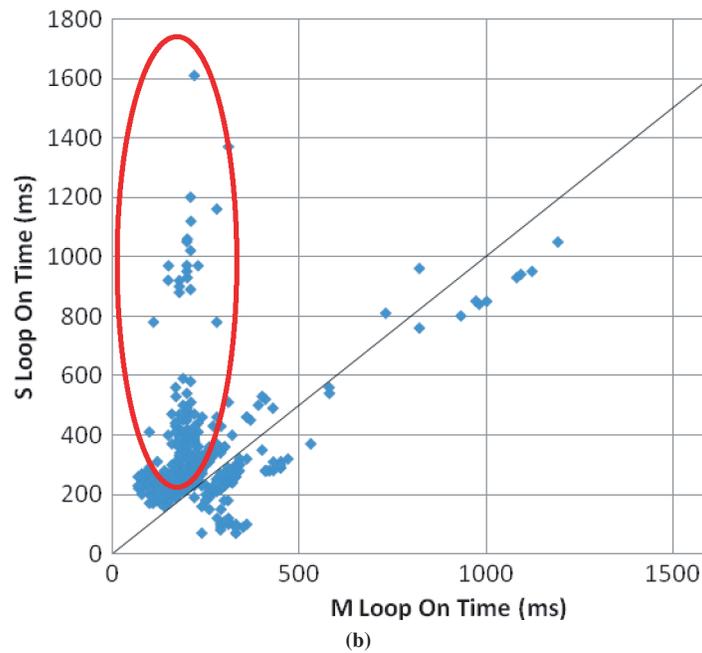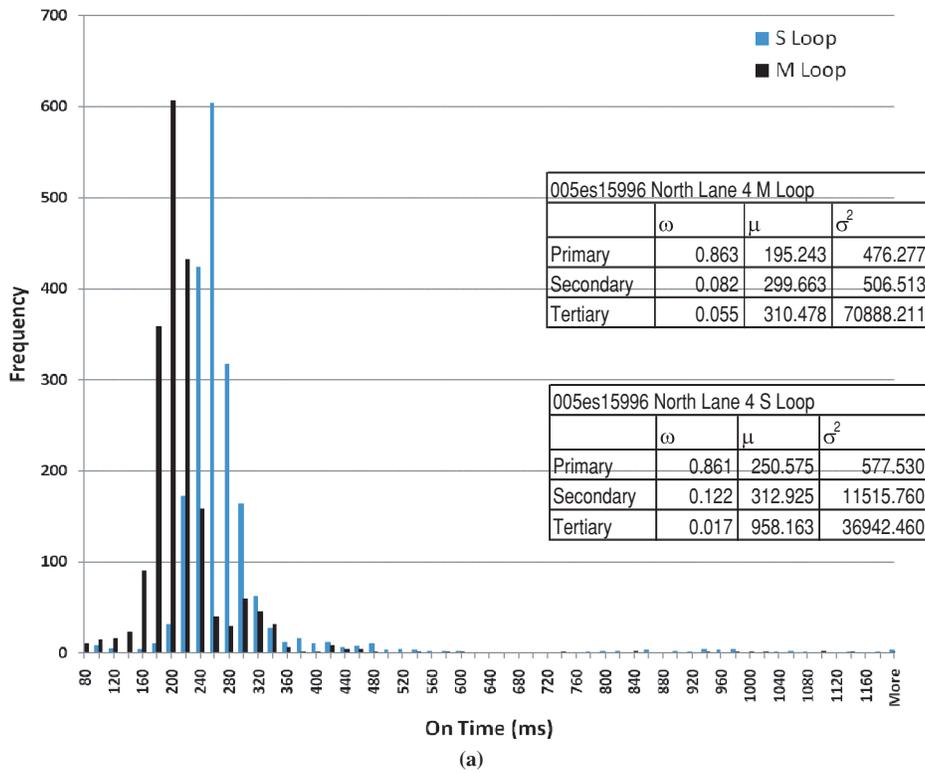
005es15996 North Lane 4 M Loop			
	ω	μ	σ^2
Primary	0.863	195.243	476.277
Secondary	0.082	299.663	506.513
Tertiary	0.055	310.478	70888.211

005es15996 North Lane 4 S Loop			
	ω	μ	σ^2
Primary	0.861	250.575	577.530
Secondary	0.122	312.925	11515.760
Tertiary	0.017	958.163	36942.460

FIGURE 4   Borderline dual-loop detector: (*a*) Station 005es15996 northbound Lane 4 and
(*b*) Station 005es15996 northbound Lane 4 (on-times of each M and S loop by vehicle).

over less than a week at each station. The larger time increment can also be expected to have some impact because 20 ms is the smallest increment instead of 10 ms, roughening the fitting process.

Table 1 shows the GMM fit parameters for the southbound Lane 4 dual-loop detector at Station 005es15652. The M loop fit is very close to the same between the two data sets; in particular, the primary distribution means are less than 1% different. The S loop is not

quite as good a match between the aggregated and event data fits, but the primary distribution mean is still within 2% difference. The weighting factor has dropped, however. Researchers using aggregated data as a primary data source would be advised to examine the thresholds they use for error analysis. Overall, the two data sets would produce comparable results with similar low dual-loop speed errors and comparable detection zone offset values.

