Massively parallelizable approach for evaluating signalized arterial performance using probe-based data

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ABSTRACT
Effective performance of arterial corridors is essential to community safety and vitality. Considering the dynamic nature of traffic demand, efficient management of these corridors require frequent updating of the traffic signal timings through various strategies. Agency resources for these activities are commonly scarce and are primarily by public complaints. This study provides a workflow using probe-based data to measure and compare different segments on arterial corridors in terms of the traffic signal performance measures that can capture travel time dynamics across signalized intersections. The proposed methodology identifies a group of dynamic days followed by evaluation of travel rate based upon remaining non-dynamic days. Dynamic days represent the variability of traffic on a segment. Consequently, a corridor having high number of dynamic segments along with poor performance during normal days would be a candidate for adaptive control. Further, to handle the large-scale data source collected from city-wide or statewide traffic signals, the study adopts parallel computation-based strategy using MapReduce technique. A case study was conducted on 11 corridors within Des Moines, Iowa, to demonstrate the efficacy of the proposed approach, which identified two arterial corridors, Merle Hay Road and University Avenue, to be suitable for adaptive traffic signal control.

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Introduction
Transportation agencies install traffic signals to optimize traffic flow, reduce crash frequency, and prioritize particular roadway user type or movement (Chandler et al., 2013). Federal Highway Administration (FHWA) states that the operation and performance of the 300,000 signals in the United States (US) are addressed predominantly on the basis of citizen complaints (FHWA, 2017). Recognizing that a complaint-driven process is inefficient, many transportation agencies have sought objective methods for identifying and prioritizing corridors that require signal re-timing or the implementation of advanced signal control systems.

In order to “move people through an intersection safely and efficiently,” traffic signals need to be maintained and improved (Koonce et al., 2010). The three primary operational modes for traffic signals – pre-timed control, semi-actuated control, and fully actuated control (Koonce et al., 2010) are improved by periodic signal retiming (Curtis, 2017; Gordon, 2010). This retiming is invoked through public requests, changes in land use pattern, traffic conditions like oversaturation, and detectors showing significant changes in congestion (Gordon, 2010). Retiming involves minimizing a delay-based objective function or maximizing arterial throughput through progression (Gordon, 2010) which do not always represent the real scenario in the field (Day et al., 2010). Also, the cost of retiming increases when data are not accessible or require manual collection from the sites (FHWA, 2017). To circumvent these situations, the Adaptive Signal Control Technology (ASCT) came into existence (Curtis, 2017). The ASCTs tend to maximize the capacity of the existing system based upon the information collected from the field to reduce cost of the system users and the operating agencies. They are useful in locations with traffic variations rather than repetitions in traffic (Stevanovic, 2010). They have been reported to reduce travel times by 35–39% (Sims & Dobinson, 1980), reduce stops by 28–41% (Hicks & Carter, 1997), and also reduce crashes by 35% (Anžek et al., 2005). However, they involve a high initial cost for installation.
both infield and at traffic management center (Stevanovic, 2010). The initial tune-up and additional sensors tend to make the task tedious and troublesome. The typical cost of implementing adaptive control ranges from $6,000 to $65,000 per intersection (Sprague, 2012), which restricts a city-wide implementation. Even with higher costs, one-third of the ASCT was found to be problematic in oversaturated traffic conditions (Stevanovic, 2010). Studies have reported that ASCT has been removed from a corridor as it showed deterioration in performance due to non-ideal sensor performance, lack of trained staff, or inability of adaptive algorithms to respond to the site traffic conditions (Stevanovic, 2010). Only a few cities have implemented city-wide adaptive control due to current costs and sensor dependencies. Therefore, it is more common to find ASCT only on a few selected corridors.

Another method of signal optimization for traffic performance has been the introduction of Reinforcement Learning (RL). RL extracts information from existing traffic patterns and comes up with the best viable option to maneuver traffic across the corridor. The primary advantage is that multiple traffic states are observable over period and thus, RL agents can reproduce the most efficacious results. However, the methods are mainly restricted to simulation environments and bringing them to real-world scenarios is a safety issue (Wei et al., 2021).

