Investigating Impacts of Communication Loss on Signal Performance with Use of Event-Based Data

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Reliable communication in a traffic signal network is essential for responsive traffic management. However, communication malfunctions often go unnoticed by transportation agencies because of unfamiliarity with the potential problems and inefficiencies that can arise from poor communication quality. Therefore, this paper focuses on the critical effects of communication loss on data quality and signal coordination. On the basis of regionwide event-based data collected in the city of Tucson, Arizona, a data quality control method with criteria specifying the completeness of event-based data was proposed and implemented. The quantified analysis provides a better understanding of data completeness than is possible by simply scanning real-time monitoring states. The proposed method provides an effective tool that will enable practitioners to diagnose problems with missing data and to evaluate the health and capability of a communication network for event-based data collection. A further investigation of how signal performance is affected by communication loss found unexpected changes in traffic progression, a situation identified by using a statistical analysis method and evaluated by monitoring control delay. The evaluation results for test cases found significant increases in the control delays between 27% and 720% when communication losses occurred. This study provides an innovative data-driven approach that supports smarter asset management of signal communication networks and ultimately will enhance signal performance.

Reliable communication between traffic management centers and traffic signal controllers is essential for responsive traffic management. However, practitioners can find difficulty in prioritizing maintenance activities for communication networks, especially with large networks and limited funding resources. Communication malfunctions often go unnoticed by transportation agencies unless a significant failure, such as a loss of signal coordination, is reported. Therefore, a better understanding of the potential problems and inefficiencies that arise because of poor communication quality is necessary for both troubleshooting and developing of more cost-effective maintenance plans.

Poor communication quality is often blamed for severe missing data problems in real-time data collection applications. With higher uploading frequency, high-resolution data could be more vulnerable to communication failures than aggregated data uploaded every few minutes. High-resolution signal event–based data ("event-based data" in this paper) is an emerging data source that is collected from modern signal controllers (*1, 2*). It is typically reported at 1-s or higher resolution and includes records of individual events such as phase activations and terminations, vehicle detector on and off times, and coordination. Many studies have demonstrated methods for achieving more effective signal management by replacing traditional aggregate data with newly available event-based data, either for generating more-accurate and -detailed performance measures (*3–6*) or for more-sophisticated traffic modeling and signal optimization (*7, 8*). It is therefore timely for practitioners to reevaluate the health and capabilities of current communication networks for implementing applications that use event-based data. However, to date, few studies have done so. Li et al. demonstrated the resilience provided by local data buffering within a high-latency network that experiences occasional service disruptions (*9*). Four states were defined in their study to evaluate the health of a data collection system and the communication network. However, those four states were simply categorized by whether or not data records existed and ping responses were recorded. The extent of missing data was not examined, but such information is important because some presence of data does not necessarily mean the whole data set is complete, especially for online systems without data-buffering protections.

Another commonly encountered problem caused by communication loss is controller clock drifting. In an interconnected coordination system, the communication network is responsible for broadcasting synchronized time–clock information, so any failures will likely cause the controller clock to drift (i.e., it will run either faster or slower and cause changes in the offset). As a consequence, signal coordination may become less efficient or, in some extreme cases, even be entirely interrupted. Unfortunately, direct monitoring of the status of a controller is almost impossible when it is disconnected. Lin et al. conducted a simulation-based analysis to evaluate the potential degradation of traffic performance in a coordinated system in which the clock was drifted randomly at each intersection (*10*). Their simulation results showed a 6% to 22% increase in travel time for corridors with as few as 10 intersections. Although these simulation results can raise awareness of the negative impacts, more field-based studies are always needed. Manufacturers are beginning to incorporate a GPS timer in their latest controller models to correct the clocks whenever communication is interrupted, but older controllers still rely on a central computer to synchronize their internal clocks. Thus, the authors see as desirable development of a method using field-collected data that are capable of identifying and evaluating the degradation of signal performance associated with com-

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munication loss to enable practitioners to make more cost-efficient and specific decisions.

This paper examines the critical effects of communication loss on data quality and signal coordination, particularly those effects that could most strongly affect signal performance under prevailing time-of-day signal control. First, a data quality control method with criteria specifying the completeness of the event-based data is proposed and implemented. Then, unexpected changes in traffic progression caused by communication loss are identified on the basis of a statistical analysis method and evaluated by monitoring the control delay. Limitations and recommendations for future research are also discussed on the basis of results and findings presented here.

TEST SITES AND DATA DESCRIPTION

Event-Based Data Collection

To instigate the signal communication issues, event-based signal data are required. Tucson, Arizona, is one of the few cities capable of collecting regionwide event-based traffic signal data. The city has recently deployed a MaxView advanced traffic management system (ATMS) consisting of 638 controllers, of which 104 are HAWK pedestrian crossing systems (*11*). The majority of the controllers are ASC/2, and the rest are ASC/3 models. The framework for the event-based data collection is shown in Figure 1. The event-based data, including signal, detector, and pedestrian events, were generated by signal controllers. The ATMS collected and archived every event in the system's database in real time. This study used 2 months of archived data covering September 14 to November 10, 2015.

Types of Communication Loss

The system communication network is built on both agency-owned fiber and wireless networks. The MaxView server logs the communication event data, including total communication attempts, failed communication attempts, average response time, and percentage of communication loss (POCL), at approximately 5-min intervals via a ping-checking process to field controllers (*11*). In relation to POCL, four distinct types of communication performance, as shown in Figure 2, can be identified:

Type 1, without loss. The desired situation, when all ping attempts are successful.

Type 2, temporary loss. All ping attempts fail for a temporary period, which may be as long as several days, before communication is recovered.

Type 3, partial loss. Some ping attempts fail.

Type 4, continuous loss. All ping attempts fail over a sustained period.

Generally, data loss is less likely when communication is successful (Type 1), while partial or entire data sets may be lost when communication is unstable (Type 3) or all data lost throughout the period when the link is out of action (Types 2 and 4). For time–clock synchronization, the controller may fail to correct the internal clock when communication is unstable or totally lost, so when this failure occurs, any clock drifting will depend on the precision of the internal clock in the affected controllers.

IMPACT ON EVENT-BASED DATA QUALITY

Once communication losses occur, the server may have difficulties in collecting event-based data from the signal controllers. The direct result of communication loss is poor-quality data, much of which are actually missing data. Without high-quality data, researchers find difficulty in conducting an in-depth investigation of signal performance because such investigation depends on accurate and reliable event-based data. Missing data are the main focus of the current study because this issue is closely linked to communication loss. Therefore,

FIGURE 1 Event-based data collection in Tucson: (*a*) video-based detectors, (*b*) pedestrian push button, and (*c*) MaxView ATMS.

