Australasian Transport Research Forum 2021 Proceedings
8-10 December, Brisbane, Australia
Publication website: http://www.atrf.info

Modelling network-wide travel time variability: A case study

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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. The aim of this paper is to investigate two approaches to determine travel time variability at a network level. The first approach is a novel technique referred to as the Approximate Route Standard Deviation (ARSD) method. ARSD estimates the route travel time variability by applying a correction factor to the sum of the standard deviation values of the links forming a travel route. The second approach utilises the Strategic User Equilibrium (StrUE) traffic assignment approach to determine travel time variability given day-to-day changes in origin-destination demands and/or link capacities. This paper utilises traffic data from Sydney as a case study to demonstrate the application of ARSD and StrUE, and the results demonstrate merits and challenges pertaining to each method. The findings from this paper can provide meaningful insights to practitioners in evaluating network-wide travel time variability benefits in a road network and utilise it in transport planning and economic appraisal applications.

1.Introduction

This paper presents the findings of the Project TAP6234 (ATAP, 2021). The project investigated approaches to quantify road travel time reliability for inclusion in the Australian Transport Assessment and Planning (ATAP) guidelines. In the context of transport, travel time reliability describes the consistency of travel times for a particular journey (origin-destination pair). Travel time reliability has been an active area of research in the past decade, owing to its repercussions on traffic congestion within 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 for a project, as shown in Equation 1 below.

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

This paper aims to investigate methodologies to estimate the latter quantity, that is, a way to predict changes in travel time reliability at a network-wide scale, while the estimation of WTP associated with travel time reliability is beyond the scope. The mathematical models developed to forecast travel time variability 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 can recalibrate the models using data specific to a project or case study.

This paper focusses on travel time variability modelling at a network level. The more microscopic elements such as links and routes are not in the scope of this paper. A companion paper that focuses on the detailed travel time variability modelling for these two elements has been prepared alongside this paper.

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.

2.2 Travel Time Variability in Network Modelling

Network models that measure road network performance are tools used by practitioners to develop strategic infrastructure plans and prioritise transport investment. Accordingly, considerable efforts have been made to enhance the realism of these network models, especially in the context of improving traffic assignment methodologies. The traffic assignment process concerns the allocation of travel demand on feasible routes for each origin-destination (OD) pair within a road network model. This allocation is governed by factors which affect travellers' route choice such as travel time, cost as well as travel time reliability.

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

There is an extensive body of literature concerning the incorporation of travel time reliability within network modelling approaches. Taylor (2013) and Uchida (2014) provide comprehensive documentation of the research history, while recent papers by Gupta et al. (2018) and Mishra et al. (2018) discuss the application of travel time reliability within the transport planning appraisal process. Sun et al. (2018) categorise equilibrium-based traffic assignment models that account for travel time reliability summarised in Table 1.

Table 1: Equilibrium-Based Traffic Assignment Models that account for travel time reliability

Model Type	Description	Examples
Mean-variance approach	These traffic assignment models include either expected travel time, travel time variance or SD of travel time to estimate the link/route travel cost. Travellers choose routes to minimise this travel cost (to avoid late arrival) – which could be interpreted as a travel time budget. These models may account for uncertainties in supply, demand or both.	• Lo et al. (2006) (Travel time Budget – TTB Model) • Wu (2015) (TTB Model) • Shao et al. (2006) (TTB Model) • Nie (2011) (Percentile Travel Time Model) • Chen et al. (2011) (Mean excess traffic equilibrium) • Dixit et al. (2013) (StrUE) • Clark and Watling (2005) (SUE)
Game-theoretic	These models assume that travellers choose routes to avoid link failure (avoid unreliability) and that disruptors maximise the damage to the network. The traffic assignment methodology is then formulated as a Cournot-Nash game.	• Szeto et al. (2007)
Prospect-theory based	Travellers choose the route with the largest prospect value to complete a journey. Travellers are risk-averse in positive (gain) scenarios and risk-prone in negative (loss) scenarios.	• Gao et al. (2010) • Chorus (2012) • Li et al. (2016)

Travel time reliability models (e.g. Szeto et al. (2006)) relevant to the metrics identified earlier in the report focus on the 'mean-variance' approach where link cost functions or route decision rules consider either the variance, SD of travel time or percentile of travel time as a component. This mean-variance approach will be pursued in more detail within the models developed in this paper.

3. Methodology – Model Development

The literature review highlights several approaches to account for travel time reliability within a road network performance assessment. This paper has been built from the studies by Gupta et al. (2018), Mishra et al. (2018), Dixit et al. (2013) and Moylan et al. (2018) to test two methodological approaches, given below, that incorporate travel time reliability into strategic network modelling:

- Inclusion of a reliability metric (SD of travel time) within the link cost function for the network accounting for the additive properties between links and routes of the network

- Application of the Strategic User Equilibrium (StrUE) approach which inherently accounts for SD of travel time as a variable within the assignment process.