TABLE 1   Station 005es15652 Southbound Lane 4 and Station 005es15996 Northbound Lane 4: Event Data and 20-s Aggregated Data

	Event Data			20-s Aggregated Data		
	ω	μ	σ^2	ω	μ	σ^2
005es15652 Lane 4 South						
M loop						
Primary	0.883	200.215	289.339	0.870	201.082	503.429
Secondary	0.107	258.281	4,766.954	0.110	266.039	3,305.956
Tertiary	0.010	780.269	23,092.750	0.020	716.922	117,852.796
S loop						
Primary	0.937	197.648	314.736	0.808	193.882	407.691
Secondary	0.053	227.641	4,828.224	0.163	233.563	427.981
Tertiary	0.010	758.154	17,254.650	0.029	539.890	55,756.877
005es15996 Lane 4 North						
M loop						
Primary	0.863	195.243	476.277	0.786	196.293	536.211
Secondary	0.082	299.663	506.513	0.203	257.338	3,134.329
Tertiary	0.055	310.478	70,888.211	0.011	569.420	56,321.321
S loop						
Primary	0.861	250.575	577.530	0.766	255.283	305.282
Secondary	0.122	312.925	11,515.760	0.171	260.830	18,393.291
Tertiary	0.017	958.163	36,942.460	0.062	307.948	125.010

Table 1 also shows the aggregated and event data GMM fits for the northbound Lane 4 dual-loop detector at Station 005es15996. The primary distribution means for both aggregated data fits are still within 2% of the corresponding event data GMM fits. A correction attempt with either data set would yield similar results. Unfortunately, the weighting factors for the primary distributions are also lower and would indicate that both ILDs suffer from Type 2 error. Again, researchers using aggregated data for their analyses would be advised to consider their threshold values.

Table 2 shows the detection zone offsets calculated with event data and aggregated data as well as the difference between the two. From Table 2, it can be seen that even small differences in the primary distribution mean have a relatively large percentage effect on the detection zone offsets. However, even the large percentage changes are smaller when the loop length is included for calculations. The 005es15652 southbound loop has approximately a 13% change in its detection zone offset, but only 6% in the detection zone. The 005es15996 southbound loop difference equates to about a 5% change in actual detection zone size even though it is a 19% change in offset size.

Overall, either event data or aggregated data would yield similar correction results. The wider availability of aggregated data makes them the more desirable data source for sensitivity analyses. The aggregated data analysis may require revising the thresholds used to determine error types but has the advantage of not requiring any site visits or hardware installation. In addition, the error detection and correction methodology could be built into a database.

TABLE 2   Detection-Zone Offsets

Loop Detector	Event Data	20-s Data	Difference (%)
005es15652 M loop	−1.20	−1.16	3.38
005es15652 S loop	−1.32	−1.50	13.35
005es15996 M loop	−1.44	−1.39	3.43
005es15996 S loop	1.16	1.38	19.04

CONCLUSION

The GMM method presented here has potential for description and analysis of ILD data. The GMM has enabled this research by allowing the research team to statistically isolate short vehicles for comparison with published research. Combining the isolation of the short-vehicle population with Athol's algorithm (*21*) makes it possible to generate correction factors that enable a more realistic mathematical representation of the ILD's detection zone.

Calculation and application of the detection zone offset have allowed the research team to correct the speed and length measurements made at one dual-loop station to satisfactory levels. The Station 005es15652 southbound Lane 4 dual-loop detector showed moderate errors in its component ILDs. These errors were approximately 12% for length and single-loop speed estimation. The fact that both ILDs had similar sensitivity errors kept the dual-loop speed error under 1%. Station 005es15996 northbound Lane 4 shows the limits of the technique. Once an ILD begins to incorrectly detect trucks, there is little that can be done to correct the data completely. Nevertheless, even though this dual-loop detector was not completely corrected because of missing trucks, it was corrected to a significantly more reasonable level of accuracy, which would be acceptable until the ILD could be corrected at the hardware level. This error detection and correction technique is suitable to correct moderate sensitivity-level errors and to identify ILDs that must be corrected at the hardware level.

The methodology can also be applied to aggregated data with results that are similar to those obtained with event data. This approach has the advantage of allowing error analysis across a broad range of ILDs without the difficulties inherent in collecting event data. A correction analysis by using aggregated data can also be used to correct historical data.

This methodology offers researchers and practitioners the opportunity to assess the health of the ILDs whose data they are using. Once the ILDs have been inspected for errors, the ILDs with Type 1 or Type 2 errors can be inspected by maintenance personnel. ILDs suffering from Type 3 error can be corrected by using the calculated

detection zone offset. The use of aggregated data allows practitioners to identify the ILDs most in need of adjustment and allows efficient deployment of resources to reduce labor and equipment costs. For researchers, the use of aggregated data allows identification of flawed data for exclusion or correction and enables increased accuracy with relatively minimal expenditure of effort.

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