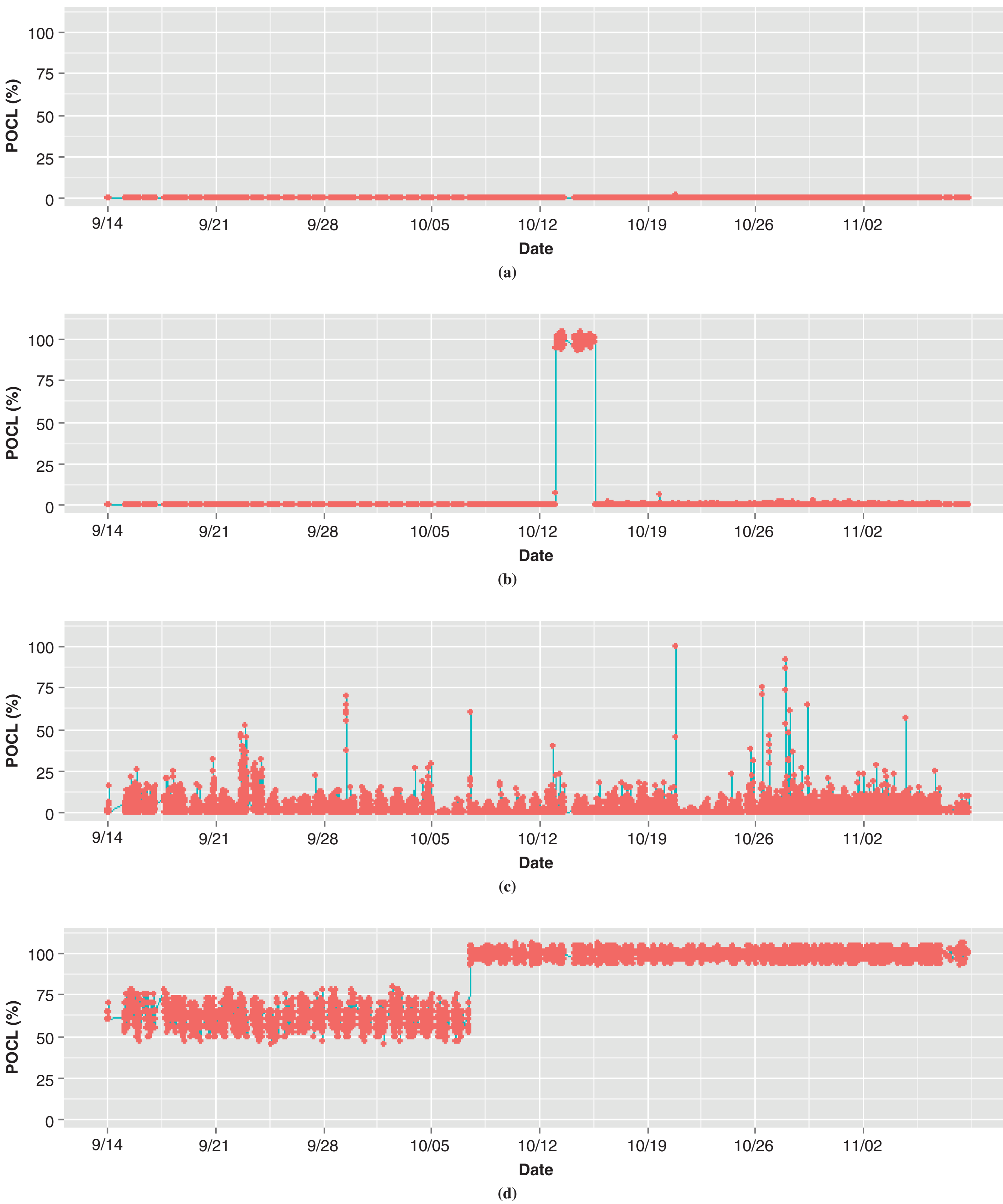


FIGURE 2 Types of communication performance: (*a*) Type 1, without loss; (*b*) Type 2, temporary loss; (*c*) Type 3, partial loss; and (*d*) Type 4, continuous loss.

a data quality control method with criteria specifying completeness of event-based data is proposed and implemented here to explore the data quality issue.

Diagnosis Procedure

Although communication loss is the most common reason for data loss, missing data have other possible causes. To address these issues and facilitate analysis in a regionwide network better, a two-step procedure was proposed, as illustrated in Figure 3. The first step is to check whether the system is archiving data all the time. The next step is to check whether any information is missing in the data at every intersection in the network. The network data set includes all system-generated data (e.g., communication events data) and controller-generated data (e.g., phase events data), while the controller data set includes only controller-generated data.

Three major causes are also illustrated in Figure 3:

- Interface-related issues do not depend on communication status; these therefore suggest a problem with either the system or the controller interface (e.g., failure in data archiving in Figure 3).

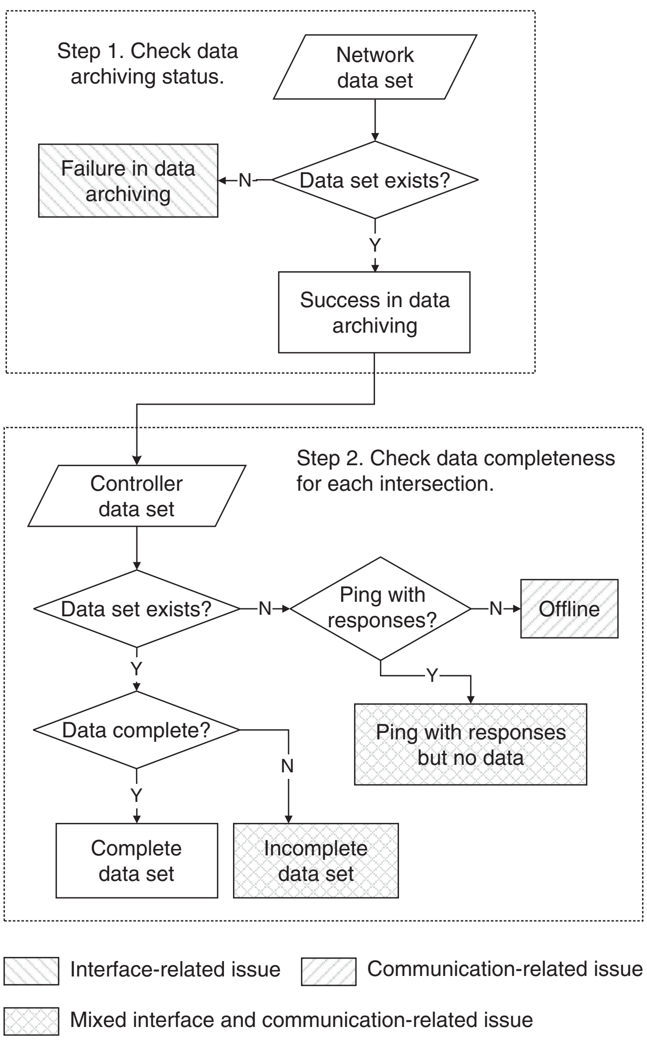


FIGURE 3 Two-step procedure for diagnosing missing data.

