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Modelling Travel Time Variability within Transport Networks: A Practitioner Oriented Approach

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Abstract

The Australian Transport Assessment and Planning (ATAP) guidelines have been developed to assist planning, assessing, and developing transport systems and initiatives. It is widely recognised that travellers take into consideration travel time reliability in their travel decision making. Therefore, the benefits of improved travel time reliability ought to feature in appraisal of transport related initiatives. While modelling travel time variability has been widely studied by researchers, the methods lack a practitioner-friendly approach. The aim of this work was to propose calibrated, practitioner-ready models to determine travel time variability at a resolution of a link and a route. Specifically, the team used data (observed travel times and their standard deviations) from different jurisdictions across Australia to develop models that can be applied to a range of road stereotypes (capacity and congestion). For the link travel time variability, an exponential functional form was developed, referred to as the ATAP model, and was found to outperform other shortlisted models. Separate ATAP model parameters were calibrated for arterial and freeway links. The calibrated models were also validated using travel time data from Australian states. For the route travel time variability, a Correlation Route Model (CRM) is recommended which comprises two components: ATAP model and the Correlation Coefficient Model (CCM). This paper utilises the Western Australia Wanneroo Road Duplication project as a case study to demonstrate the application of CRM on a defined route to estimate the change in travel time reliability and compare against the measured change from field data. The case study results substantiated the accuracy of CRM in predicting observed route travel time SD. This work provides simple equations which can be quickly applied by practitioners to determine expected travel time variability in a road network and utilise it in transport planning and economic appraisal applications.

1. Introduction

This paper presents the findings of the study TAP6234 (ATAP 2021), which was to develop an approach for measurement of road reliability for inclusion in the Australian Transport Assessment and Planning (ATAP) Guidelines. In the context of transport, travel time reliability is used to describe how certain the travel time is for a journey for a road user. Travel time reliability has been an active area of research in the past decade owing to its repercussions on traffic movement and congestion in a road network. The benefit of changes in travel time reliability expressed as a monetary amount can be applied in Cost–Benefit Analysis (CBA) of transport projects and/or policy changes. This benefit is estimated by multiplying the road users' Willingness-To-Pay (WTP) (measured in $/h) to reduce travel time variability by the predicted changes in travel time reliability improvements from a transport project, as shown in Equation 1 below. This study aims to develop a methodology and calibrated parameter values to estimate the latter quantity, that is, a way to predict changes in travel time reliability. The estimation of WTP for travel time reliability is beyond the scope of this work. The mathematical models developed to forecast travel time reliability for different elements in a road network need to be readily usable by practitioners. While parameter values estimated from available data (across several jurisdictions in Australia) are provided, practitioners should be able to recalibrate the models using their own data.

Value of a travel time reliability improvement benefit ($) = Unit value of reliability ($/min) x Saving in travel time variability (mins) [EQ 1]

This paper focusses on travel time variability modelling in link and route levels only. A companion paper that focuses on the detailed travel time variability for network modelling has also been prepared.

2. Background

2.1. Understanding Travel Time Variability and Reliability

Travel time variability has been defined as the distribution/spread or dispersion of travel times over a journey and over time (Osterle et al., 2017). Although a simple concept, MRWA (2016) and PIARC (2019) found that there is no global standard or industry agreed definition of variability. On the other hand, travel time reliability, as noted by Moylan et al. (2018), has been introduced using several definitions in the literature. In the context of transport, travel time reliability is used to describe how certain the travel time is for a journey. Travel time variability is a good measure of travel time reliability and is typically used by transport agencies. Travel time reliability is then calculated as a statistical measure using travel time variability (Austroads, 2011).

Several models have been developed in the past to measure travel time variability, namely the mean variance model, scheduling model, mean lateness model, options approach, vulnerability approach, and other general models[1] (Austroads, 2011; Moylan et al., 2018; MRWA, 2016; PIARC, 2019). This paper adopts the mean–variance approach for practical applications in CBA and toll road patronage forecasting. The justification behind this recommendation was that the mean–variance approach results in a single unit value of reliability that represents the marginal value of one Standard Deviation (SD) of travel time.

[1] For a full description see Section 4, Austroads (2011)

2.2 Link Travel Time Variability

A link is a continuous section of the entire road segment that facilitates movement of vehicles and depicts homogeneous physical and traffic characteristics (e.g., discontinuities such as going from three lanes to two, presence of a signalised intersection on a straight road, and connections between on/off ramps to motorway are all represented as separate links). A literature review shows that several models have been developed to forecast the SD of travel time on links and routes. Table 1 lists the dependent and independent variables of the 11 models and their dependent variable limits.