Therefore, a set of robust performance measures are needed to identify traffic intersections’ appropriate evaluation methodology. Two major data sources can be used to evaluate traffic signal performances for re-timing considerations. These data sources include – (a) infrastructure dependent data sources such as Bluetooth, cameras, loop detectors, or any kind of fixed/mounted sensors, and (b) non-infrastructure dependent data sources like probe-based data.

Infrastructure dependent methods can be divided into two categories – (i) Automated Traffic Signal Performance Measures (ATSPMs) extracted from advanced traffic signal controllers, and (ii) sensor data collected using mounted sensors such as cameras and Bluetooth. The ability to extract ATSPMs is only available in newer traffic signal controllers purchased after 2010. Table 1 presents the performance measures obtained using high-resolution traffic signal data. Apart from ATSPMs, travel time data collection using fixed/mounted sensors has been found to be useful as corridor performance measure. Several automated travel time determination methods have been developed, including anonymous address matching, cellular phone subscriber identity matching, and automatic license plate number matching (Singer et al., 2017, Venkatanarayana, 2017, Quayle et al., 2010). These have proven reliable but require installing and maintaining roadside sensors, which represent biased sample of traffic stream (Chitturi et al., 2014). Other drawbacks include underestimation of the traffic volume if the queue extends too far beyond the farthest-upstream loop (Smaglik et al., 2007) and the difference in detection rates at Bluetooth stations based upon a vehicle’s position (Vo, 2011).

Non-infrastructure dependent GPS-based probe data overcomes some of these limitations since acquiring the data requires no roadside infrastructure, and the data aggregation and de-identification ensure that all the privacy concerns are appropriately addressed. Probe-based signal performance measures have been reported to have higher accuracy rate than the controller based data (Q. Li, 2013). They are also used for determining intersection performance measures, as noted in Table 1. Further, they are used to investigate relationships between travel time and travel time reliability for arterials (Hu et al., 2016).

While travel time provides an excellent proxy of traffic conditions within a single segment, they have an inherent aggregate-level comparison problem (Day et al., 2014). Hence, the travel rate, which is inverse of

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**Table 1.** Methods to measure performance measures of arterial corridors and intersections.

| Performance measure | Methods used to measure |
|---------------------|-------------------------|
| Delay               | Stop bar and advanced detectors* (Sharma & Bullock, 2008), Video recording* (Sharma & Bullock, 2008). High-resolution event data* (Day & Bullock, 2010). Video recording* (Fernandes et al., 2015), Connected Vehicle+ (Argote-Cabaiero et al., 2015). Stop bar and advanced detectors* (Sharma & Bullock, 2008). Video recording* (Sharma & Bullock, 2008). Stop bar and advanced detectors* *(Sharma & Bullock, 2008). Stop bar and probe data combined# (Comert, 2013). Detector occupancy and Lighthill–Whitham–Richards (LWR) shockwave theory* (Liu et al., 2009). Probe data+ (Zhang et al., 2020) Stop bar and setback detectors* (Smaglik et al., 2007). High-resolution event data* (Day et al., 2014) |
| Number of stops     |                         |
| (Maximum) queue length |                         |
| Arrival Type, Arrival rate on green, Degree of intersection saturation, Volume/capacity ratio, Level of progression, Split failure | Stop bar and advanced detectors* (Sharma & Bullock, 2008), Video recording* (Sharma & Bullock, 2008). High-resolution event data* (Day & Bullock, 2010). Video recording* (Fernandes et al., 2015), Connected Vehicle+ (Argote-Cabaiero et al., 2015). Stop bar and advanced detectors* (Sharma & Bullock, 2008). Video recording* (Sharma & Bullock, 2008). Stop bar and advanced detectors* *(Sharma & Bullock, 2008). Stop bar and probe data combined# (Comert, 2013). Detector occupancy and Lighthill–Whitham–Richards (LWR) shockwave theory* (Liu et al., 2009). Probe data+ (Zhang et al., 2020) Stop bar and setback detectors* (Smaglik et al., 2007). High-resolution event data* (Day et al., 2014) |

