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Evaluation of changes on traffic corridors: A data-driven approach

Mostafa Khatami[1], Chelsee Home[2], David Gyles[2], Frans Dekker[2], Ashish Bhaskar[1], Alexander Paz[1]

[1]School of Civil and Environmental Engineering, Queensland University of Technology, Brisbane, QLD 4000, Australia

[2]Queensland Department of Transport and Main Roads (TMR), Brisbane, QLD 4001, Australia.

Mostafa.khatami@qut.edu.au Alexander.paz@qut.edu.au

1. Introduction

Transport agencies, such as the Queensland Department of Transport and Main Roads, routinely monitor roadway conditions and performance measures, and make necessary changes to enhance performance. These changes may be in response to road user complaints, staff observations of specific traffic problems, or systematic upgrades to traffic corridors. The impact of upgrades should be systematically evaluated to review the operational conditions of roadways/intersections. Though, evaluating the effects of upgrades, commonly performed with a before-after analysis, can be challenging due to (*i*) heterogeneous data sources, (*ii*) various performance measures, and (*iii*) underlying patterns in the data that could mask the real benefits (if any) of the changes.

This study proposes a systematic framework to quantify the effects of upgrades to road infrastructure, such as signal timing plans. Accurate travel time data is a key input in an upgrade evaluation process, and there are a variety of methods to collect this data, such as Global Positioning System (GPS) probe data and Bluetooth. Depending on the source of data, spatial and/or temporal aggregation may be required, which has an important impact on travel time statistics (Büchel and Corman, 2020). There are several studies comparing these data collection methods. For example, Berzina et al. (2013) performed a statistical analysis to evaluate three different data collection methods, while Zhang et al. (2015) proposed a scheme to validate arterial travel time based on GPS probe and Bluetooth data as two independent sources.

Various measures are available to evaluate the performance of a corridor. In addition to mean and median travel time as central tendency measures, reliability measures can capture the reliability/dependability of travel time experienced by travellers. Reliability measures evaluate variation/uncertainty in day-to-day origin-destination travel time. Studies have investigated the concepts, applications, and methodological developments of reliability measures, such as Taylor (2013) and Zang (2022). There are also measures to quantify the congestion of a corridor. The proposed systematic framework incorporates central tendency, reliability, and congestion measures as part of a before-after analysis.

Different factors can contribute to variation in origin-destination travel time, some of which are irregular, such as severe weather events, while others are linked to underlying patterns, such as the day of the week. The effect of an upgrade/change on a corridor can vary for different underlying patterns, and benefits and disbenefits may cancel out in an aggregated evaluation. In the proposed framework, a pattern analysis is incorporated to overcome this issue.

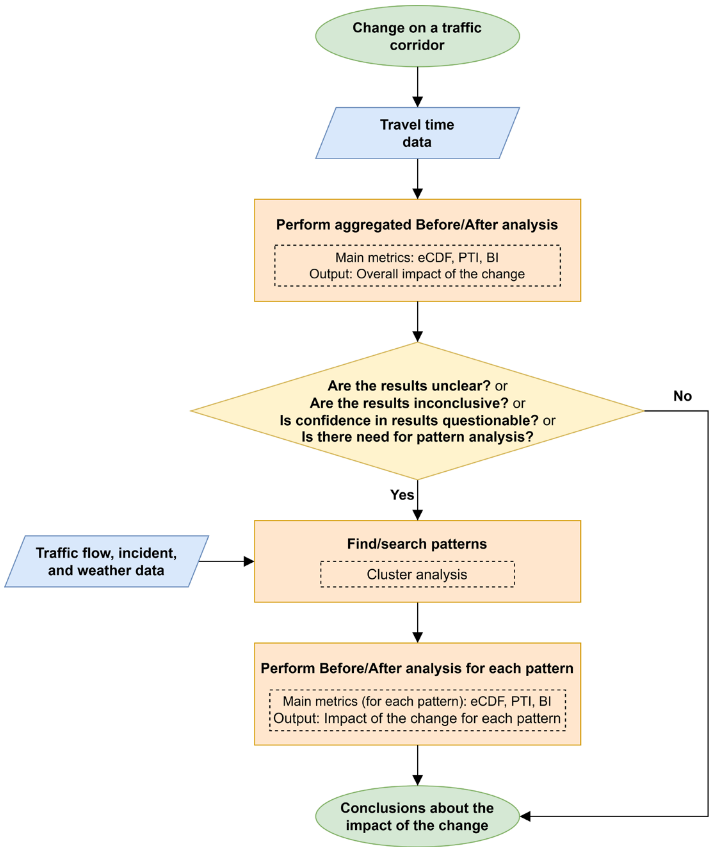
While studies have investigated the effects of upgrades on corridors, they have mostly focused on specific aspects of the evaluation process rather than proposing a unified approach. For example, Li et al. (2015) quantified the route travel time performance for an arterial south of