3.1. Inclusion of a Reliability Metric – ARSD

The first method can be readily adopted in traditional network assignment techniques (such as User Equilibrium (UE)), but would require a simplifying assumption on the estimation of route travel time SD. This approach, referred to as the Approximated Route Standard Deviation method (ARSD), assumes that the route travel time SD can be approximated by Equation 2. The ARSD equation does not take into consideration travel time correlation between all links within a route. While this approximation is not sufficient for estimating route travel time SD, it will greatly simplify the calculation involved in determining network equilibrium. The route travel time SD can be estimated using more accurate models post route assignment, such as the Correlation Route Model (CRM) (ATAP, 2021).

$$\sigma_r \approx \gamma \sum \sigma_l \tag{2}$$

Where:

σ_r = SD of travel time on route
σ_l = SD of travel time on links
γ = correction factor

3.2. Strategic User Equilibrium Modelling

An approach that has been tested within this paper is the StrUE traffic assignment formulation (Dixit et al., 2013). StrUE is a novel formulation that accounts for the variability that exists in road networks while still maintaining the beneficial properties such as consistency and convergence of traditional traffic equilibrium models. StrUE considers that travellers recognise the variability in the system in terms of road capacity, demand and travel time and rationally choose routes while weighting the expected travel time and its variance. StrUE is defined such that "at Strategic User Equilibrium all used paths have equal and minimal generalised cost over expectation and variability of network demand".

StrUE assignment relies on the following user behavioural assumptions:

- There is a known probability function for network demand
- Each user will select the minimum generalised cost path (over expectation and variability)
- Each user will follow the minimum generalised cost path under each demand realisation where that user is present.

It is important to recognise that under StrUE conditions, the path (and link) proportions will not change day-to-day. However, the actual link flow volumes will vary as a function of the realised demand (since the link flows would be the product of the realised demand and the link proportions), meaning equilibrium conditions are unlikely to be met for each independent demand realisation. This outcome is consistent with real-world road networks where equilibrium conditions are not observed on a day-to-day basis. One of the strengths of this approach is that the uncertainty in travel times and flows can be analytically tied back to demand uncertainty.

The StrUE traffic assignment approach could theoretically replace the final step of traditional 4-step strategic transport models and is a promising modification to capture the concept of travel time reliability. This paper includes an application of StrUE on the Sydney road network to determine travel time SD on a few selected routes. A detailed discussion on StrUE is available in ATAP (2021).

4. ARSD Model Calibration

4.1. Dataset

The Network Performance Reporting System (NetPReS) dataset from Perth, WA was used to calibrate the ARSD model. The Perth NetPReS data originally consists of 29 arterial and freeway routes in both directions. The range of link lengths that make up the Perth network span between 20 m and 37,920 m. 22 links, which are greater than 10 km in length, were not considered typical metropolitan links and were excluded from the analysis. As a result, two arterial routes were excluded, and the remaining 27 routes were used for the analysis.

The characteristics of filtered datasets are summarised below:

- Covers the metropolitan Perth area
- Comprises bi-directional speed and volume data for arterials, controlled-access highways and freeways
- Speed data was collected from multiple sources such as TomTom, AddInsight, Network Performance Insight (NPI), Intelligent Roadway Information System (IRIS), Intelematics
- Data duration: 4 months (from 1 August 2018 to 31 November 2018)
- Data resolution: every 15 min between 5am and 9pm
- Number of links: 947
- Total road length: 1076 km.

Figure 1 shows the distribution of links by link lengths in the filtered dataset. The figure shows that 58.9% of the links in the dataset are short links of less than 1 km in length, and 1.1% of the links are long links greater than 5 km in length.

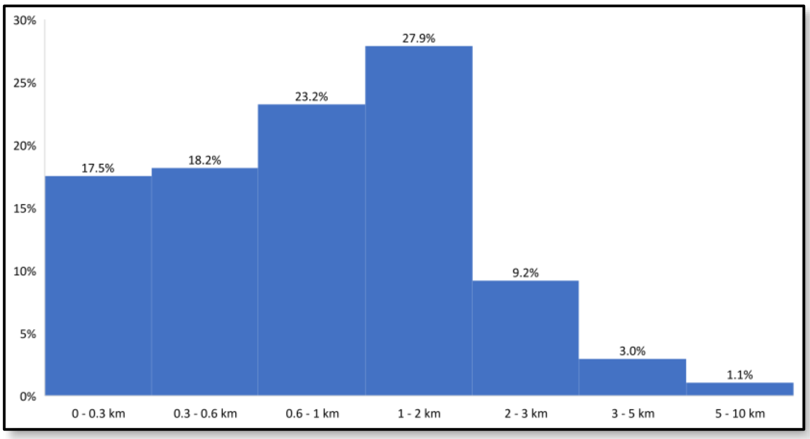

Figure 1: Distribution of links in Perth NetPReS Dataset by link length

Examination of the raw speed data was conducted to identify potential outliers, as a slow speed observation could significantly impact the travel time SD value and potentially skew the results. Inspection of the cause of the slow speed observations did not reveal any unusual event such as extreme weather or incidents. It was considered appropriate to consider the speeds below 10 km/h as unsuitable and excluded from the analysis. 15,803 out of 5.66 million (0.28%) observations were excluded as a result.

4.2. Calibration

The NetPReS dataset was segregated into two segments: arterials and freeways which also includes Controlled Access Highway (CAH) sections. The value **γ** for each route was calculated as the ratio of the route travel time SD (obtained from the CRM) and link travel time SD (obtained from the ATAP model) (ATAP, 2021). The travel time SDs were determined for the AM peak period only. Table 2 shows the route-specific correction factors (γ) values along with other characteristics.