Table 1: Variables and limits of the eleven existing models to estimate travel time variability

	Model	Dependent variable	Independent variable(s) included	Limits of dependent variable
1	UK Model (UKM) $CoV = a\left(\frac{T}{T_f}\right)^b D^2$	CoV	• Congestion index specified as the ratio of mean and free flow travel time • Length of travel	• Minimum = a • Maximum = ∞
2	Log-linear Model (LLM) $ln(Cov) = ln(a) + b \cdot ln\left(\frac{T}{T_f}\right) + c \cdot ln(D)$	CoV	• Congestion index specified as the ratio of mean and free flow travel time • Length of travel • Road type assigns different parameters	• Minimum = a • Maximum = ∞
3	New Zealand Model (NZM) $\sigma = \sigma_0 + \frac{\sigma_1 - \sigma_0}{1+exp\left[b\left(\frac{V}{C}-a\right)\right]}$	SD	• Congestion index specified as the ratio of volume (in terms of demand) and capacity • Road type assigns different parameters	• Minimum = σ_0 • Maximum = σ_1
4	Unified Reliability Model (URM) $\sigma = KT^{\alpha}D^{\beta}$	SD	• Travel time • Length of travel	• Minimum = a function of capacity, time-of-day and type of route • Maximum = ∞
5	Linear Model (LM) $\sigma + a + bT$	SD	• Travel time	• Minimum = a • Maximum = ∞
6	Length Standardised Linear Model (LSLM) $\frac{\sigma}{L} = a + b\left(\frac{T}{L}\right)$	SD per unit length	• Unit travel time (that is inverse of speed)	• Minimum = a • Maximum = ∞
7	Length Standardised Cubic Model (LSCM) $\frac{\sigma}{L} = a + b\left(\frac{T}{L}\right) + c\left(\frac{T}{L}\right)^2 + d\left(\frac{T}{L}\right)^3$	SD per unit length	• Unit travel time (that is inverse of speed)	• Minimum = a • Maximum = peaks at a defined unit travel time then declines to negative values

	Model	Dependent variable	Independent variable(s) included	Limits of dependent variable
8	Exponential Coefficient of Variation Model (ECVM) $CoV = exp\left[a + b\left(\frac{T}{T_f} - 1\right) + c\left(\frac{T}{T_f} - 1\right)^3\right]$	CoV	• Congestion index specified as the ratio of mean and free flow travel time	• Minimum = exp(a) • Maximum = peaks at a defined congestion index then declines to zero
9	Power Mean Delay Model (PMDM-1) $\sigma = aD^b$	SD	• Congestion index specified as mean delay (that is difference between travel time and free-flow travel time	• Minimum = a • Maximum = ∞
10	Polynomial Mean Delay Model (PMDM-2) $\sigma = a + bD + cD^2 + dD^3 + eL + fcL^2$	SD	• Congestion index specified as mean delay • Length of travel	• Minimum = a • Maximum = ∞
11	Dutch model (DM) $\sigma = a + bD + c \cdot log_{10}(D + 1) + dL$	SD	• Congestion index specified as mean delay • Length of travel	• Minimum = a and increases linearly with length • Maximum = ∞

Note: a, σ_0 and σ_1 are the calibration parameters which define the boundaries of the dependent variable

The literature review indicated that using CoV as the dependent variable provides better model fits when compared to SD forecasting models. The estimated CoV is then converted back to SD to measure the monetary cost of travel time reliability to be used during the CBA. It was found that some link models could forecast ever increasing values of CoV as the V/C or the CI increases. This mathematical aspect, however, is not consistent with observed real-world traffic phenomenon where travel time variability tends to change at a much lower rate beyond a certain threshold. It is worth noting at this point that this rate of change in the SD of travel time can be positive (that is increasing) or zero (that is constant). Thus, both potential options need to be explored using two types of trendlines: 1) where the rate of increase in SD of travel time is gradual (that is no cubic or exponential forms), and 2) where the SD of travel time stabilises and takes the shape of a plateau beyond the threshold value.

2.3. Route Travel Time Variability

The review identified two approaches to modelling route travel times, one of which is the SD of travel time based route model such as Correlation Route Model (CRM) which is discussed next.

2.3.1. SD of Travel Time Based Route Model

The SD of travel time based route model involves forecasting the link travel time SD (using the models discussed in Section 2.2) followed by combining the link travel time SDs to form the travel time SD for a route. There are two approaches for SD of travel time-based route models, either assuming that there is (i) a correlation between links or that (ii) the travel time variability of each link is uncorrelated.