Indianapolis, Indiana, evaluating controller synchronization and offset optimization using travel time distributions and the percentage of vehicles arriving on green. Li et al. (2019) assessed a signal upgrade project in southeastern Salt Lake County, exploring the use of link-based travel times from probe data to estimate two metrics, median and interquartile range travel time. In this paper, we demonstrate that failing to consider all aspects of an evaluation process can result in incomplete or inaccurate conclusions. Particularly, we propose an easy and unified approach in which data preparation and aggregation, analysis of performance measures, and analysis of underlying patterns are incorporated into a systematic framework.

2. The proposed systematic framework

The proposed systematic framework, as shown in Figure 1, begins with an upgrade/change to a traffic corridor. After collecting the travel time data and conducting necessary data preparation processes, an "aggregated" before-after analysis is performed to evaluate the impact of the change on the corridor. The analysis is performed using all available data, i.e., no data segmentation is performed at this stage. Several metrics are utilised to quantify the effect of the change, resulting in quantifying the "overall" impact of the change. If the results of this overall analysis are unclear or inconclusive, if the confidence in the obtained results is questionable, or if, for any other reason, there is a need for re-performing the before-after analysis with clustered data, a pattern analysis is performed. The intent is to cancel out the performance differences between the before and after period, which are unrelated to the upgrade/change to the traffic corridor. Cluster analysis is the approach to find patterns in the data, for which additional data such as traffic flow, incident data, and weather data are required. Once distinctive patterns are identified, a before-after analysis is performed for each pattern separately to determine the impact of the change on each pattern. This provides the analyst with more in-depth insights and conclusions into the effect of the performed change.

Figure 1: Flowchart of the proposed systematic framework



2.1. Data preparation

The proposed framework can utilise data from any dependable travel time data source, as long as all data is from the same source.

Since most reliability and congestion measures provide route-level statistics, spatial aggregation of travel times may also be required.

Depending on the data source, temporal aggregation of travel time data may be required. For that, small time intervals (e.g., 1 to 5 min) will cause significant fluctuations, and may also be encountered with missing values, while large intervals (e.g., 60 min) could lead to aggregation errors (see, e.g., Steinmaßl et al., 2021). Therefore, 15-min aggregation intervals are recommended. Temporal aggregation uses traffic flow as a weight to calculate a weighted average travel time.

The framework is also augmented with a sample size recommendation based on the variability of the data. To estimate the mean travel time with a tolerance of $\pm\Delta$ seconds at a confidence level of $x\%$, the recommended minimum sample size is calculated using the formula z^2s^2/Δ^2, where z is the z-score for $x\%$ confidence level and s is the sample standard deviation.

2.2. Before-after analysis

After determining the minimum sample size and preparing the travel time data, the proposed framework utilises three primary metrics, namely, empirical Cumulative Distribution Function (eCDF) (Tufuor et al., 2020), Buffer Index (BI) (Lyman and Bertini, 2008), and Planning Time Index (PTI), to conduct a before-after analysis on the travel time data before and after the proposed upgrades/changes.

2.2.1. Empirical Cumulative Distribution Function (eCDF)

eCDFs are a commonly used statistical tool that allow for easy visualization and efficient comparison of travel times in before-after analyses. The proposed framework compares eCDFs using five statistics, in addition to a statistical hypothesis test. These statistics include (1) the median (50th percentile) travel time in seconds, which is a central tendency measure less affected by outliers than the mean travel time, (2) the interquartile range (IQR), which is the difference between 75th and 25th percentile travel times in seconds, representing the variability in travel time without excessive influence by the tails of the distribution, (3) the 95th percentile travel time in seconds, which is the input for BI and PTI metrics as well, (4) the slope of eCDF within IQR (denoted by IQR slope) in percentage per minute, which is the percentage change in cumulative frequency by one minute increase in travel time within IQR region, and (5) the average slope in percentage per minute, which is similar to IQR slope measured within the 5th and 95th percentage travel time region. A smaller median, IQR, and 95th percentile travel time in the after period indicate improvement, while a larger IQR slope and average slope in the after period represent smaller variability, corresponding to improved travel time reliability. We also include the non-parametric Kolmogorov-Smirnov test to statistically measure the difference between the two eCDFs, based on the largest distance between the two distributions. The null hypothesis is that the before and after distribution functions are not statistically different.