*Infrastructure dependent; + non-infrastructure dependent; # combined.
speed can be used as an alternative. Travel rate can be easily displayed using a cumulative distribution function (CDF) (Mathew et al., 2017). For example, normalized travel rate was used in ranking the performance of arterial corridors in Indiana (Day et al., 2015). However, this study did not remove the abnormal/anomalous days, defined as dynamic days in this study, when the travel rate differed significantly from the normal due to events such as special events, construction, or adverse weather. Further, the authors also did not group the intersections based upon similar geometric properties (such as traffic volume), which can skew different arterial segments’ rankings.

The present work addresses the above shortcomings by grouping and then evaluating the performance of the segments under similar geometric properties. To handle the large-scale traffic data collected from city-wide or statewide level, this study adopts a massively parallelizable technique that can process hundreds of gigabytes within a few minutes and compute performance of any number of segments that make up a corridor. This analysis of arterial corridors also involves parallel computation to evaluate the traffic signal performance. The analysis starts with empirical CDF plots of travel rate which are used to evaluate the performance of arterial corridors using the following measures:

- Identifying abnormal days, defined as dynamic days, using CDF plots. A large number of dynamic days can indicate non-repetitive traffic patterns where ASCT could be a viable alternative. Where appropriate, dynamic days can be evaluated separately to identify the extent of the anomalies and potential interventions relevant to unusual situations.
- Evaluating travel rate metric for normal days using Median Travel Rate (MTR), Within-Day Variability (WDV) of travel rate, between-days variability of travel rate (Minimum Travel rate Dispersion (MTD), and two Overall Travel rate Variabilities (OTV_POLY and OTV_LINEAR)). The final prioritization threshold is based upon dividing the segments by geometric characteristics – Annual Average Daily Traffic (AADT) per lane and intersection density. A principal component analysis was conducted on these parameters to identify segment performance as good or poor. These two measures are used to determine the necessity for adaptive control evaluation. If a corridor is dynamic and it is performing poorly on normal days, should require attention first. This should be followed by the ones which are not dynamic but they are still behaving poorly on normal days.

The need to implement changes to traffic control can be asserted based on these measures. The corridors which turn out to be dynamic and perform poorly needs to be addressed first. This should be followed by the ones performing poorly only on normal days.

The rest of the paper is divided into three categories. First, it provides the details of the data used in this study and methodology adopted to identify performance of the segments. Then a case study is computed using this methodology to compare segments within the Des Moines, Iowa. Finally, a conclusion is
Table 2. Descriptive statistics of travel rate of all corridors.

| Road            | 2nd Ave | 22nd St | Ashworth Rd | Fleur Dr | Grand Ave | Hickman Rd | Jordan Creek Prkwy | Merle Hay Rd | Mills Civic Pkwy | SE 14th St | University Ave |
|-----------------|---------|---------|-------------|----------|-----------|------------|---------------------|-------------|------------------|------------|-----------------|
| Inter-quartile range | 0.40    | 0.55    | 0.32        | 0.25     | 0.27      | 0.44       | 0.63                | 0.46        | 0.50             | 0.38       | 0.54            |
| Maximum         | 60      | 60      | 20          | 60       | 60        | 60         | 60                  | 60          | 60               | 60         | 60              |
| Median          | 2.14    | 2.61    | 2.00        | 1.71     | 2.00      | 1.67       | 2.14                | 2.14        | 2.14             | 1.76       | 2.31            |
| Minimum         | 0.98    | 1.20    | 1.13        | 0.98     | 0.98      | 0.80       | 1.18                | 0.90        | 1.00             | 0.80       | 0.98            |

drawn based upon the results observed for the case study.