- Communication-related issues refer to bad communication quality. For example, the controller may be offline so that no controller-generated data can be archived (e.g., offline in Figure 3).
- Mixed issues could be both interface- and communication-related issues. Generally, communication issues should be checked first, as these are more likely and easier to handle; investigation should move to interface-related issues only when necessary.

Criteria for Data Quality Control

Because missing data are the focus of this study, the control criteria are based on the completeness of the phase and detector event data, as these are most frequently used and comprise the majority of the data set. Three specific criteria are proposed to characterize the missing data in phase and detector events: (*a*) "phase always on" looks at the completeness of phase events, while (*b*) "unpaired on and off" and (*c*) "long duration" are used for detector events. These criteria are described next:

- Phase always on. An activated phase always exists at any time for a functional controller, as the termination of one phase is followed by the activation of another phase. If this sequence is not the case, one or more phase events are missing.
- Unpaired on and off. Ideally, detector on-and-off events are paired and represent individual vehicle actuations. If any data are missing, combinations of either on–on or off–off events are likely in the time sequence, so these unpaired events indicate a problem with incomplete data.
- Long duration. A time gap between a detector on–off or off–on that exceeds a certain time threshold may also indicate missing data. Long-duration events are considered suspicious because they may arise from either very congested or no-vehicle situations.

Figure 4 illustrates time gaps identified by these three criteria within the data for a typical day at a typical intersection; measures of the POCL are shown in Figure 4*e*. The times for each phase activation and termination and detector on and off are paired and represented by rectangular blocks (Figure 4, *a* through *d*). Both the width and height (limited to 120 s) of each block represent the time duration, and time gaps with unknown phase status or wrong combinations of detector events are highlighted as red blocks. A long duration (taken to be longer than 5 min for this study) between detector on–off or off–on events is shown as an orange block. All the green blocks represent healthy data.

As Figure 4*e* shows, occasional increases in POCL (even when small) result in missing data (Callout i). During the period from 2 to 8 a.m., all the data were lost; such a loss may indicate a data-archiving problem (Callout ii). Of the three criteria, the phase always on best captures the time gaps with missing data issues and shows a high correlation with an unstable communication state. In this study, phase always on is mainly used to quantify the completeness of the event-based data.

Analysis of Regionwide Data Quality

On the basis of the two-step diagnosis procedure described earlier, the entire network across the city of Tucson could now be analyzed

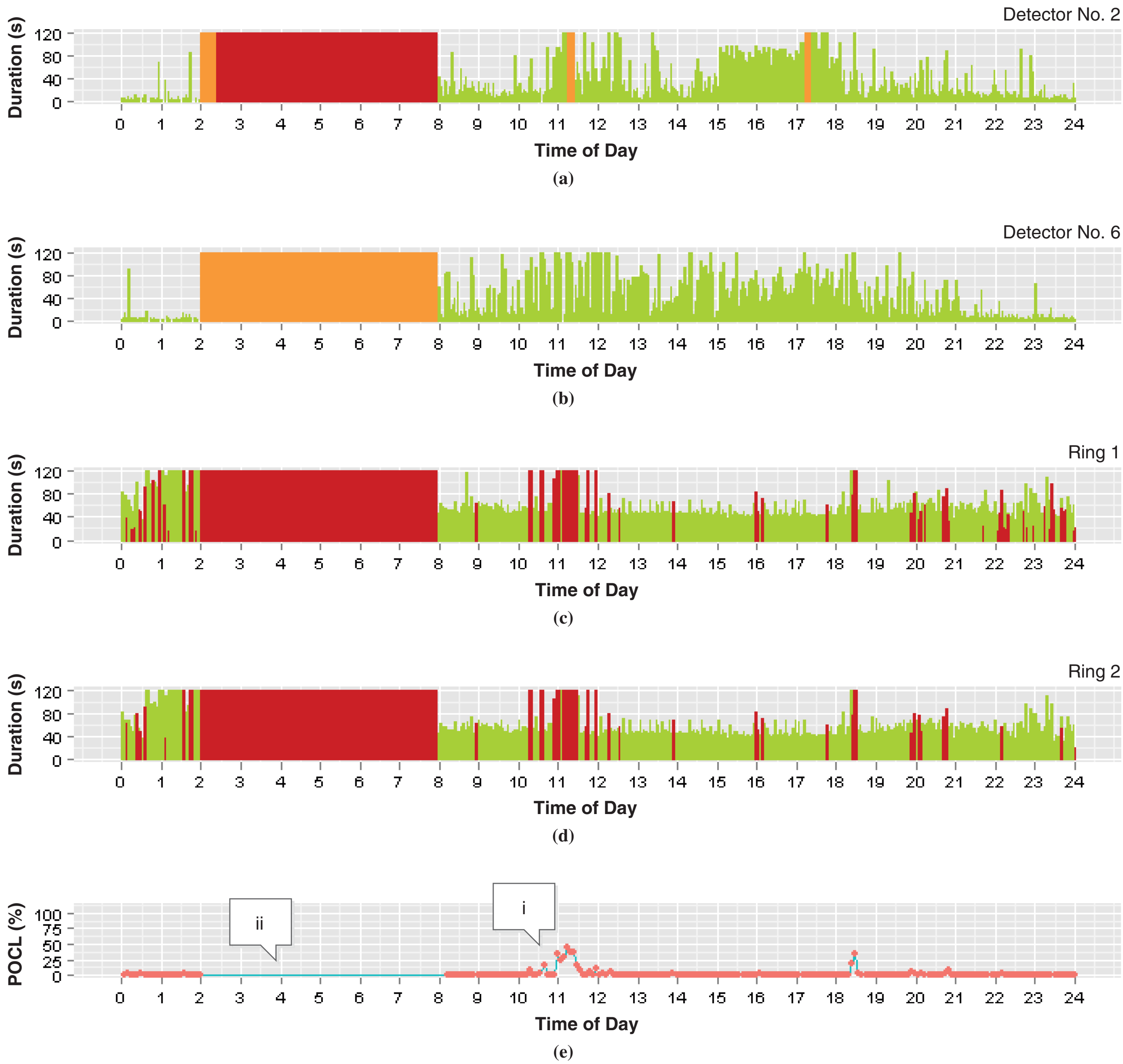


FIGURE 4 Time gaps showing data missing across day at typical intersection: (*a*) Detector 2, (*b*) Detector 6, (*c*) phases in Ring 1, (*d*) phases in Ring 2, and (*e*) POCL.