Table 2: Estimated γ value from available routes in Perth network and its level of correlation between links

Route	Direction	Length (Km)	Road Type	γ (AM Peak)	AM Covariance as % of the route
Albany Hwy	Inbound	51.2	Arterial	0.34	43%
Albany Hwy	Outbound	51.2	Arterial	0.30	33%
Armadale Rd	Inbound	15.88	Arterial	0.43	58%
Armadale Rd	Outbound	15.88	Arterial	0.40	49%
Canning Hwy	Inbound	16.26	Arterial	0.39	44%
Canning Hwy	Outbound	16.26	Arterial	0.34	48%
Graham Farmer Fwy	Inbound	6.81	Freeway	0.67	61%
Graham Farmer Fwy	Outbound	6.81	Freeway	0.53	53%
Great Eastern Hwy Inner	Inbound	13.94	Arterial	0.40	48%
Great Eastern Hwy Inner	Outbound	13.94	Arterial	0.35	40%
Great Eastern Hwy Outer	Inbound	47.53	Arterial	0.47	53%
Great Eastern Hwy Outer	Outbound	47.53	Arterial	0.42	42%
Guildford Rd	Inbound	11.01	Arterial	0.43	59%
Guildford Rd	Outbound	11.01	Arterial	0.39	50%
Karrinyup-Morley Hwy	Inbound	15.12	Arterial	0.40	66%
Karrinyup-Morley Hwy	Outbound	15.12	Arterial	0.36	52%
Kwinana Fwy	Inbound	57.03	Freeway	0.48	57%
Kwinana Fwy	Outbound	57.03	Freeway	0.30	46%
Leach Hwy	Inbound	23.6	Arterial	0.36	30%
Leach Hwy	Outbound	23.6	Arterial	0.34	24%
Marmion Av	Inbound	12.2	Arterial	0.51	51%
Marmion Av	Outbound	12.2	Arterial	0.47	45%
Melville Mandurah Hwy	Inbound	48.23	Arterial	0.30	71%
Melville Mandurah Hwy	Outbound	48.23	Arterial	0.27	64%
Mitchell Fwy	Inbound	35.04	Freeway	0.43	52%
Mitchell Fwy	Outbound	35.04	Freeway	0.33	36%
Orrong Rd	Inbound	10.16	Arterial	0.45	60%
Orrong Rd	Outbound	10.16	Arterial	0.42	50%
Reid Hwy	Inbound	21.39	CAH	0.48	59%
Reid Hwy	Outbound	21.39	CAH	0.42	48%
Roe Hwy	Inbound	34.09	CAH	0.41	53%
Roe Hwy	Outbound	34.09	CAH	0.38	39%
South St	Inbound	12.48	Arterial	0.43	51%
South St	Outbound	12.48	Arterial	0.40	47%
Stirling Hwy	Inbound	13.85	Arterial	0.45	7%
Stirling Hwy	Outbound	13.85	Arterial	0.37	6%
Thomas Rd	Inbound	18.5	Arterial	0.70	13%
Thomas Rd	Outbound	18.5	Arterial	0.68	15%
Tonkin Hwy North	Inbound	7.68	CAH	0.79	58%
Tonkin Hwy North	Outbound	7.68	CAH	0.75	50%
Wanneroo Rd / Indian Ocean Dr	Inbound	59.17	Arterial	0.34	24%
Wanneroo Rd / Indian Ocean Dr	Outbound	59.17	Arterial	0.30	33%
West Coast Hwy	Inbound	14.09	Arterial	0.55	43%
West Coast Hwy	Outbound	14.09	Arterial	0.41	33%
Arterial median				**0.41**	**49%**
Freeway median				**0.45**	**51%**

The fifth column in the table gives the resulting γ value for each considered route. The last column shows the covariance term of the CRM as a percentage of route variance. It gives the proportion of route travel time variance accounted for by correlation between links, ranging from 6% to 71%. This shows the importance of travel time correlation between links and that it certainly cannot be ignored.

5. Case Study

5.1. Sydney Road Network Data

Moylan et al. (2018) collected a variety of data for the Sydney Greater Metropolitan Area (GMA) to study travel time reliability. This paper utilised the travel time data from Moylan et al. (2018), which was collected using the Google Maps Directions API. Travel times prevailing on 37 routes, 74 routes when considering bi-directional movement, spread across the study area were collected. The data was collected by pinging the Google Maps Directions API 55 times a day, storing the real-time travel time value provided under the field 'duration in traffic' in the API for a period of 14 months (February 2017 – March 2018). The routes within the Sydney network considered in the data collection and modelling exercise includes 1256 links, with link length spans between 1m and 6,279m. The travel times on the links forming these routes were also collected using the Google Maps Distance Matrix API. In addition to Google data, traffic counts data, including motorway loop detectors, were also collected as part of this study. For each query time for each route in the Sydney case study, the component links were summed up to estimate an instantaneous route travel time.