**Data and methodology**

**Data description and data reduction**

One of the challenges of such probe data is reliability. Previous studies show that the probe data provided by commercial provider INRIX are more than 40% real-time data on non-freeways, mostly during daytime (Sharma et al., 2017). They can also detect incidents at an accuracy of at least 63% with a latency of 12 minutes compared to baseline scenario for non-freeways (Adu-Gyamfi et al., 2017). Hence, they can appropriately represent the traffic pattern of an entire day. The same data source obtained minute-wise, is used in this study. INRIX provides data based upon a particular confidence score and c-value (reliability score). Confidence score 10 comprises of historical data, score of 20 indicates real-time and historical data, and the score of 30, used in this analysis, is based on real-time data only. The corridors were so chosen that they had more than 40% of daytime data. This yielded 11 corridors of 300 segments within the Des Moines Metropolitan Area, with an overall real-time availability of 34% (5am to 10 pm). These corridors (Figure 1) consisted of 2nd Avenue, 22nd Street, Ashworth Road, Fleur Drive, Grand Avenue, Hickman Road, Jordan Creek Parkway, Merle Hay Road, Mills Civic Parkway, Southeast 14th Street, and University Avenue. The corridors were made up of 300 segments, of which 51 were under existing adaptive control (22nd Street, Jordan Creek Parkway, Mills Civic Parkway, and University Avenue). The descriptive statistics are shown in Table 2.

The dataset comprised of 150GB per month for 51,000 segments, stored in the distributed file system, Apache Hadoop, where it was reduced by parallel computation using Apache Pig within 10-12 minutes. Parallel computation meant that the entire dataset was mapped into 16 machines and then the computation (calculation of CDF values) was done simultaneously on them. The computed results were finally collected, reduced, and filtered to produce the CDF plots of required segments. As 16 machines with storage memory of 3TB each processed the 150GB data simultaneously, parallel computation reduced the processing time to 10-12 minutes.

**Methodology**

This section defines the methodology used as summarized in Figure 2. Raw data were acquired and converted to CDF plots for identifying the dynamic days in different segments. The dynamic days were used to identify dynamic corridors (arterials having a high percentage of dynamic day segments). After identifying and removing dynamic days, the remaining normal days were used to evaluate the performance measures in terms of MTR, WDV, OTV_POLY, OTV_LINEAR, and MTD. Using these, Principal Component Analysis (PCA) was carried out to characterize each segment’s behavior, which helped identify the corridors where adaptive control is necessary. Based on this methodology, agencies can adopt their own thresholds by reproducing the methodology, or they can directly use the thresholds obtained from the case study.

**Identifying dynamic days using travel rate CDF plots**

The minute-wise variation of speed in a day for 736 minutes can be represented, as shown in Figure 3(a). For evaluating the daily performance, it was converted to a CDF plot at 5th percentile interval. A CDF plots the probability of speed below a certain value. For example, if one says the 60th percentile is 36 mph (point “a” in Figure 3(b)), implies that the probability of traveling below 60% of times the speed lower than 34 mph was observed at this segment.

Since they could not be added together to evaluate the entire corridor’s performance, speed CDFs were converted into travel time CDFs by dividing travel speeds with length of segments (Day et al., 2014). This transformed point “a” on Figure 3(b) into marked “a” on Figure 3(c).

The travel time CDF cannot compare segments of unequal length. Thus, they were normalized by the
Figure 2. Flowchart of the methodology.

Figure 3. Plots of (a) Speed Variation, (b) Cumulative Distribution Plot for speed, (b) Cumulative Distribution Plot for travel time, and (c) Cumulative Distribution Plot for travel rate for a segment throughout a day.
The length of the segment to obtain travel rate CDF plots. Figure 3(d) represents the travel rate CDF corresponding to the travel time CDF from Figure 3(c). The travel rate CDF looks identical to the travel time CDF except for the values plotted on the X-axis. Further, point marked “a” on Figure 3(c) got translated to an identical point in Figure 3(d).