for event-based data completeness. For Step 2 in Figure 3, a quantified data completeness index (DCI) is proposed for each intersection, defined as follows:

$$\text{DCI} = \frac{100 * \max((T_{\text{dm}} - T_{\text{af}}), 0)}{T_{\text{ap}}}\% \tag{1}$$

where

T_{dm} = sum of time gaps with missing phase status (data missing) in Ring 1 or 2 during analysis period,

T_{af} = sum of time during which system failed to archive any data (archiving failures),

max( ) operator = means to avoid negative result caused by errors, and

T_{ap} = analysis period (e.g., 1 day).

The results of a test case are illustrated in Figure 5, where Figure 5*a* shows the data archiving failures for the period Monday, September 14, to Friday, September 18, 2015, over the entire network dataset. A polar coordinate system was used to present the timeline. The gaps colored gray indicate no single event datum exists for that interval. Figure 5, *b* and *c,* show the summary of the analysis results

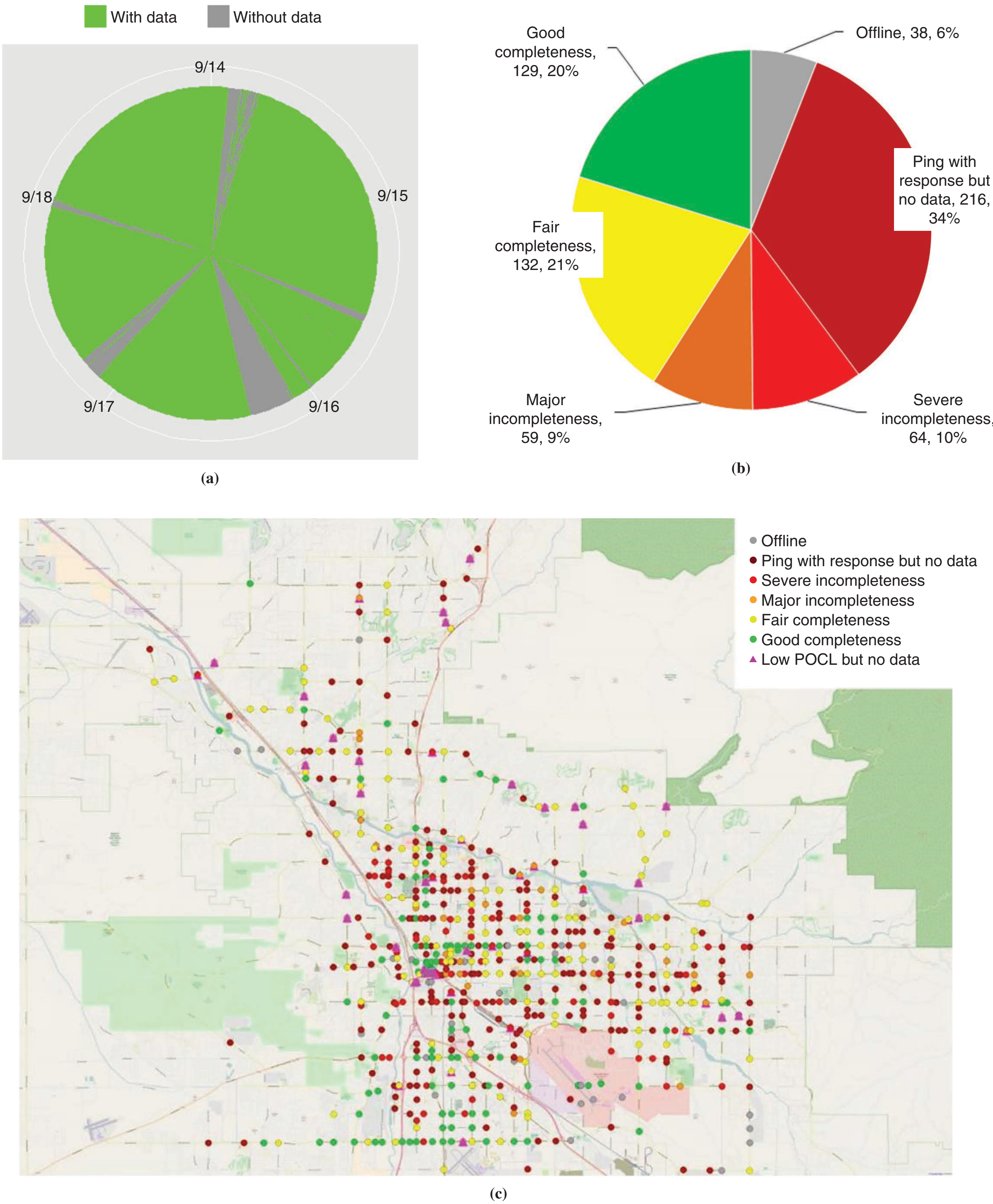


FIGURE 5 Regionwide data analysis: (*a*) data archiving failures for September 14 to September 18, 2015; (*b*) intersections grouped by data completeness level for September 17; and (*c*) intersection responses visualized on a geographic information system map of Tucson for September 17.

for all intersections of the network on Thursday, September 17, 2015. Intersections are categorized into six data completeness levels, as described below:

- Both Completeness Levels 1, offline, and 2, a ping with response but no data, correspond to 100% DCI and are distinguished by a 1-day average POCL of 100% or less.
- Completeness Levels 3, severe incompleteness; 4, major incompleteness; 5, fair completeness; and 6, good completeness, are defined as DCI within the ranges 70% to 100%, 40% to 70%, 10% to 40% and 0% to 10%, respectively.