The first approach, shown in Equation 2, referred to as the CRM, was recommended by Nicholson (2015) to include consideration of travel time correlation between all links within a route. Variance of route travel time is defined as the sum of the variances of link travel times and the sum of the covariances between any two links' travel time. This is in fact the most accurate measure of variance between datasets by using the variance sum law from statistical theory. However, this model increases the level of complexity in the calculation of variance and it is heavily reliant on available data to determinate the correlation coefficient of travel time between any two links. Nicholson (2015) also developed a Correlation Coefficient Model (CCM) to estimate the correlation coefficient, $\boldsymbol{\rho_{i,j}}$, to simplify the calculation.

$$\boldsymbol{\sigma_r^2 = \sum_{i=1}^{n} \sigma_i^2 + 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \rho_{i,j} \sigma_i \sigma_j}\,, i < j \qquad \text{[EQ 2]}$$

Where:

σ_r^2 = variance of travel time of route with n number of links

σ_r = SD of travel time of route

σ_i^2 = variance of travel time of link i

σ_i = SD of travel time of link i

σ_j = SD of travel time of link j

$\rho_{i,j}$ = correlation coefficient of travel time between links i and j

The second approach, as shown in Equation 4, assumes that the estimate of trip reliability for a journey could be built up using individual variability on links and junctions (measured in terms of variance) and that there is no correlation effect in the variance between the links and junctions (Osterle et al., 2017).

$$\boldsymbol{\sigma_r^2 = \sum_{i=1}^{n} \sigma_i^2} \qquad \text{[EQ 3]}$$

The NZTA Economic Evaluation Manual also assumes that travel times are independent, thereby the correlation coefficient is assumed to be zero (NZTA, 2013). If the correlation coefficient is zero, then Equation 2 simplifies to Equation 3.

Moylan et al. (2018) determined that expressing the SD of route travel time as Equation 3 results in under-estimating SD of route travel time by 43.5% with their field data. Nicholson (2015) using field data estimated that the contribution of the variance term in (that is first term in Equation 2) is around 9% or the covariance term is roughly 10 times greater (that is the second term in Equation 2).

3. Methodology – Model Development

An extensive literature review was undertaken at the start of the study to determine the state-of-the-art in modelling travel time reliability for links, routes, and at a network level.

3.1. Link

An Australian Transport Assessment and Planning (ATAP) model was developed. The ATAP model utilises a nonlinear equation expressing travel time Coefficient of Variation (CoV) as a function of the Congestion Index (CI; defined as the ratio of prevailing travel time and free-flow travel time) on a link. CoV was selected as the dependent variable, over SD, because CoV represents a standardised measure that facilitates comparison between links of varying lengths. Similarly, CI was chosen over volume-to-capacity ratio because capacity is not easily measurable. Unlike the other models, the ATAP model curve increases sharply at lower CIs, and follows a declining growth rate at higher CIs. This trend is consistent with real-world traffic dynamics where the improvements in travel time reliability are significant at lower congestion levels and miniscule at higher congestion levels. Thus, the ATAP model (shown below) was chosen as the recommended approach for forecasting link travel time variability.

$$\boldsymbol{CoV = a\left[\frac{(CI-1)}{CI}\right]^{b}\ \forall\ CI \geq 1} \qquad \text{[EQ 4]}$$

Where:
CoV = coefficient of variation, $\frac{\sigma}{T}$
CI = congestion index = $max\ (1, \frac{T}{T_f})$, where T = mean travel time (minutes) and T_f = free-flow travel time (minutes)
a = calibration parameter that sets the upper limit of CoV, $a \mid a > 0$
b = calibration parameter that determines the rate at which CoV approaches the maximum, $b \mid b \in (0, 1)$

For calibration purpose, Equation 4 was converted into the linear-log form below by taking log from both sides of the equation:

$$\boldsymbol{Ln(CoV) = Ln(a) + b.Ln(\frac{CI-1}{CI})\ \forall\ CI \geq 1} \qquad \text{[EQ 5]}$$

3.2. Route

For the route model, the CRM (Equation 2: $\sigma_r^2 = \sum_{i=1}^{n}\sigma_i^2 + 2\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\rho_{i,j}\sigma_i\sigma_j, i < j$), which follows the statistical theory (Mood, Graybill, & Boes 1974, cited in Nicholson 2015), was selected as the recommended approach to determine route travel time variability