The analysis can only be conducted when there is “enough” representation of a particular day. For this reason, the computation was only conducted for those days that had at least 75 minutes of real-time data across the entire day, that is 75 or more probe-based vehicles had actually passed over the segment. To incorporate peak period performance, days that had at least 30 minutes of data during each of the peak periods (6am-9am and 3 pm-6pm during morning and evening respectively) were used for the analysis. For justifying these durations, segments lying on the Fleur Drive corridor were randomly chosen. Two filters were applied – variation of total minutes in a day (50,
75, and 100 minutes) and variation of the peak hour duration (30, 45, and 60 minutes). It was determined that there was no change in number of days for the total minutes of 50, 75, and 100 minutes. In the case of peak hour duration, the Kolmogorov–Smirnov test failed to show any significant difference between the three sets of data of 30, 45, and 60 minutes, which justified the values chosen for the analysis. The minimum daily real-time data availability threshold of 75 minutes and peak hour real-time data availability of 30 minutes led to removal of 122 days per segment.

Subsequently, the dynamic days were identified for each segment. The purpose of detecting dynamic days is to remove inaccurate travel rates from the analysis and to identify the necessity of a demand-driven signal re-timing. The detection of dynamic days started with the daily travel rate CDF plots for each segment. Figure 4(a) displays example plot of the daily travel rate CDFs for the Water Works Park’s southbound direction on the Fleur Drive corridor for 314 days. Plots of different segments, on the same corridor (Fleur Drive) and same direction (southbound), were further merged together to create a travel rate plot representative of the southbound direction of Fleur Drive. The principle of commonotonicity was applied to achieve the resultant plot. The principle states that for monotonically increasing functions, resultant nth percentile can be obtained as.

\[
Res_n = \sum_{j=1}^{p} n(j)
\]

where \( Res_n \) represents the resultant nth percentile of the segment obtained by adding all the nth percentiles for p days.

Previous studies show that the above method has an error of 6% (Chen et al., 2010) for travel time. Applying this on the independent and identical plot for different days for the southbound direction of Fleur Drive, the representative plot was obtained (Figure 4(b)). To compare the daily CDF plots to the representative CDF, the horizontal difference of the fifth percentiles (Holland, 2002) between the representative day and each day was evaluated as shown for an example day in Figure 4(c). This would yield 21 values, one for each 5th percentile. The daily mean and standard deviation of these points was used as measures of dispersion. These measures were then utilized to evaluate the Local Outlier Factor (LOF) score for each day. The Local Outlier Factor considers a minimum number of neighboring points and calculates that point’s likeliness to its neighboring points. Thus, “similar” days of a segment would have a lower LOF value. It is a type of density-based clustering algorithm, the details of which can be obtained from (Breunig et al., 2000).

Each day, the LOF was used to determine an elbow method cutoff which located the “higher than average” LOF values. Based on the LOF and some data-driven threshold, the 17 dynamic days were separated from the 297 normal days as described for Water Works Park segment in Figure 4(d). In order to analyze the results visually, a comparison of normal days and dynamic days can be made using the average 5-minute heat map plotted for the segment in Figure 4(e). From Figure 4(d) and (e), it can be concluded that some of the dynamic days were mainly caused due to heavy congestion. Some of the reasons have been shown in Figure 4(d).

Using this algorithm, dynamic segments were identified as ones having high volume of dynamic days, with the value determined using the elbow-cutoff point and fixed LOF value. Dynamic segments were used to identify dynamic corridors that had one or multiple dynamic segments.

**Evaluating the travel rate metric for the normal days of the segment**

Having removed the anomalous days, the consequent analysis deals in developing the performance measures obtained from the travel rate CDF plots for each segment. The overall nature of the CDF plots was described based on their location (MTR), spread (WDV), and the overall shape (OTV_POLY, OTV_LINEAR, and MTD). These measures are further defined as.

- **MTR** – It represents the location measure of the CDF plots. It was the median time required to
cross one mile of the segment. MTR was obtained as the 50th percentile of the median of each day’s travel rate. The median travel rate is shown as point “a” in Figure 5.