As Figure 5*b* indicates, nearly 60% of the city's intersections (377 of 638) suffered significant missing data problems that day, with more than half being a ping with response but no data. Another 21% of intersections (132 of 638) occasionally lost data, a situation that may not be immediately obvious when real-time monitoring states are being scanned. At the time the study was conducted, few of the city's corridors were eligible for a systemic traffic progression analysis such as a Purdue coordination diagram because of the interruptions at one or more intersections with unknown traffic states (Figure 5*c*) (*3*). In addition, many of the intersections were possibly experiencing failures in time–clock synchronization, so efficient signal coordination could not be sustained. Those intersections with less than 1% 1-day average POCL at Levels 2 through 5 are highlighted in the category for low POCL without data in Figure 5*c;* these intersections represent a particular situation in which communication was well established but no data were being archived. In such cases, a potential interface problem exists in either the ATMS or the controller.

IMPACT ON SIGNAL PERFORMANCE

Communication loss could cause the controller clock to drift, and this condition will affect or even interrupt signal coordination. To investigate such impacts, a statistical method is proposed to identify any traffic pattern changes caused by communication loss; any changes identified can then be further evaluated by monitoring the control delay. Data quality issues must also be carefully considered to ensure the accuracy and reliability of the analysis results.

Analysis of Traffic Progression Patterns

One-way analysis of variance (ANOVA) was used to compare the equality of K-population means, where $K \geq 2$. Typically, the observations or samples (the dependent variable) are grouped by a categorical or treatment factor (the independent variable) to test whether the effects of treatments differ between groups by more than would be expected from random sampling fluctuation within the groups.

In this study, the dependent variable is "cyclic occupancy in seconds" (COIS), defined as the time in seconds during which the detectors monitoring coordinated movement are occupied during a cycle. The means of COIS during a certain analysis interval are considered a measure of the quality of traffic progression. Generally, COIS increases when the traffic progression becomes worse under comparable traffic conditions. COIS was chosen here because the detectors are single channeled and located close to a stop bar, with a pocket space of approximately five or six vehicles, in the case of the city of Tucson. An alternative measure could be the "waiting time before green," which is the time between the arrival of the first vehicle at a red light and the light turning green again, although this is a less reliable metric because only a single vehicle, rather than a group, is tracked. More precise measures, such as percentage on green, are preferable where detectors are far from the stop bar and for lane-by-lane detection (*3*).

Because communication loss is the cause of both clock drifting and missing data, traffic progression at the intersections of interest cannot be measured directly. Instead, the coordinated movements at the adjacent downstream intersections can be measured. These two-intersection pairs are selected on the basis of the following criteria:

- Both are in the same coordination system, with common cycle lengths.
- The upstream intersection has experienced a temporary or continuous loss in communication.
- The downstream intersection has a DCI of Level 5 or 6 to ensure sufficient reliable data to be of use.

As time-of-day traffic patterns are commonly assumed to be similar across weekdays, individual weekdays are treated as independent variables, and as clock drifting is considered to be slow changing, its effect on traffic progression should be measurable. Thus, the null hypothesis (H_0) tested in the one-way ANOVA was that the means of the COIS will be equal across weekdays for the same analysis interval (e.g., 9 to 10 a.m.). The alternative hypothesis (H_a) is that at least one weekday mean will differ significantly from the others. The analysis interval was selected as being one particular hour during the off-peak period with a same time-of-day signal coordination plan. An off-peak period was selected to avoid any potential issues caused by the tendency for COIS readings to become identical under very congested conditions.

Before this type of analysis is applied, one must determine whether the assumptions of the one-way ANOVA are satisfied. The one-way ANOVA is robust with respect to violations of assumptions, except in the case of unequal variance and sample sizes, which could change the Type 1 error rate (e.g., $\alpha = .05$) (*12*). In this study, the equality of sample sizes was ensured by a data completeness analysis, which led to the removal of one particular day with significant missing data. Although a certain heterogeneity in variances may still exist, the effects on the Type I error rate will be minimal as long as the sample sizes are approximately equal.

Once the ANOVA has indicated the presence of a statistically significant difference among groups (weekdays in this study), Tukey's honestly significant difference (HSD) test is used to conduct a post hoc comparison to specify the type and and location of these differences (*12*). One-way ANOVA followed by the Tukey HSD test is applied to identify unexpected changes in traffic progression patterns in this study. To maximize the reliability of the method, multiple hours (e.g., three continuous hours) within the analysis (off-peak) period are reviewed at the same time. If all hours give similar results, any changes in traffic progression actually exist and are not caused by random fluctuations in the traffic.

Twenty eligible pairs of intersections on six of the city's arterial roads were investigated. Three continuous hours during the off-peak period for 24 weekdays between September 14 and November 5, 2015, were analyzed. According to the results, most of the hours in the one-way ANOVA ($\alpha = .05$) showed statistically significant differences. However, under Tukey's HSD test ($\alpha = .05$), only 3 of the

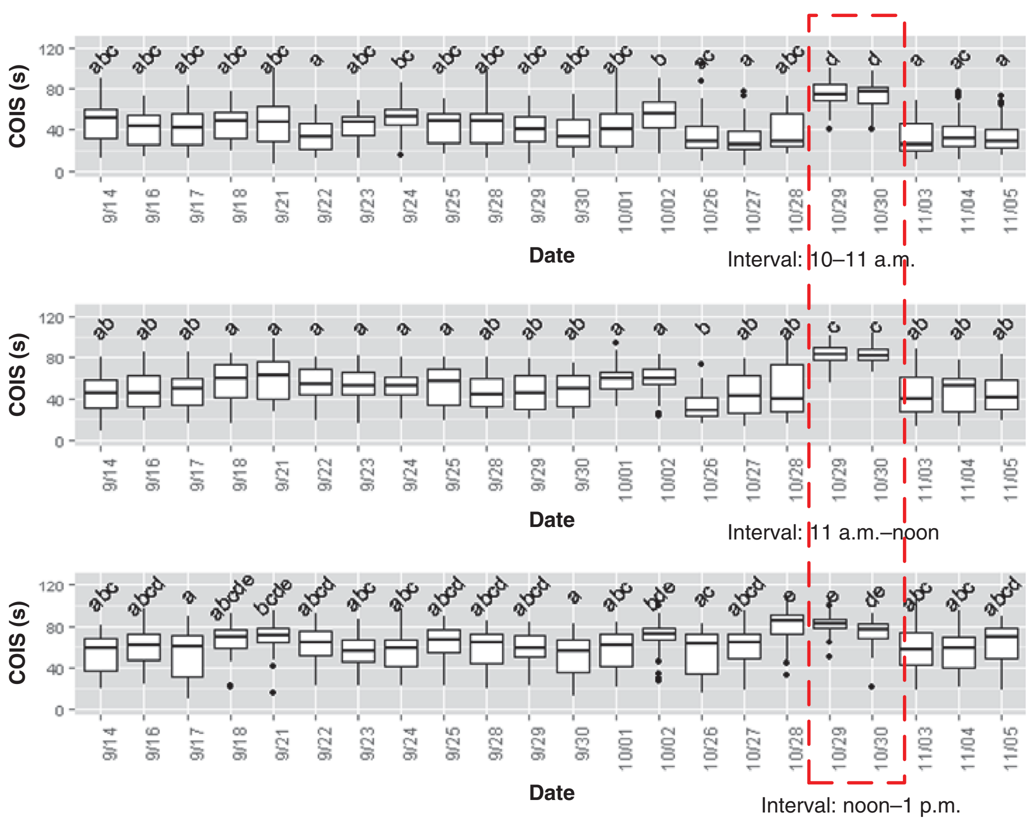
20 pairs were found to exhibit clear and similar changes in the means of COIS for all 3 h. Significant differences in the remaining 17 pairs were randomly distributed across the 3 h. These "unclear" results could be explained by one or more of these reasons: (*a*) the weekday traffic flow had more fluctuations than expected; (*b*) COIS may not have been precise or sensitive enough to capture the changes in traffic progression; and (*c*) the detection accuracy could have been an issue because the video-based detectors are widely used in Tucson. Nevertheless, drivers experiencing worse traffic progression than usual at the three identified intersections seemed unlikely. As no changes in signal timing plans and no special events (e.g., bad weather or sports activities) occurred, the controller clocks very likely drifted at these three intersections when disconnected.