The CRM comprises of two sub-models: 1) the ATAP model (Equation 4) that determines travel time SD of individual links, which $\sigma = CoV \times T$, and 2) the CCM predicts the degree of correlation among links forming a given route. The CCM (shown below) is a linear-log model relating the degree of correlation to the log of distance between the mid-points of two links within a route.

$$\boldsymbol{\rho_{i,j} = Max[0, a.\mathrm{Ln}(L) + b]} \qquad \text{[EQ 6]}$$

Where:
$\rho_{i,j}$ = correlation coefficient of travel time between links i and j where i < j
L = distance between the midpoints of two links (kilometres)
a, b = parameters

4. Model Calibration

4.1. Datasets

The data for this exercise was obtained from different jurisdictions across Australia: Perth (provided by MRWA), Gold Coast and Brisbane (provided by TMR) and Sydney (available from UNSW). The Perth network performance reporting system (NetPReS) dataset used is hybrid traffic data for 29 arterial and freeway routes in the Perth metropolitan area collected over 2018 to 2020. The data included traffic speed for each 15-minute period during the day for each link. The NetPReS dataset was used to calibrate the ATAP, and CCM. The Queensland data comprised daily NPI and Bluetooth data (by 15-minute periods) for arterials and freeways, and the Sydney data comprised travel time information for around 35 routes in Sydney collected using the Google API. Besides calibration and validation of the models, this study also tested two case studies using the Gold Coast and Perth data to assess the goodness of the CRM. This was considered desirable because the CRM includes the ATAP and CCM as sub-models. A detailed description of the datasets used in this study can be found in the Appendix of the ATAP project report (ATAP, 2021).

4.2. Link

Individual ATAP models, $CoV = a\left[\frac{(CI-1)}{CI}\right]^{b} \forall\, CI \geq 1$, were calibrated for forecasting travel time reliability for arterial and freeway links. Four months of traffic data (August to November 2018) between 5am and 9pm, which equates to 64 15-minute time intervals, was used to calibrate the model. The data was aggregated by each month for a given time interval for a link. This allowed the determination of day-to-day changes in link travel time within a 15-minute time interval on a month-by-month basis, which brings a fair bit of variability in the results as some months correspond to a particular traffic activity. The free-flow speed was taken as the 99th percentile of all speed values (in 15-minute periods) observed across all weekdays, excluding public holidays, in a month. All the speeds were then converted into travel times using link length information. The data were then filtered to remove any observations from which data were missing or where the CI was less than 1 because travel time should always be greater than or equal to free-flow travel time.

Table 2 shows the calibration statistics for the two models, Equation 5, i.e. $Ln(CoV) = Ln(a) + b.Ln(\frac{CI-1}{CI})\ \forall\ CI \geq 1$, which was then converted back into Equation 5, i.e. $CoV = a\left[\frac{(CI-1)}{CI}\right]^{b} \forall\, CI \geq 1$, the ATAP Model.

Table 2: ATAP model calibration results

Parameter/Statistic	Arterial Model	Freeway Model
No. of observations in filtered dataset	162,301	79,655
Calibrated Parameters		
Ln(a)	-0.521*** (0.003) [-176.388]	-0.234*** (0.007) [-34.484]
a *(antilog of Ln(a))*	0.5939***	0.7913***
b	0.968*** (0.002) [453.793]	1.08*** (0.003) [400.759]
Goodness-of-Fit Statistics		
RMSE *(Ln(CoV))*	0.4727	0.652
RMSE *(CoV)*	0.1067	0.1235
R-squared *(Ln(CoV))*	0.559	0.668

*Note: asterisks denote statistical significance: * at 10%, ** at 5%, *** at 1%.*
Standard errors of parameters reported in (.).
T-statistics of parameters reported in [.].

As shown in Table 2, the p-values of the estimated parameters were less than 0.05, which implies that they are statistically significant at 95% confidence level across both models. The parameter Ln(a) is the intercept term in Equation 5, which was converted back into the parameter a in Equation 4 by taking the antilog. For example, if Ln(a) is equal to –0.521 for arterials, then a will be $e^{-0.521} = 0.5939$. The magnitudes of the calibration parameters (a and b) are lower for arterials when compared to freeways. Given a CI of 2, the estimated CoVs for arterials and freeways are 0.30 and 0.37, respectively. Thus, the freeway dataset showed a higher travel time variability than the arterial dataset for a given CI level. This observation can be justified as follows: as the operating speeds of freeways are significantly higher, phenomena such as traffic oscillations occur at relatively lower congestion levels (than arterials) which lead to a spike in travel time variability.