- WDV – This represents the spread of the CDF plots. The WDV was the difference between the median 95th and 5th percentiles of a segment and reflects a segment’s daily variability. High WDV values meant that there was significant fluctuation in travel rate for that segment. The WDV for a segment is shown as point “b” in Figure 5.

- OTV_LINEAR, OTV_POLY, and MTD – The variation in the shape of the CDF plots were captured using three measures. First, a 90% confidence envelope (refer to Figure 6(a)) was obtained by joining the 5th and 95th percentiles of each 5th percentile (0, 5, 10, … 100) values of the travel rate CDF data as shown in Figure 6(b). Next, horizontal intermediate quantile differences were calculated for each twenty-one percentiles (0, 5, 10, and so on) (Holland, 2002) and a second-degree polynomial equation (quadratic) was fitted to the resulting data points as shown in Figure 6(c). Thus the points which are “x,” “y” and “z” change accordingly from Figure 6(b) to (c). The equation is of the form.

\[ Y = OTV_{POLY} \times x^2 + OTV_{LINEAR} \times x + MTD \]  

Where, the coefficient OTV_POLY represented the quadratic nature of the change of quantiles, the coefficient OTV_LINEAR represented the linear change of quantiles, and MTD referred to the variability for the fitted travel rate at the 0th percentile.

OTV_POLY and OTV_LINEAR can have different combinations in the real-world scenario. However, in the analysis, the former was always seen to be positive, the latter was seen to be negative, and the focus of the parabolic shape obtained was within 0 to 100. This gave rise to Figure 6(c). This meant that the difference of the percentile would first decrease for some percentile values and then keep on increasing. The coefficient MTD represented the variation of the travel rate during free flow conditions. High values of
MTD meant that the free flow variation in travel time was significantly high. Using these five parameters, the poor performing segments were identified. Since each segment had variability in traffic flows and number of intersections, they had to be divided based upon the following geometric parameters: AADT per lane (AADT density) and number of intersections per mile of a segment (intersection density or ID). An agglomerative clustering algorithm was used to divide them into a similar type of geometric performance (Abraham et al., 2014). Complete linkage which provided the maximum distance between two sets was used to cluster the elements as this would ensure that the groups were far apart from each other. In order to determine the appropriate number of intersection groups, the average silhouette score was determined for different cluster groups (Abraham et al., 2014). This is calculated based on the mean intra-cluster distance and the mean nearest-cluster distance for each segment.

For each of these groups, PCA was conducted using the five parameters of each segment. Based on the principal components’ variance (refer Figure 7), three types of poor performing segments were identified.

- Poor Type I – These segments had all the measures performing poorly.
- Poor Type II – These segments had the WDV, OTV_POLY, OTV_LINEAR, and MTD parameters performing poorly.
- Poor Type III – These segments only had the MTR parameter performing poorly.

Segments can behave as good, poor type I, poor type II or poor type III. Based on them, the segments which are Poor Type I would be the worst ones in performance.

Segments were finally aggregated in terms of the percentage of different behavior at a corridor level. Dynamic corridors and the performance of the corridors on normal days were used to judge the overall performance of any corridor. The corridors that were dynamic and poorly performing on normal days should be the

**Figure 7.** Performance of the segments based upon percentage of variance explained by the Principal Component(s).

**Table 3.** Reasons for some of the top dynamic days.

| Rank | Date          | Total number of segments (Number of dynamic segments) | Percentage of segments with dynamic days | Reasons               |
|------|---------------|------------------------------------------------------|----------------------------------------|-----------------------|
| 2    | 11/26/2016    | 45(8)                                                | 17.78                                  | Thanksgiving weekend  |
| 3    | 11/27/2016    | 23(4)                                                | 17.39                                  | Thanksgiving weekend  |
| 5    | 9/5/2016      | 65(10)                                               | 15.38                                  | Labor Day             |
| 6    | 12/17/2016    | 85(13)                                               | 15.29                                  | Snow                  |
| 7    | 1/19/2016     | 252(37)                                              | 14.68                                  | Snow                  |
| 8    | 1/24/2016     | 68 (9)                                               | 13.24                                  | Fog                   |
| 10   | 9/3/2016      | 121(15)                                              | 12.40                                  | Des Moines Triathlon  |
first ones to implement the adaptive control. This can be followed by the corridors performing poorly on normal days because a corridor is expected to perform well on normal days. This information can be used to support the traffic engineer’s decision making when considering adaptive control as well as prioritizing the remaining signals that need retiming.