Figure 6 illustrates three cases of analysis of traffic progression patterns. The letter labels above each box plot were generated by Tukey's HSD and indicate which two or more groups are similar (without significant differences). In Case 1 (Figure 6*a*), COIS was measured on the northbound through lanes at the intersection of First Avenue and Limberlost Road. The upstream intersection at First Avenue and Roger Road experienced a temporary communication loss from October 26 to October 30, 2015. Statistically significant differences (shown as increases in the means of COIS) were identified in all 3 h on October 29 and 30 (area enclosed by red dashed line in Figure 6*a*). After communications were recovered, COIS returned to the levels seen before the communication breakdown. That the controller clock drifted on October 29 and 30 at First Avenue and Roger Road seems highly likely. In Case 2 (Figure 6*b*), COIS was measured on the westbound through lanes at the intersection of Grant Road and Beverly Avenue. The upstream intersection at Grant Road and Craycroft Road was under a continuous communication loss situation. As the figure shows, the increases in the COIS means after October 26 were sustained, with all the subsequent days exhibiting the same distinct labels (area enclosed by the red dashed line in Figure 6*b*). However, a longer outage is required to confirm whether the other changes would also recur. Case 3 (Figure 6*c*) shows a very similar pattern in the COIS means at the downstream intersection (Speedway Boulevard and Stone Avenue) across multiple weekdays, even though no communication was available for the upstream intersection (Speedway Boulevard and Sixth Avenue).

Evaluation of Control Delay

The analysis of traffic progression was designed to address whether and when any unexpected changes in traffic progression happened. The next important question is, "What is the impact of these changes?" The authors therefore conducted a control delay–based evaluation to quantify the impact of communication loss on signal performance, specifically signal coordination.

To estimate the control delay by using event-based data, a revised break point–based model adapted for single-channel detection was used (*13*). The critical step in this model, originally proposed by Liu et al., is to reconstruct the shock wave profile by identifying break points (*14*). With the shock wave profiles, the control delay for each cycle can be estimated by calculating the area between the



(a)

FIGURE 6 Case studies of traffic progression pattern: (*a*) intersection with temporary communication loss.

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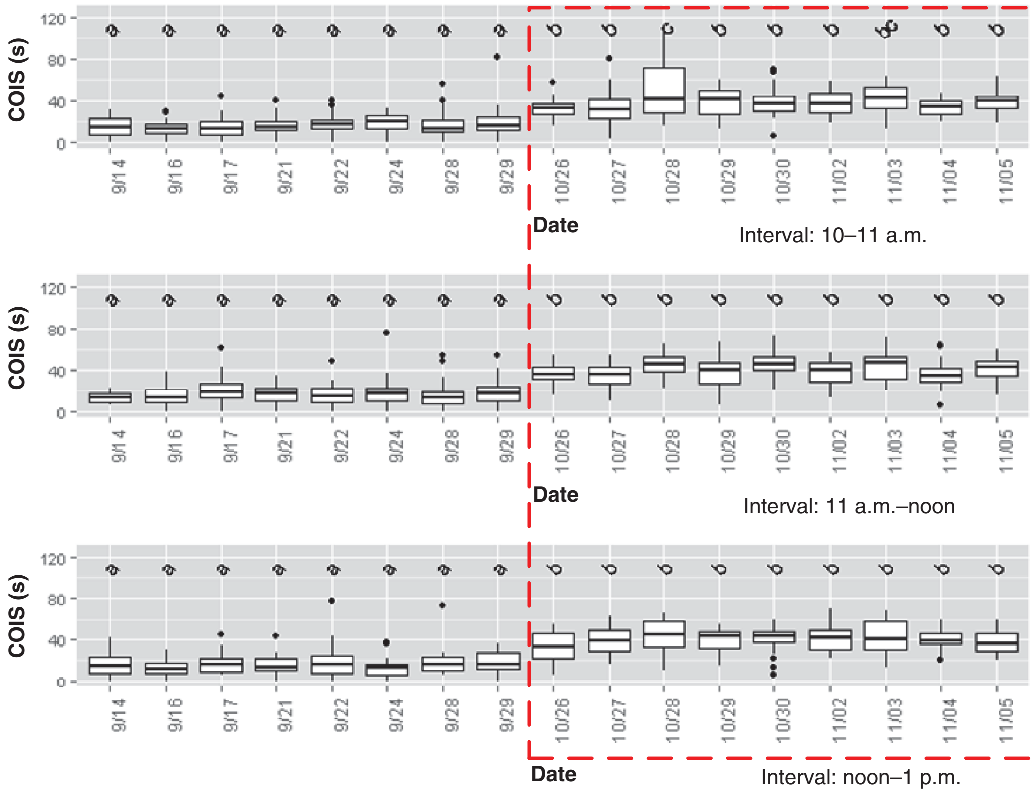