2.2.2. Buffer Index (BI)

Buffer Time (BT) is a recommended extra travel time that travellers should consider adding to their average travel time to ensure that they can reach their destination on time 95 percent of the time, i.e., $BT = T_{95\%} - \mu$, where $T_{95\%}$ and μ represent the 95th percentile and mean travel time, respectively. Based on that, BI is calculated by dividing BT by mean travel time, i.e., $BI = \frac{BT}{\mu}$. Intuitively, BI is the extra percentage of travel time required to reach a destination on time 95 percent of the time. Larger BT or BI are typically associated with longer delays and decreased travel time reliability.

2.2.3. Planning Time Index (PTI)

PTI is the ratio of the 95th percentile travel time to the Free-flow Travel Time (FTT), i.e., $PTI = \frac{T_{95\%}}{FTT}$, where FTT is the mean travel time in free-flow or light traffic conditions, e.g., 10 PM to 5 AM. It represents the extra time that should be budgeted relative to FTT. The PTI denotes the near-worst case travel time as compared to travel time during free-flow traffic. PTI suggests the level of congestion, i.e., the severity of delay as compared to free-flow conditions. Often, the more congested a corridor is, the more unreliable it can be. Hence, one can potentially infer the level of reliability from the PTI metric. However, a corridor can be congested and still experience consistent travel times, thereby considered reliable (Ale-Ahmad, 2020).

2.3. Pattern analysis

Hierarchical clustering is a widely used approach for clustering time-series data, which involves grouping objects based on a similarity/dissimilarity measure. A distance metric is used to quantify the distance between pairs of time-series data, resulting in a "distance matrix". Various distance measures have been proposed, with the Euclidean distance performing well in many cases (Ding et al., 2008). The output of a hierarchical clustering algorithm is presented in an agglomerative dendrogram, where objects start in individual clusters and merge as they move up the hierarchy. Cluster analysis is conducted separately for morning and afternoon peak periods to identify different patterns in each period. Combining them may obscure the ability to distinguish between the patterns. After the cluster analysis for a corridor is performed, potential causes such as incidents, weather events, average flow, and day of the week are considered to explain observed patterns. Statistical testing of correlations between travel times and potential causes, such as day of the week, is performed using Pearson's correlation test, which assesses the linear relationship between two continuous/categorical variables.

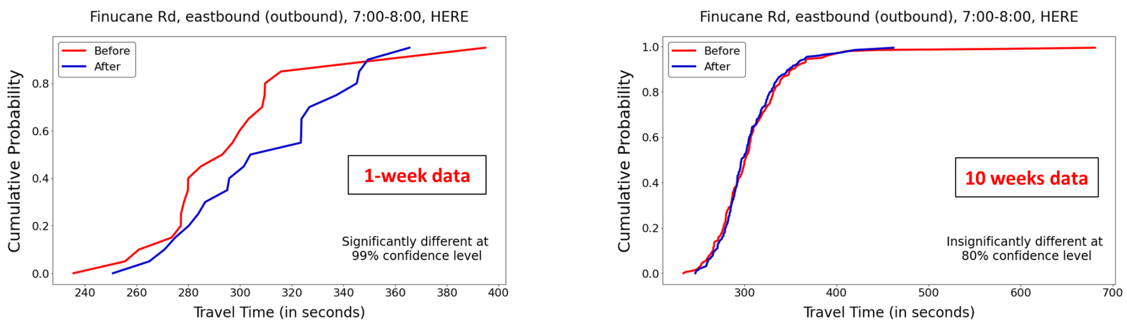
3. Results

The proposed framework has been tested on three traffic corridors in South East Queensland. The first case study is Finucane Rd, a 4-km long corridor situated in Redland City. The signal timing plan for this corridor was changed on July 30, 2020, and implemented from 7-9 AM and 4-7 PM. The second case study focused on Wembley Rd, a 5.1-km long corridor located in Logan City. The signal timing change for this corridor was implemented between June 21 and June 27, 2021, from 7-9 AM and 2-7 PM. The third case study examined Moggill Rd, a 12-km long corridor in Brisbane. Unlike the first case study, no changes to the signal timing plan have been implemented on this corridor. It serves as a control case to verify the accuracy of the results. In particular, if there are significant differences observed in this corridor, seasonal effects may have influenced the before-after analysis. However, if no significant differences are found, it can be concluded that the improvements observed in the case study with performed changes are solely due to the signal timing changes made. The reference point used to divide the before and after periods is set to July 30, 2020, which is consistent with the first case study.