5.2. ARSD Application

The ARSD model was applied to the link specific traffic information for the AM peak period (7am-9am) in the Sydney dataset, which comprises 74 (37 routes times bidirectional flow) arterial and freeway routes. The link-level travel time SD is initially computed using the ATAP link model for arterials and freeways (ATAP, 2021). It is then multiplied by the median γ values of 0.41 and 0.45, respectively, to obtain the route travel time SD. Figure 2 and Figure 3 show the inbound and outbound travel time SD for the arterial and freeway routes, respectively. The figures show the travel time variability for the arterials and freeway routes considered in this case study.

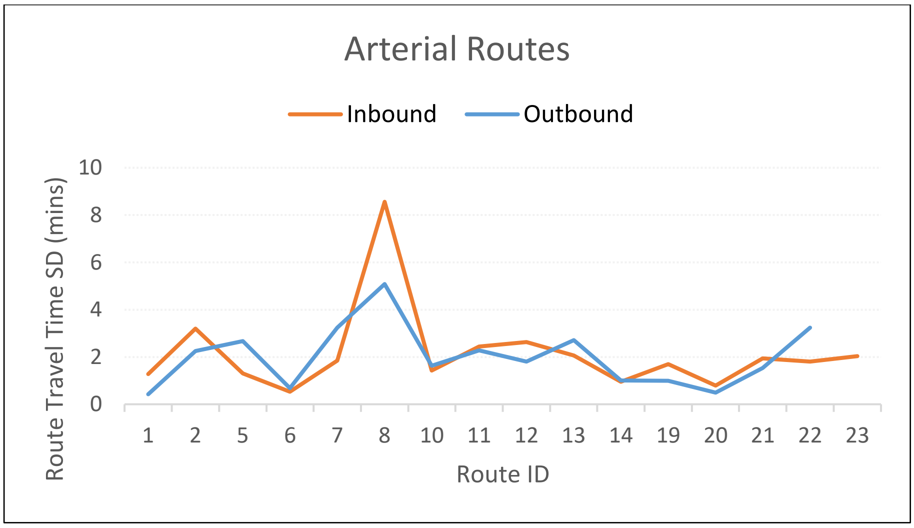

Figure 2: Bidirectional travel time SD for arterial routes in Sydney

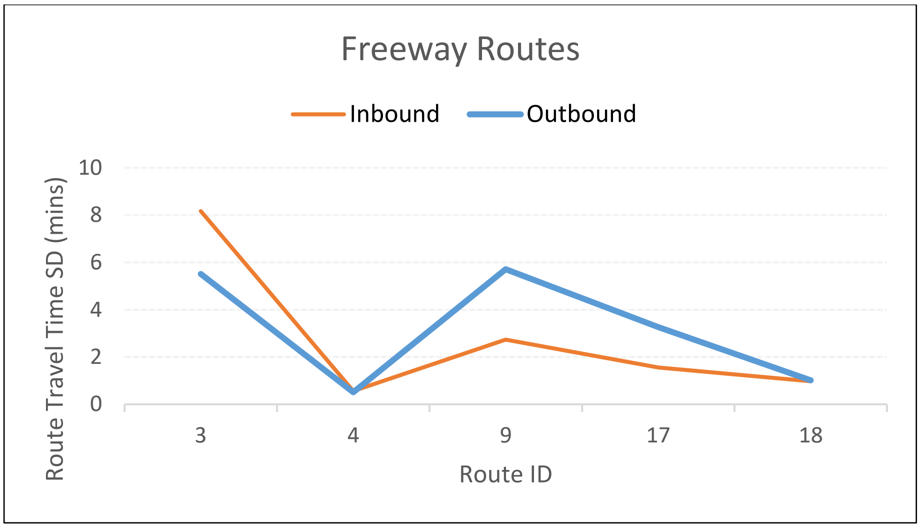

Figure 3: Bidirectional travel time SD for freeway routes in Sydney

The plots show that the routes with the highest travel time SD in both directions are route 8 (A34) for arterials and route 3 (M5) for freeways. The travel time SD is generally higher for the inbound direction than the outbound direction (except for routes 9 and 17. For route 9 which is the Princess Highway between Haymarket and Arncliffe, which is probably due to higher users travelling towards Sydney airport (via the CBD) and its neighbouring employment hubs). A step-by-step procedure for applying the ARSD model on the Sydney case study has been described in the ATAP travel time reliability guideline document (ATAP, 2021).

5.3. StrUE Application

Calibration and Validation Data: Travel time data for 69 routes in Sydney collected for a period of 6 months from April to September of 2018 using Google Maps API. The expected and SD of travel time have been calculated during the defined morning peak hour of 8am-9am, which is a subset and reflection of the broader AM peak period used for ARSD calibration mainly due to higher computational effort required in StrUE calibration.

Demand Data: The trip table for the network was estimated using a machine learning approach[2] such that the expected route travel times match with that of Google. Given that the OD matrix estimation is an underdetermined problem, multiple solutions for a trip table can exist that result in similar expected route travel times. Therefore, the developed matrix in the study may not be an accurate representation of real-world data[3] and needs further calibration and validation. However, as the purpose of this case study is to understand the application process, the feasible outputs and how they can be beneficial in measuring reliability as well as evaluating projects, this is not a critical component in this context. The total expected demand of the network has been estimated to be 467,000 across a 1-hr peak period (8AM-9AM). However, the StrUE framework assumes a demand distribution, and this cannot be obtained through traditional household travel surveys. Therefore, for this demonstration, it is assumed that the demand follows a lognormal distribution with a mean demand of 467,600. The lognormal distribution ensures that the demand is always positive, unlike a normal distribution.