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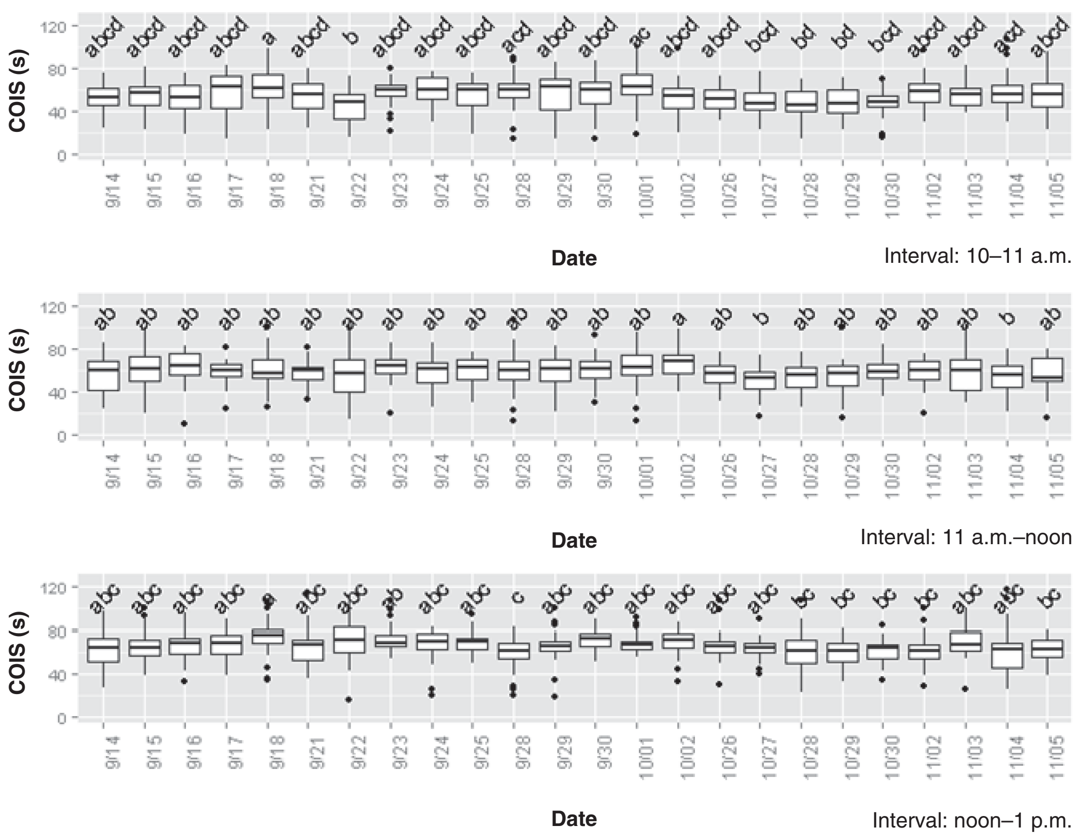

(c)

FIGURE 6 *(continued)* Case studies of traffic progression pattern: (*b*) intersections with continuous loss and different COIS and (*c*) intersections with continuous communication loss and similar COIS.

back-of-queue (arrival rate) and the discharge wave (service rate) (*15*). Although the delay estimation model in this study was not fully calibrated, because only typical default values of parameters were used, the model was still deemed sufficiently reliable for a relative-comparison analysis.

All three of the intersection pairs identified in the previous section were investigated. To understand better how the overall delay is affected by communication loss, the cumulative control delay was calculated to observe the trend of this effect. These evaluations were conducted separately for each analysis hour across multiple groups (weekdays) as explained in the section on analyzing traffic progression patterns. Not every cycle was included in each analysis hour because of issues with missing data, but the time sequence was maintained throughout and the same numbers were used for all groups. The results are shown in Figure 7. The red lines represent the cumulative delays of those groups that were affected by communication loss (the affected group in the figure), and the blue lines represent the cumulative delays of those groups that were not affected (the nonaffected group). During the study period, the average delay increased by 27%, 720%, and 80% at, respectively, the intersections of First Avenue and Limberlost Road, Grant Road, and Beverly Avenue, and Speedway and Columbus Boulevards. These results indicate that the traffic progression can be seriously affected by communication loss, with significant increases in delay for particular coordinated movements.

CONCLUSIONS AND RECOMMENDATIONS

A reliable communication network is always desirable, not only for data collection and time–clock synchronization but for the implementation of more advanced traffic management technologies,