The goodness-of-fit was measured using the Root Mean Squared Error (RMSE) value, which is defined as the square root of the mean squared error, that is, $\sqrt{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2/n}$. For the linear-log model, Equation 5, the RMSE was found to be 0.4727 and 0.652 for arterial and freeway models respectively. Upon inserting the estimated parameters (a and b) into Equation 5, the RMSE value with respect to Equation 5 was also calculated and found to be 0.1067 and 0.1235 for arterial and freeway models respectively. The R-squared values for Equation 5 were found to be 0.559 and 0.668 for arterial and freeway models respectively. The R-squared values for Equation 4 were not calculated as these statistics do not truly convey the goodness-of-fit for non-linear models (Statistics by Jim, 2021).

An alternative functional form was tested alongside the ATAP model. The alternative functional form produced a marginally better fit than the ATAP model in terms of RMSE but was rejected because it was more difficult to calibrate, requiring non-linear regression, and the curve flattened out significantly at high congestion levels. Equation 7 shows the alternative model which represents a non-linear relationship between CoV and CI, with a and b as calibration parameters. By definition, the model defines CoV as zero for $\mathrm{CI} \geq 1$. The CoV increases sharply at lower CIs, but eventually stabilises to a constant value for higher CIs. Equation 7 was calibrated using the same dataset in the SPSS software package.

$$\boldsymbol{CoV = a.\left(1 - b^{(CI-1)}\right) \forall\, CI \geq 1} \qquad \text{[EQ 7]}$$

Table 3: Calibration results for the alternative model specification

Parameter/Statistic	Arterial Model	Freeway Model
No. of observations (CI ≥ 1; CoV > 0; Speed > 10km/h)	162,301	79,655
a	0.35*** (0.001) [350.0]	0.336*** (0.002) [118.0]
b	0.112*** (0.001) [112.0]	0.036*** (0.001) [36.0]
RMSE *(CoV)*	0.1038	0.1154

*Note: asterisks denote statistical significance: * at 10%, ** at 5%, *** at 1%.*
Standard errors of parameters reported in (.).
T-statistics of parameters reported in [.]

Table 3 shows the calibration results for Equation 7. Like Table 1, the parameters a and b are statistically significant at 95% confidence levels. The R-squared values for Equation 7 were not calculated as these statistics do not truly convey the goodness-of-fit for non-linear models. The RMSE has to be used to compare the goodness-of-fit for the models. The alternative functional form produced a marginally better fit than the ATAP model in terms of RMSE but was rejected because it was more difficult to calibrate, requiring non-linear regression, and because the curve flattens out significantly at high congestion levels.

Figure 1 compares the ATAP model (Equation 4; in Red) and the alternative model (Equation 7, in Yellow) on arterial and freeway datasets. Both models show a sharp rise in CoV for CI values up to 2. However, while Equation 7 stabilises and remains constant for higher CIs, the ATAP model (Equation 4) continues to grow at a decaying rate. This means that Equation 8 will predict no improvement, i.e., a constant travel time variability for any infrastructural changes or policies in areas subjected to severe traffic congestion. This behaviour is considered counterintuitive as it is expected that minor improvements are possible in such scenarios. On the other hand, Equation 5, which depicts the law of diminishing returns, can account for gradual improvements in travel time variability at higher traffic congestion (CI values). Thus, Equation 5 was chosen as the preferred link model and referred to as the ATAP model.