[2] Genetic Algorithm method has been used in determining the OD matrix (Chand et al. 2021).

[3] The main purpose of the case study is to demonstrate the applicability of the StrUE model rather than the calibration of the OD matrix.

5.3.1. Calibration and Validation

Like other strategic models, there are numerous mechanisms to calibrate a network model using StrUE as a traffic assignment technique. The options include:

- Comparing observed and modelled performance metrics (link volumes, link travel times and route travel times) using statistical approaches
- Trend analysis and distribution fitting to ensure that the relationship between two performance metrics are consistent between observed and modelled conditions
- Utilising Geoffrey E. Havers (GEH) metrics considering link volumes and travel times (Roads and Maritime Service Guide to Traffic Modelling, 2013).

The second option was selected to calibrate and validate the case study presented in this guideline. Different SD of demand (σ) values are considered for the demand distribution. σ represents the spread of the distribution, which implies that an increase in this parameter widens the distribution of total demand. The "μ" parameter which denotes the mean of the distribution, was held constant so that that the average demand stays at the value of 467,000.

Figure 8 presents the estimated relationship between the Coefficient of Variation (CoV) vs Congestion Index (CI) for various σ parameters of the StrUE model compared with the observed CoV vs CI values of the Google travel time data (points demarcated as X) of all the links along all the routes considered in the study. For a given CI, an increase in the σ parameter results in an increase in the CoV. Calibration involved comparing observed data to the modelled outputs. To effectively discern trends in the large quantity of observed data and also to compare with modelled outputs, a data synthesis process was carried out using an "average-range" method to reduce noise. The method involved averaging CoV estimates for ranges of CI. Root Mean Square Error (RMSE) has been calculated between the observed (scatter points marked as X) and predicted CoV (trendline for a given σ) for different σ parameters, and the one with the lowest RMSE was chosen, that is σ = 0.10 as the best-fit to the observed data. Therefore, in the context of this case study, the model has been adequately calibrated.

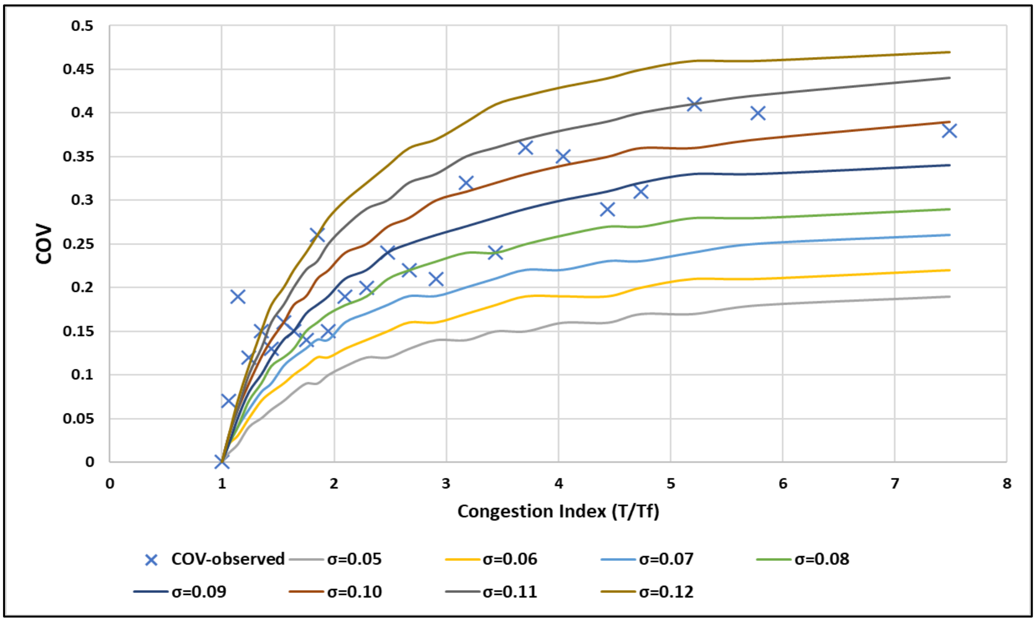

Figure 8: Observed vs predicted relationship between CI and CoV of Google links

Note: The CoV-observed data are the averaged values for covariance ranges of all link data across all the routes. This representation serves as a reflection of all the observed data

5.3.2. Scenario Testing

This section highlights both the reliability metric outputs that can be directly obtained from utilising the StrUE traffic assignment approach as well as the value of the approach in evaluating changes to the network from a reliability perspective. Within the ATAP guidelines, several scenarios were tested to understand the capabilities of the modelling approach (ATAP, 2021). This paper describes one of the scenarios where "**The capacity of all links in the network increased by 10%**" depicting the impacts of a network-wide change. The other scenarios can be found in ATAP (2021).

The assumptions made for the scenario testing are: (i) the average demand is 467,000, and (ii) SD of demand, σ is 0.10. The StrUE framework allows testing of the impact of network modifications on travel time reliability, thus facilitating a before-versus-after comparison.