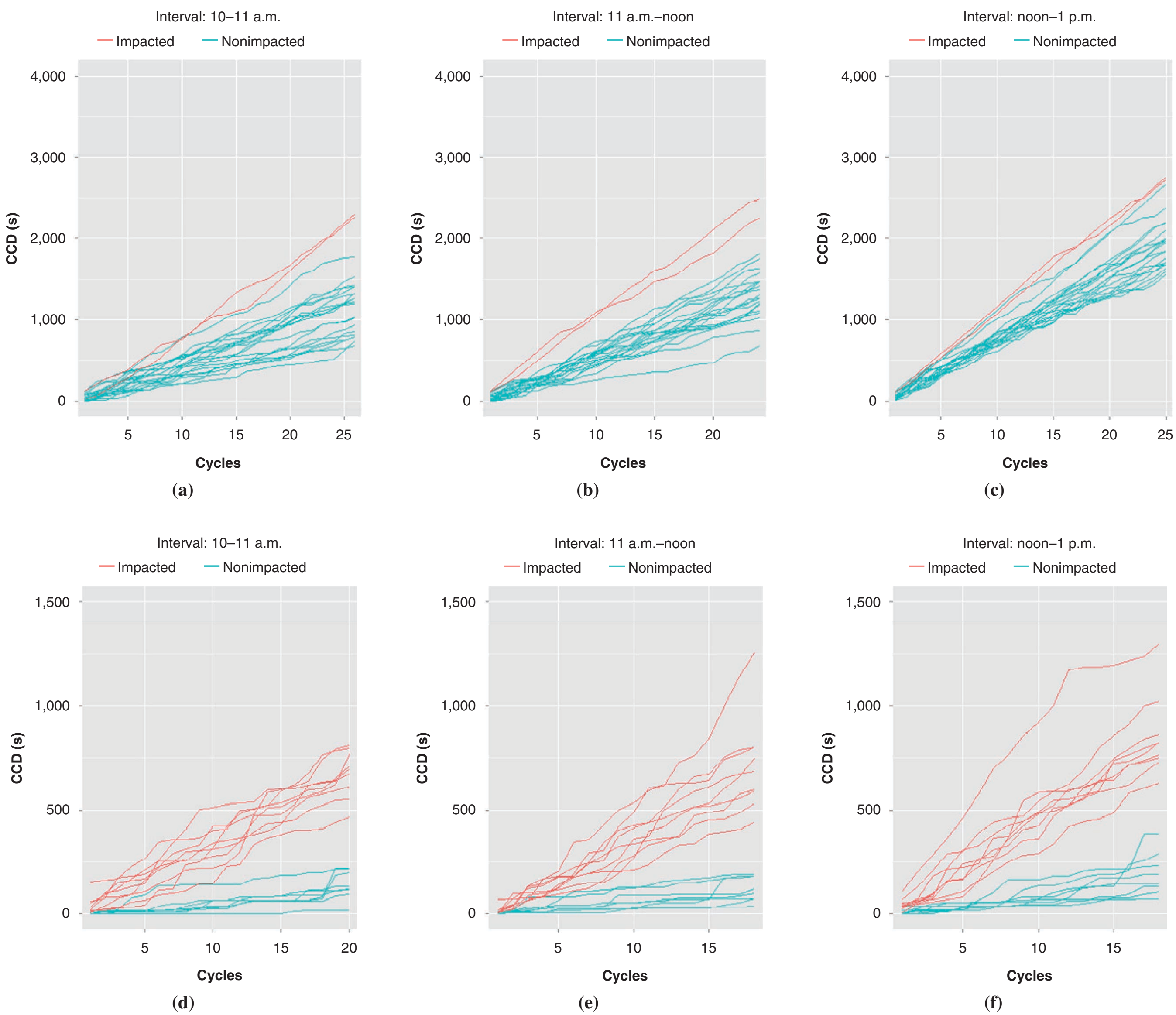

FIGURE 7 Cumulative control delay estimation for three time intervals on (*a* through *c*) northbound through lanes at First Avenue and Limberlost Road and (*d* through *f*) westbound through lanes at Grant Road and Beverly Avenue.

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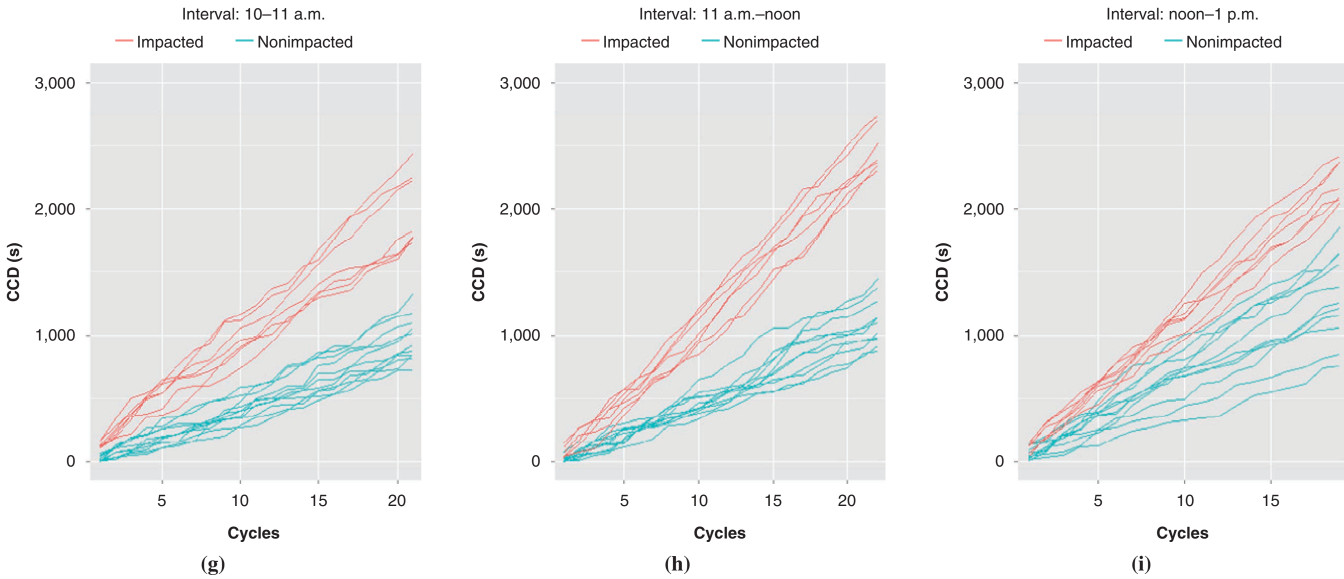

FIGURE 7 *(continued)* **Cumulative control delay estimation for three time intervals on (*g* through *i*) westbound through lanes at Speedway and Columbus Boulevards.**

(e.g., responsive and adaptive signal control). The critical impacts of communication loss on data quality and signal coordination were the focus of this paper. This study provided an innovative data-driven approach to support smarter asset management of signal communication networks. A data quality control method that includes criteria specifying the completeness of event-based data was proposed and implemented. The results revealed that an unstable communication status with even slight degradations can lead to instances of missing data. The quantified analysis using regionwide data conducted for this study provided a better understanding of the data completeness than is possible by simply scanning real-time monitoring states. The proposed method could be an effective tool that enables practitioners to diagnose problems with missing data and evaluate the health and capability of a communication network to improve signal performance by using event-based data.

A statistically based method adopting one-way ANOVA and Tukey's HSD test was also proposed and applied to investigate the traffic progression patterns between 20 pairs of coordinated intersections along six arterial roads; three intersection pairs were found to be significantly affected by communication loss. The proposed method was able to distinguish real changes in traffic progression patterns from random fluctuations in traffic flow. The impact for signal performance was further evaluated by monitoring the control delay. The results indicate that significant increases in the control delays for particular coordinated movements, ranging from a few dozen percent to many multiples, were caused by communication loss issues. The proposed method could help practitioners make more cost-effective decisions and encourage them to maintain the communication network better and thus sustain desirable signal coordination.

To address the missing data issues, installation of additional memory or devices in the controllers for data buffering would be helpful for providing some tolerance of intermittent communication interruptions. In this study, the data completeness was mainly considered in relation to its impact on data quality. In the future, other aspects of data quality (e.g., accuracy of vehicle detection) would benefit from further investigation. More field-based studies are also needed to understand the impacts of the signal performance issues identified here.

To address the time–clock synchronization issues, an additional GPS timer could also be a useful way to sustain the precision of a controller's internal clock when it becomes disconnected from the central system. In this study, the impact of communication loss on signal coordination was conducted by using an offline analysis, but to monitor traffic patterns in real time is clearly more desirable to enable more responsive actions to be taken to assess the precision of the controller clocks.

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