Results and discussions

This section describes the application of this methodology to the Des Moines metropolitan corridors identified in section above.

Dynamic days for different locations

The days with a LOF value greater than 2 (Cheng, 1995) and those beyond the elbow-cutoff point, were seen to be significantly different from the others for most of the segments and was determined to be the threshold for dynamic days. Using this ideology, the dynamic days were identified for each segment, collected daily, and some of the top listed days are noted (Table 3). Weather was observed as the major cause of dynamic behavior, suggesting that the speed of traffic was highly influenced by weather in Iowa. The percentage of dynamic days show the variability in traffic demand. Higher percentage of dynamic days correspond to wider variability of travel rate over that segment. Analysis of the dynamic days revealed that the highest dynamic days were located on Grand Avenue and Ashworth Road. A segment is defined as a dynamic segment if it had more than 6% of dynamic days, which was determined by the elbow cutoff point on the percentage of dynamic days. Dynamic segments were used to identify dynamic corridors (Table 4), which identified Ashworth Road and Grand Avenue corridors as having the highest percentage of dynamic segments, which is apt as the former is influenced by the largest church in the state and later one by major entertainment events within the downtown area.

Evaluation of travel rate metric

The travel rate metric was determined for the remaining normal days. The five parameters – OTV_POLY,
OTV_LINEAR, MTD, MTR, and WDV were calculated for each segment. The segments were then grouped based on AADT density and Intersection Density. To have an optimum number of clusters, the maximum number of clusters was limited to 15. The average silhouette measure yielded an optimum cluster number (maximum average silhouette measure) of 9 for the given segments. Out of these, 3 were outliers and the remaining analysis was conducted using the other 6 clusters which were named according to their values. Also, 90% confidence bounds for each group and the descriptive statistics are shown in Tables 5 and 6, respectively.

These measures were used to define the performance of the segments on normal days. To capture the variation using fewer and more precise parameters, PCA was calculated for all the segments within each group. Based on the percentage of variance explained by the first two principal components (Table 5), it was seen that the groups: Low AADT with Low ID, High AADT with Medium-high ID, and High AADT with Medium-low ID (Group 2) required two principal components. The different types of poor performance meant that the segment did not behave well in some respect of the travel rate. For this analysis, the poor performance was defined as follows.

- **Poor Type I** – This type included all the segments that have:
  - A positive principal component 1 for Group 1 (Figure 8).
  - A positive principal component 1 and positive principal component 2 for High AADT with Medium-low ID.
  - A positive principal component 1 and negative principal component 2 for all other members of Group 2 (Figure 9).

- **Poor Type II** – This type included all the segments that have:

![Figure 8](image-url)

**Figure 8.** (a) Principal Component 2 versus Principal Component 1 for segments on Group 1 (Low AADT and High ID) color-coded based on PC 1 and (b) Normalized values of MTR (MTR Norm), WDV (WDV Norm), OTV_POLY (OTV_POLY Norm), OTV_LINEAR (OTV_LINEAR Norm), and MTD (MTD Norm) for segments on Group 1 (Low AADT and High ID) color-coded based on PC 1.
Poor performing Group 2 segments with respect to principal component 1 only (Figure 9). These are represented by positive value on principal component 1 only.

Poor Type III – This type included all the segments that have:

- Poor performing Group 2 segments with respect to principal component 2 only (Figure 9). These are represented by positive value on principal component 2 only.
- Poor performing Group 2 segments with respect to principal component 2 for High AADT with Medium-Low ID negative value on principal component 2 for other group members of Group 2 (Figure 9).