The impact of increasing capacity of all the links by 10% on expected travel time, the SD of travel time, and CoV of travel times on all links in the network is analysed. Expectedly, for almost all the links, these metrics have decreased when compared to the base scenario. Figure 4 and Figure 5 show the percentage change in expected travel times and SD of travel times for routes from each zone to the Central Business District (CBD) (roughly located within the Yellow circle in both figures). The expected travel times decreased by 12% to 26%, whereas SD decreased by 7% to 41%, with most improvements seen in the North-west region of Sydney (highlighted in dark green in Figure 5). The change in expected travel times is more homogeneous than SD. While there is a significant reduction in expected TT from the North Shore and Inner West regions of Sydney, the reduction in SD of TT is not as much when compared to other regions.

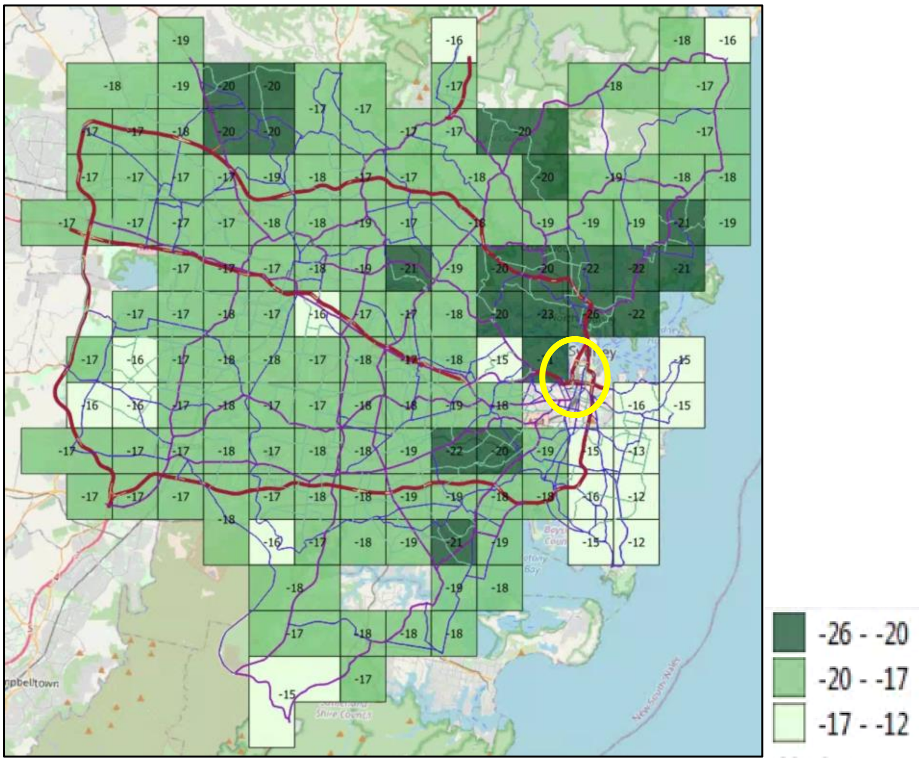

Figure 4: Scenario-1 - Percentage decrease in expected TT from different zones to CBD

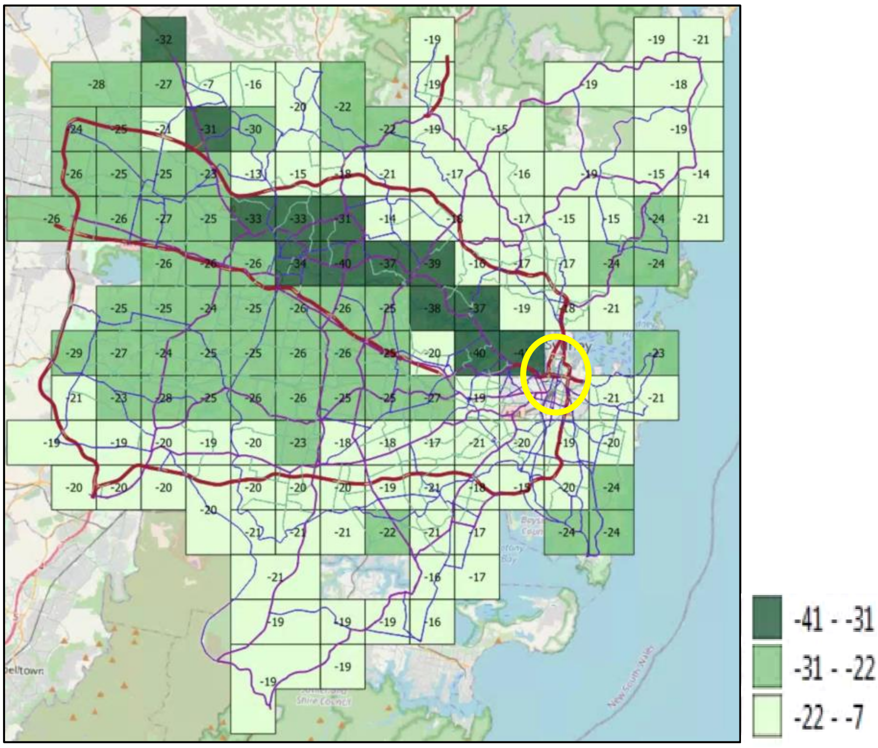

Figure 5: Scenario-1 - Percentage decrease in SD of TT from different zones to CBD