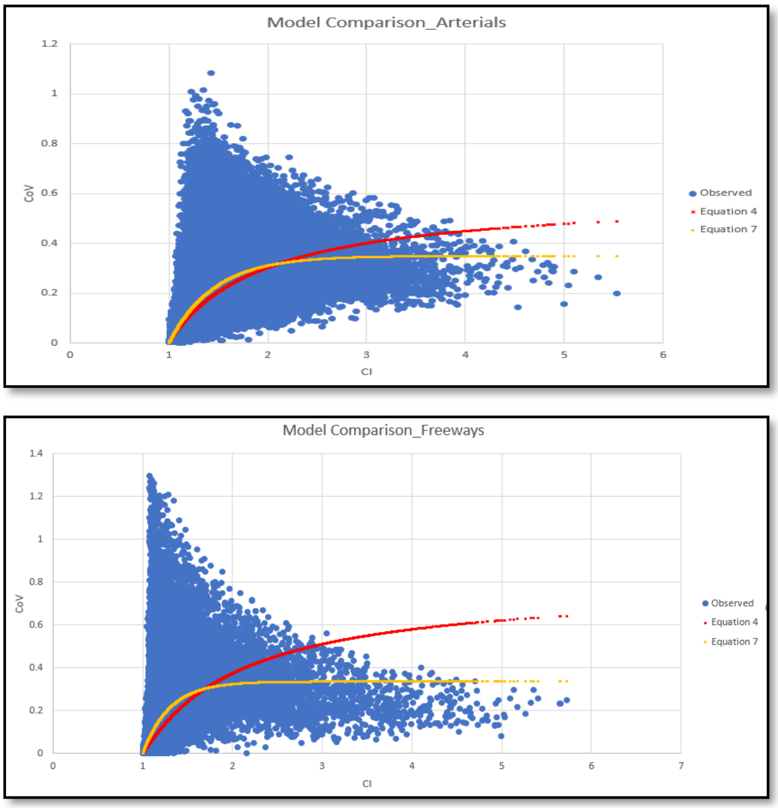


Figure 1: Link model comparison – NetPReS dataset

The calibrated ATAP models, Equation 5, based on the full NetPReS data are shown below.

$$\boldsymbol{Arterial: CoV = 0.5939.\left(\frac{CI-1}{CI}\right)^{0.698}}$$

$$\boldsymbol{Freeway: CoV = 0.7913.\left(\frac{CI-1}{CI}\right)^{0.108}}$$

4.3. Route

To develop the CRM, the CCM was calibrated first using the NetPReS data. A separate CCM was calibrated for the following categories: (1) freeway and arterial, (2) inbound and outbound, and (3) AM (7-9am), Inter-peak (9am-3pm), PM (3-6pm) and Off-peak (5-7am and 6-9pm). Thus, there were 16 sets of calibration parameters. The CCM was initially calibrated on the exponential form proposed by Nicholson (2015). The calibration results showed poor goodness-of-fit using NetPReS data. Therefore, a linear-log CCM, Equation 6, was developed and calibrated. Table 4 shows the calibration results of the linear-log CCM, Equation 6.

Table 4: Calibrated parameters for the proposed CCM

Road type	Direction	Time-period	a	b	R^2	RMSE
Arterial	Inbound	AM peak	-0.0482***	0.1658***	0.2148	0.1012
		Inter peak	-0.0236***	0.0638***	0.1248	0.0665
		PM peak	-0.0308***	0.0848***	0.1415	0.0961
		Off peak	-0.0445***	0.1590***	0.2239	0.1091
	Outbound	AM peak	-0.0302***	0.1076***	0.1176	0.0912
		Inter peak	-0.0234***	0.0631***	0.1460	0.0623
		PM peak	-0.0393***	0.1121***	0.2265	0.0838
		Off peak	-0.0391***	0.1362***	0.2083	0.0871
Freeway	Inbound	AM peak	-0.1098***	0.3477***	0.3476	0.1483
		Inter peak	-0.0870***	0.2653***	0.3129	0.1287
		PM peak	-0.0991***	0.3045***	0.3084	0.1473
		Off peak	-0.0992***	0.3128***	0.3285	0.1362
	Outbound	AM peak	-0.0620***	0.2078***	0.2286	0.1161
		Inter peak	-0.0745***	0.2293***	0.2871	0.1184
		PM peak	-0.1207***	0.4181***	0.3475	0.1710
		Off peak	-0.0979***	0.3539***	0.3248	0.1464

The ATAP model together with the CCM were utilised to determine the estimated route travel time SD. It was compared against the measured route travel time SD, which was determined as follows: 1) summing up the individual link travel times for a given 15-minute time period across all weekdays, excluding public holidays, in the month and then finding its SD. Figure 2 shows the comparison of the measure route SD with the estimated route SD from CRM for the AM peak by road type. Detailed information on other time periods can be found in ATAP (2021). As Figure 2 showed, the CRM gives a reasonable model fit to the measured route travel time SDs, with most points clustered around the 1:1 (45-degree) trend line. The clustering around the dashed line is denser in the case of arterials when compared to freeways. Deviations from the 45-degree line can be explained by factors not taken into consideration by the CRM such as number of roundabouts and bottlenecks, geometric conditions, and negatively correlated links etc. which information was not available in the NetPReS dataset used for model development. Other factors such as incidents, weather, or events could also impact on the accuracy of the estimation. Given that the CRM comprises two sub models, it seems reasonable to suspect that most of the error in the CRM is due to inherent errors in these sub-models, and when models are applied together the error can compound.