After classifying the segments for each category, they were accumulated at corridor level (Figure 10). The results so obtained had 44.88% as good and 36.4% as poor and the remaining 18.72% as combination of either type of poor segments.

They were also grouped into adaptive and non-adaptive group to determine the performance of these groups separately. It was found that 22nd Street and Jordan Creek Parkway were the ones that remained problematic despite having ASCT installed on them. University Avenue, Merle Hay Road, and Grand Avenue were the non-ASCT based corridors that had high percentage of problematic segments. The main cause for 22nd Street was that the segments were shorter (average of 0.27 mile) as compared to other corridors (average of 0.49 mile), which led to high variation in traffic. Despite currently being under adaptive control, Jordan Creek Parkway performed rather poorly as it is the major arterial corridor connecting University Avenue and Ashworth Road to freeways. Like Ashworth Road, Jordan Creek Parkway serves both businesses, churches, and a regional mall, which increases corridor travel times. The overall performance of the
corridors, in terms of dynamic days and normal days’ performance, is shown in Figure 11.

To convert non-ASCT corridors to ASCT, Grand Avenue, University Avenue, and Merle Hay would be considered the three most suitable locations. However, it would be difficult to implement ASCT on Grand Avenue as parts of it is in the downtown area where signals run on fixed time coordination patterns to serve pedestrian mobility as well. Hence, ASCT would benefit University Avenue and Merle Hay Road. A
thorough investigation can also be conducted on the Jordan Creek Parkway to determine why it cannot perform adeptly under ASCT.

**Conclusion**

Probe-based real-time data are available from several vendors. This study uses such data source to determine segment performance and identify problematic segments on different arterial corridors by applying time-saving parallel computation.

Travel rate, defined as travel time per mile, was determined as the parameter used to evaluate these measures. CDF plots of travel rate were constructed to represent the daily variability and behavior of the segments. Unlike previous studies that used all days to capture the performance road segment, this study identified and removed each roadway segment's dynamic days. Dynamic days were then evaluated separately to identify the extent of anomalies and potential interventions relevant to unusual situations, such as special events, severe traffic incidents, extreme weather, and construction. After removing dynamic days, segments were classified into homogenous geometrical characteristics – Annual Average Daily Traffic per lane and intersections density. Five measures were further extracted for these segments to quantify the overall performance of a segment – MTR, WDV, MTD, OTV_POLY, and OTV_LINEAR. PCA was further applied to these variables to reduce dimensionality and further identify poor segments.

A case study was conducted for eleven arterial corridors within the Des Moines metropolitan area in Iowa, with real-time data above 40% of total duration during the daytime, to identify their performance. The dynamic days were extracted and segments with the highest dynamic days were found on Grand Avenue and Ashworth Road. After removing the dynamic days, the remaining segments were analyzed for their typical behavior, which resulted in 36.4% of the 300 segments as problematic. The most problematic segments which already had adaptive control were located on 22nd Street and Jordan Creek Parkway due to smaller length and major arterial connecting other corridors and interstates. For those without adaptive control, Grand Avenue, Merle Hay Road, and University Avenue were the worst in performance. As Grand Avenue is near downtown, so they have fixed time coordination, the next two corridors suitable for adaptive are Merle Hay Road and University Avenue.

The poor overall grade on NTSRC reflects deficient signal retiming (National Transportation Operations Coalition, 2012). The measures used in this study will serve as a guideline to the different agencies that can regularly evaluate the performance, identify the problematic segments along corridors, and come up with quicker solutions, leading to better monitoring of the traffic signals, which would help the overall score in future evaluation. Future work can apply this methodology to other cities and test these threshold values. Through the measures defined, transportation agencies can easily automate the process of monitoring the performance of arterials to identify, screen, and prioritize signal retiming or traffic control modifications. This tool can support agency decision making, planning, and operational investments as they try to provide both throughput and safety for roadway users.

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