5.4. Comparison between ARSD and StrUE

Comparing the network travel time variability models is important to guide practitioners on use cases for both approaches. The assumptions underlying each method dictate the applications for both models. As presented in the previous sections of the report, each model serves the following purpose:

- The ARSD model provides an approximate measure of travel time reliability at a route level using historical travel time data. This model can be used in simple UE formulations to determine network equilibrium when including travel time reliability of routes. However, the model exogenously accounts for reliability and does not capture route choice behaviour where travellers consider reliability in their decision-making process.
- StrUE is a traffic assignment methodology that could be substituted as the final step of a traditional 4-step travel model (such as STM). The model endogenously accounts for reliability, capturing the concept within the route choice behaviour across the network. This means that reliability metrics such as SD of travel time are direct outputs of the model, providing a robust foundation of sensitivity testing and “what-if” scenario analysis of major infrastructure changes.

It is critical to emphasise that ARSD is useful as an efficient method to estimate variability impacts for localised modifications in the network. However, it is limited in providing a reasonable quantification of reliability for significant network changes or macroscopic policy implementation as it does not consider travel behaviour within the model framework. On the other hand, the use of StrUE within a strategic model can provide robust results for localized and network-wide changes at a system level. Accordingly, StrUE approach is the preferred option when route choice and network impacts are anticipated, such as in major infrastructure projects.

6. Conclusion, Limitations and Future Works

For the network level travel time reliability modelling, this paper explored two novel methodologies, namely, ARSD and StrUE. The ARSD method applies a correction factor to the summation of individual links SD to obtain route travel time SD. Another numerical experiment was developed to assess the impact of the correction factor in the ARSD method. The correction factor value was then calibrated using the arterial and freeway routes in the full NetPReS dataset. The ARSD approach was applied to the Sydney case study to determine travel time variability on a few selected routes. Similarly, the application of StrUE model was also developed on the same Sydney case study to assess the impact of route travel time reliability in network assignment. StrUE is able to evaluate network-wide reliability impacts, as it endogenously considers the impact of variability on route-choice and vice-versa. While the ARSD is an efficient method to estimate variability impacts for localised modifications in the network, it does not take into consideration its impact on route choice. On the other hand, StrUE, although more complex to develop than ARSD, is a more methodologically robust approach that endogenously takes into consideration travel time variability and its impact on route choice.

The outcomes from this paper provide practitioner the knowledge and models to determine travel time reliability at route-level in response to any infrastructural upgrade or policy intervention. The outputs from the model can provide important information to planners in conducting economic appraisals of competing projects.

As with any model development process, each phase of development is limited by scope, budget and timing. There is always room for further development and enhancements, especially in the context of travel time reliability, where a general model would be expected to require further calibration to the local network, as road networks are subtly different, regionally and locally. The calibration parameter γ value used in the ARSD method (Equation 2) has been calibrated using the NetPReS data. The parameter γ value would be improved with local calibration. Thus, practitioners are advised to recalibrate the ARSD formula using their available data, if required. The extent of this limitation is medium as every jurisdiction has its own traffic characteristics and dynamics, and using the calibrated γ value given in this report might lead to more significant errors in the method, that is, ARSD, which in itself is an approximation, to begin with. Future research work will focus on developing a formula to obtain the calibration parameter γ in the ARSD method.

7. Acknowledgements

This study was funded through the Australian Government under Part 5 of the National Land Transport Act and Austroads. Further funding contributions were also made by from DITRDC, TfNSW, QTMR and MRWA for a specific part of this work.

The authors acknowledge the technical inputs received from the Reliability Working Group, in particular, Dr Mark Harvey (BITRE), Ed McGeehan (VIC DoT), Frans Dekker (QTMR), Dr Merle Wood (QTMR) and Anya Richards (VIC DoT). The authors also acknowledge the data contributions from QTMR and MRWA which was paramount to the success of the project.

References

Asakura, Y. & Kashiwadani, M. (1991). Road Network Reliability caused by Daily Fluctuation of Traffic Flow. PTRC summer annual meeting, University of Sussex, UK, pp. 73-84.

ATAP 2021, Australian transport assessment and planning guidelines: road reliability measurement – research report, Transport and Infrastructure Council, viewed 24/05/2021, https://www.atap.gov.au/sites/default/files/documents/atap-road-reliability-measurement-research-report-for-public-consultation.pdf.

Austroads (2011). Valuation of Travel Time Reliability: A Review of Current Practice. AP-R391-11, Austroads, Sydney, NSW.

Bates, J., Polak, J., Jones, P. & Cook, A. (2001). The Valuation of Reliability for Personal Travel. *Transportation Research Part E*, vol. 37, pp. 191 -229.

Chand, S., Zlojutro, A., Niu, C., Nair, D., Zhang, X., Dixit, V., Waller, S.T. (2021) A Novel Tool for Origin-Destination Matrix Estimation Using Crowdsourced Traffic Data (Working Paper).