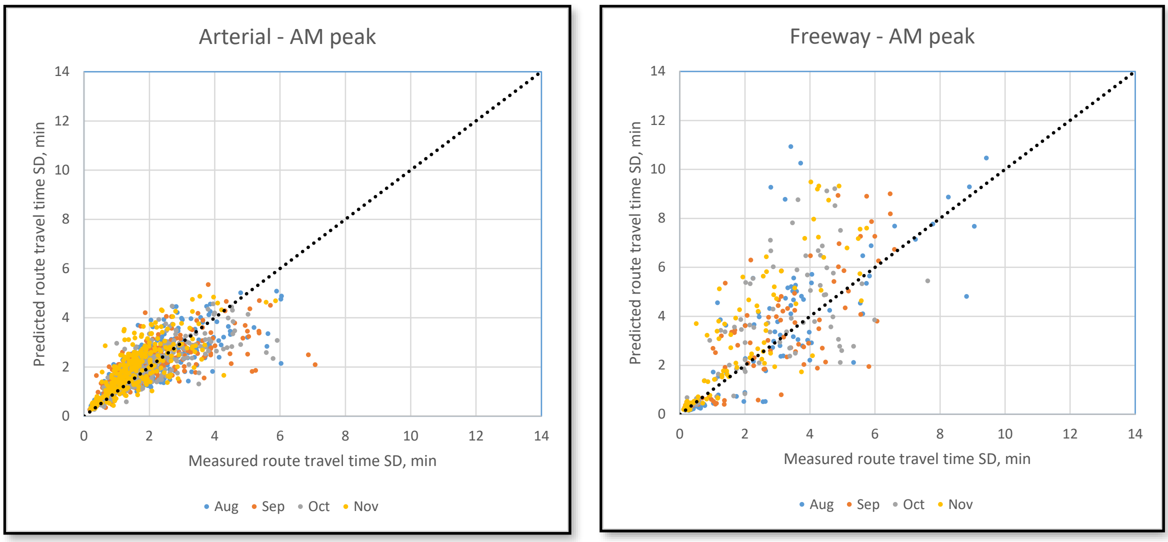


Figure 2: Route travel time SD validation across different time periods for arterials and freeways

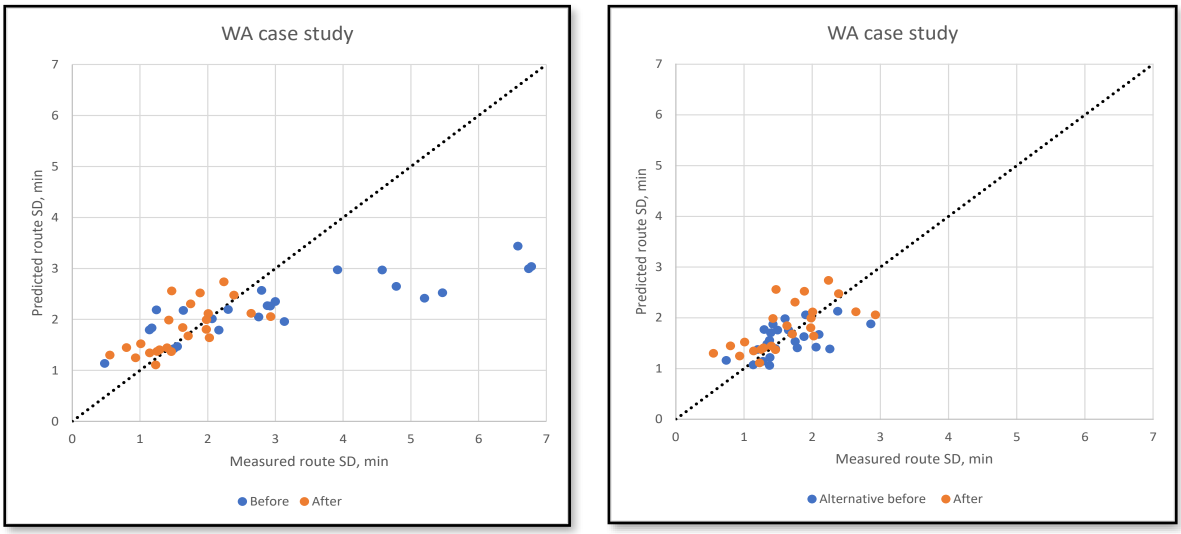
5. Perth Case Study

The Perth case study focused on an evaluation of the Wanneroo Road Duplication project's impact on the travel time reliability during weekdays, excluding public holidays, by application of CRM. The Wanneroo Road Duplication project was a $31m project to widen Wanneroo Road, located at the northern side of Perth CBD running parallel to the Mitchell Freeway, from Joondalup Dr and Flynn Dr. This section was formerly a single carriageway carrying 26,000 vehicle per day. The project converted the single carriageway into dual carriageway in both directions between the section north of Joondalup Dr and the section south of Flynn Dr. The project commenced in November 2017 and was completed and open to traffic in April 2019.