3.1. Data preparation results

In this study, we used three data sources, including STREAMS (traffic management system), Bluetooth (Bhaskar and Chung, 2013), and HERE (probe data). The minimum required sample size for each case study is calculated using the approach described in Section 2.1. As an example, consider the 7:00-8:00 HERE travel time data for Finucane Rd outbound direction. By setting the confidence level to 95% and Δ to ± 15 seconds, the minimum sample size for the before and after periods is 44 and 42, respectively. Using 15 min travel times, this leads into at least 11 and 10 days data for a 1-hour analysis. Figure 2 demonstrates how a smaller sample size can affect the results. Particularly, while a 1-week analysis results in eCDFs with significant fluctuations and showig that the after period is worse, an analysis with 10 weeks data results in smooth eCDFs and an insignificant difference between the eCDFs.

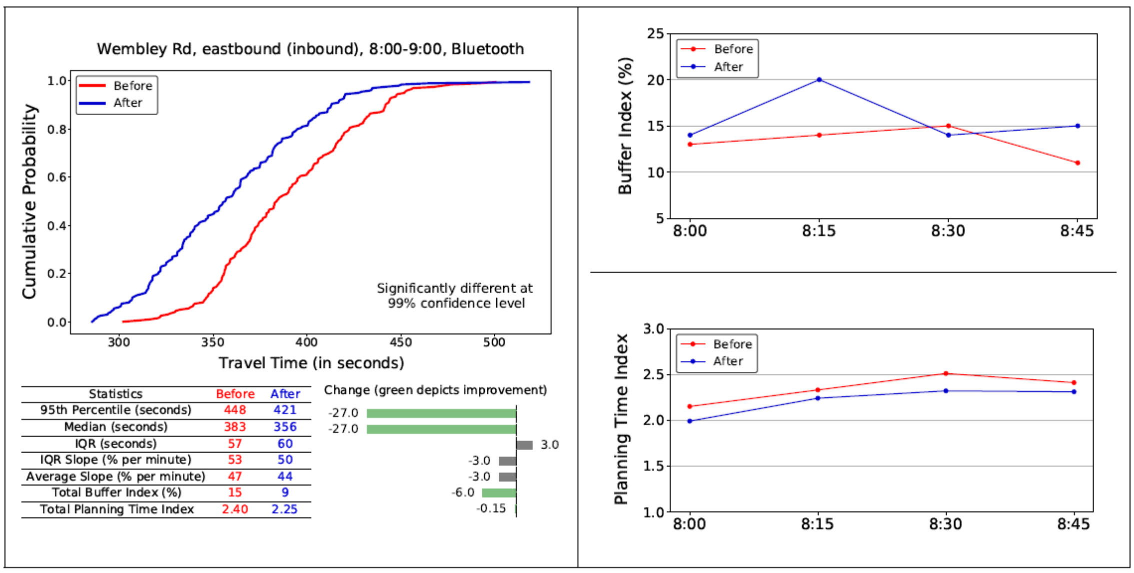
Figure 2: Before-after analysis with 1 and 10 week data (Finucane Rd, outbound, 7-8 AM, HERE data)



3.2. Before-after analysis results

After review of literature and discussion with the practitioners, a simplified tool to visually present the results of a before-after analysis is considered. Figure 3 shows an example result of the analysis applied to 8-9 AM Bluetooth travel time data for Wembley Rd. The left-hand side shows eCDFs for before and after periods, along with the five relative statistics below the eCDFs. We also present total BI and total PTI metrics, which represent these two metrics where all 15 min travel times in the 8-9 AM interval are considered. The graph is colour coded to demonstrate the changes in statistics. For this particular example, eCDFs show that there is a statistically significant difference between before and after periods. In addition, considering the total BI and PTI metrics, reliability and congestion are improved in the after period. On the right-hand side we show the BI and PTI metrics calculated for each 15 min interval individually. As can be observed, PTI is improved in the after period across all four 15 min intervals. However, BI has been similar in before and after periods for 8 AM and 8:30 AM, but inferior in the after period for the remaining two intervals.

Figure 3: Example result of the before-after analysis, Wembley Rd (inbound, 8-9 AM, Bluetooth data)



3.3. Pattern analysis results

An analysis of traffic patterns on Finucane Rd is conducted, focusing on the morning and afternoon peak periods separately. Results indicate a positive correlation between traffic flow and day of the week. Specifically, two patterns emerged during the morning peak period: Mondays/Fridays and midweek days. To illustrate the benefit of finding these patterns, before-after analysis is then performed for each pattern separately. Results show that the reliability is improved in both patterns. However the change in travel times is more evident for Mondays/Fridays than midweek days, as shown in Figure 4. However, an overall analysis does not reveal the benefits obtained in Mondays/Fridays, as shown in Figure 5. This demonstrates that with a pattern analysis, the transport agency could only apply the traffic signal improvements on the days of the week when it is beneficial.