Chen, A., Zhou, Z. & Lam, W.H. (2011). Modelling Stochastic Perception Error in the Mean-excess Traffic Equilibrium Model. *Transportation Research Part B: Methodological*, vol. 45, no. 10, pp. 1619-40.

Chorus, C.G. (2012). Regret Theory-based Route Choices and Traffic Equilibria. *Transportmetrica*, vol. 8, no. 4, pp. 291-305.

Clark, S. & Watling, D. (2005). Modelling Network Travel Time Reliability under Stochastic Demand. *Transportation Research Part B: Methodological*, vol. 39, no. 2, pp. 119-40.

Dixit, V.V., Gardner, L.M. & Waller, S.T. (2013) Strategic User Equilibrium Assignment under Trip Variability. 92nd Transportation Research Board annual meeting, Washington, DC, USA.

Gao, S., Frejinger, E. & Ben-Akiva, M. (2010). Adaptive Route Choices in Risky Traffic Networks: A Prospect Theory Approach. *Transportation Research Part C: Emerging Technologies*, vol. 18, no. 5, pp. 727-40.

Gupta, S., Vovsha, P., Dutta, A., Livshits, V., Zhang, W. & Zhu, H. (2018). Incorporation of Travel Time Reliability in Regional Travel Model. *Transportation Research Record*, no. 2672, pp. 46-57.

Li, Q., Liao, F., Timmermans, H.J. & Zhou, J. (2016). A User Equilibrium Model for combined Activity–travel Choice under Prospect Theoretical Mechanisms of Decision-making under Uncertainty. *Transportmetrica A: Transport Science*, vol. 12, no. 7, pp. 629-49.

Lo, H.K., Luo, X.W. & Siu, B.W. (2006). Degradable Transport Network: Travel Time Budget of Travelers with Heterogeneous Risk Aversion. *Transportation Research Part B: Methodological*, vol. 40, no. 9, pp. 792-806.

Mishra, S., Tang, L., Ghader, S., Mahapatra, S. & Zhang, L. (2018). Estimation and Valuation of Travel Time Reliability for Transportation Planning Applications. *Case Studies on Transport Policy*, vol. 6, no. 1, pp. 51-62.

Moylan, E., Jian, S., Wijayaratna, K.P., & Waller, S.T. (2018). Journey Time Reliability Model Development. *(Unpublished report, Research Centre for Integrated Transport Innovation, University of New South Wales, Sydney, NSW).*

MRWA (2016). Journey Time Reliability Indicators: Desktop Review, by WSP Parson Brinckerhoff, Main Roads Western Australia, Perth, WA.

Nie, Y.M. (2011). Multi-class Percentile User Equilibrium with Flow-dependent Stochasticity. *Transportation Research Part B: Methodological*, vol. 45, no. 10, pp. 1641-59.

Osterle, I., Gort, W. & Weiss, A. (2017). Forecasting and Valuing Travel Time Variability for Cost-Benefit Analysis. *Road & Transport Research: A Journal of Australian and New Zealand Research and Practice*, vol. 26, p. 21.

PIARC (2019). Journey Time and Travel Time Reliability, Technical Committee A.2 Road Transport System and Economic and Social Development, report 2019 R35EN, World Road Association. Available at https://www.piarc.org/ressources/publications/11/85139d3-31456-2019R35EN-Journey-Time-and-Travel-Reliability.pdf

Prashker, J.N. & Bekhor, S. (2004). Route Choice Models used in the Stochastic User Equilibrium problem: A Review. *Transport Reviews*, vol. 24, no. 4, pp. 437-63.

Shao, H., Lam, W.H. & Tam, M.L. (2006). A Reliability-based Stochastic Traffic Assignment Model for Network with Multiple User Classes under Uncertainty in Demand. *Networks and Spatial Economics*, vol. 6, pp. 173-204.

Sun, C., Cheng, L. & Ma, J. (2018). Travel Time Reliability with Boundedly Rational Travelers. *Transportmetrica A: Transport Science*, vol. 14, no. 3, pp. 210-29.

Szeto, W. Y., O'Brien, L., & O'Mahony, M. (2006). Risk-averse Traffic Assignment with Elastic Demands: NCP Formulation and Solution Method for Assessing Performance Reliability. *Networks and Spatial Economics*, 6(3), 313-332.

Szeto, W., O'Brien, L. & O’Mahony, M. (2007). Generalization of the Risk-averse Traffic Assignment. *Transportation and Traffic Theory*, vol. 17, pp. 127-53.

Taylor, M.A. (2013). Travel through Time: The story of Research on Travel Time Reliability. *Transportmetrica B: Transport Dynamics*, vol. 1, no. 3, pp. 174-94.

TIC (2016). A Scoping Study for Future Research into Values of Travel Time Savings for Project Appraisal and Toll Road Patronage Forecasting. 2014 National Guidelines for Transport System Management in Australia, Transport and Infrastructure Council, Australia.

Uchida, K. (2014). Estimating the Value of Travel Time and of Travel Time Reliability in Road Networks. *Transportation Research Part B: Methodological*, no. 66, pp. 129-47.

Wu, X. (2015). Study on Mean-SD Shortest Path problem in Stochastic and Time-dependent Networks: A Stochastic Dominance based Approach. *Transportation Research Part B: Methodological*, vol. 80, pp. 275-90.