Travel time reliability comparison was conducted based on the following criteria:

- Before period: August to October 2017 (Telematics data)
- Alternative before period: August to October 2018 (NetPReS hybrid data)
- After period: August to October 2019 (NetPReS hybrid data)
- Time period: AM peak, 7 am to 9 am
- Temporal granularity: 15 min
- Route: Wanneroo Road from Hester Ave to Ocean Reef Rd, a total length of 14,690 m
- Number of links: 8
- Direction: Inbound
- Exclusions: weekends, public holidays, major incident dates, and extreme weather dates.

Testing of the CRM on the case study involved measuring and estimating day-to-day changes in the route travel time on weekdays, excluding public holidays, for before-and-after periods, and comparison of predicted route travel times against the measured route travel time. It was anticipated that the CRM would predict the route travel time SD with reasonable confidence in accuracy. The initial attempt to assess the accuracy of CRM by comparing the predicted route SD with the measured route SD showed that while the CRM predicted the after-period route SD with reasonable accuracy, it underestimated the before-period route SD significantly (Figure 3 (1)) at higher levels of measured SD.



(1) Before period – Telematics data (2) Alternative before period – MRWA hybrid data

Figure 6: Measured versus predicted route SD – Perth arterial case study

Investigation into the causes of underestimation in the before period found that it was due to the before period data (Aug-Oct 2017) being a different data source (Telematics) to the after-period data (NetPReS hybrid data2). It was also noted that the CRM was calibrated using NetPReS hybrid data and that should a different data source be used, then a recalibration of the model is required.

To address this inconsistency in the data sources for the before and after periods, the study examined an alternative before period (August to October 2018) when the NetPReS hybrid data was available and assessed the duplication project's travel conditions at that time. Investigation of a series of high resolution historical aerial images of the construction sections of the study route from NearMap revealed that the travel condition was still single carriageway during the alternative before period. Therefore, it was possible for both the alternative before period and the after period to be assessed using the single NetPReS dataset. Five mean speed observations below 20km/h, which were considered as construction impact, were removed from raw datasets. Figure 3 shows the visual comparison of the measured and predicted route SDs for both before-and-after periods (using Telematics for before period and NetPReS for the after period) and alternative-before-and-after periods (using only the single NetPReS dataset). While the CRM underestimated the before period route SD due to the speed data came from the different source, it produced a superior amount of accuracy in the predicted route SD values for both the before period and after period when only the NetPReS data was used.

In summary, using the Telematics before-period data, the CRM predicts that the Wanneroo Road Duplication project would increase the route travel time SD by 0.3 minutes on average for the AM peak inbound direction of the route. This compares to the measured average change of 0.0 minutes in route travel time SD from the field data. CRM overestimates the change in travel time reliability by 0.3 minutes per vehicle. For the alternative MRWA hybrid before-period data, the average route SD value CRM predicted matches the average route SD value

[2] Hybrid data were sourced from multiple data providers such as TomTom, AddInsight, NPI, IRIS, and Telematics.

measured from field data. For the after period, the CRM on average overestimates the route SD by 0.2 minutes or 12.5%.

6. Conclusions, Limitations and Future Works

This paper presents the development and implementation of robust link and route-level models for ATAP to predict travel time reliability in a road network. This paper's contribution is to allow the ATAP guidelines to present methodologies and parameters for evaluating travel time variability.

While the models have been rigorously calibrated and validated to provide default values, it is recommended that practitioners calibrate the models using their own local data to account for traffic dynamics characteristic to a specific geography or jurisdiction. The Perth case study results also demonstrate the importance of consistency in data source that is used in calibration and application of CRM. When different data sources are used, it can lead to inferior results. Furthermore, the ATAP model calibration involved studying travel time variability on a month-by-month basis, which is a more aggregated when compared to day-to-day analysis. Thus, the methodology can be expanded to study the latter, as previous studies have developed models forecasting travel time variability at a finer resolution of a day which although provides greater insights but requires a more intense model calibration procedure.

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