Figure 4: Before-after analysis for two distinct patterns (Finucane Rd, 8-9 AM, using STREAMS data)

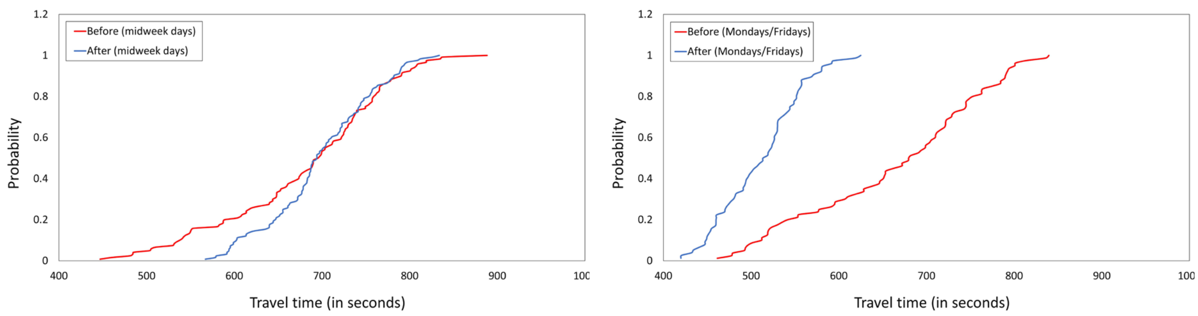
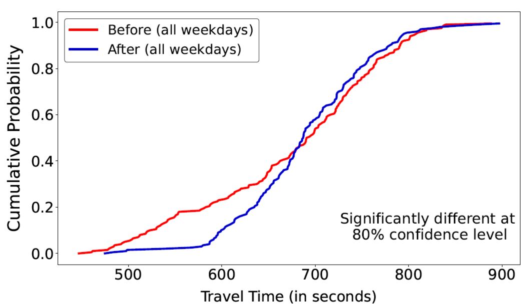


Figure 5: An overall before-after analysis without considering patterns (Finucane Rd, 8-9 AM, using STREAMS data)

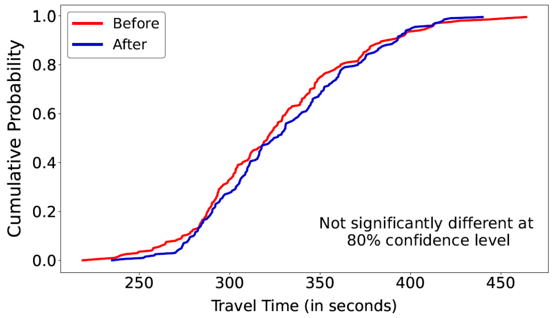


We note that in the afternoon peak period, Mondays formed one pattern, while all other weekdays formed another, which is different from the patterns observed in the morning period. This highlights the importance of performing pattern analysis for each peak period separately.

3.4. Control case study

We expect to observe insignificant differences in the control case, showing natural variation, as opposed to significant variations observed in other cases with an upgrade. Considering the Wembley Rd, the proposed framework was able to identify significant differences across all hours on both directions (an example is depicted in Figure 3). On the other hand, results for the Finucane Rd showed a significant difference for some hours (one example is shown in Figure 4). In contrast, Moggill Rd, which serves as the control case in this study, shows no significant difference in almost all hours on both directions. For instance, Figure 6 presents the eCDFs for Moggill Rd 18A, 7:00-8:00, using HERE data. The eCDFs are not significantly different at an 80% confidence level. The inconsistency in the statistics further supports the natural variation in this case, such as the improvement in the 95^{th} percentile travel time and the worsening of the median travel time in the after period.

Figure 6: Travel time eCDFs for Moggill Rd 18A, inbound direction, 7-8 AM, using HERE data.



4. Conclusions

In this study, we presented a framework for evaluating changes made to traffic corridors. Our proposed framework consists of three main components: (1) data preparation procedures, (2) a before-after analysis, and (3) a pattern analysis. To test the effectiveness of our framework, we conducted three case studies in South East Queensland. The results demonstrated that the framework was successful in providing valuable insights about the changes made to two corridors which underwent changes, as well as when the changes are more beneficial.

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