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Traffic assignment methodologies and the concept of multi-tiered traffic modelling framework: A case study from Adelaide

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Abstract

Transportation systems are critical components of cities and regions that provide mobility for people, goods, and services. Traffic congestion is one of the significant challenges faced by transportation systems worldwide, leading to wasted time, increased fuel consumption, and air pollution. Traffic modelling has been used for decades to provide insights to help transportation planners and engineers design and optimise transportation systems for better efficiency and effective mobility. Different traffic modelling methodologies have evolved to match the modelling exercise with a given study. The Tactical Adelaide Model (TAM) has been developed by the South Australian Department for Infrastructure and Transport (DIT) in collaboration with Aimsun Pty Ltd to provide a framework for traffic assignment modelling, benefitting from the multi-tier modelling approach in one platform. This paper reviews the literature related to the commonly used traffic assignment methodologies and also discusses TAM's architecture, enabling the users of the framework to utilise the most suitable traffic modelling method for a given study.

1. Introduction

Traffic congestion in urban areas has been a problem worldwide for decades. Transportation engineers and planners have since been looking for more effective and efficient ways to address the congestion problem. Modelling as a tool to provide insights was introduced in the middle of the twentieth century (Giuliano and Hanson, 2017).

Traffic assignment models are designed to allocate traffic demands between origin-destination pairs to the available road infrastructure (Ahmed, 2012, Saw et al., 2015). As such, traffic modelling involves creating mathematical or computer-simulated models that replicate the behaviour of vehicular or pedestrian traffic in a given area, such as a road network or a transportation hub. These models are typically used to predict traffic flow, congestion, travel times, and other related factors and to evaluate the impact of changes in infrastructure, policies, or other variables.

Different approaches and methodologies have been developed and evolved since the middle of the 20th century based on the intended use case of a traffic modelling exercise. At a high level,

traffic assignment models can be classified as static or dynamic based on whether their variables and parameters are time-dependent or time-invariant. The methodology used at the core of the model can also be used to classify the models into macroscopic, mesoscopic, and microscopic models. Technological advancements have made computationally powerful machines more accessible than ever, enabling the development of multi-tiered and hybrid traffic modelling frameworks (Ferrara et al., 2018c).

In the following sections of this paper, we will further discuss the model classifications, focusing on the Tactical Adelaide Model (TAM) as a case study for a multi-tiered traffic assignment modelling framework.

2. A review of traffic assignment methodologies

Classification of traffic assignment models into different groups can be approached from different angles. Traffic models can be categorised based on their time-dependency nature into static and dynamic models. In other words, static traffic assignment (STA) models use "variables that are time-invariant" whereas dynamic traffic assignment (DTA) models apply "a behaviourally sound approach" to describe time-varying network and demand interactions (Chiu et al., 2011). At a high level, the models can be classified according to their theoretical concepts. In the first category, mathematical models are used to reproduce the average behaviour of vehicles, while in the case of the latter, the behaviour of individual vehicles is simulated by taking their acceleration and deceleration into account (Song, 2019), hence categorising the models into two streams of analytical and simulation-based models. It can also be argued that models can be classified based on the level of detail used to model the available road infrastructure. When the analysis is done for links, based on agrregated values for all lanes, the model is known to be at the macroscopic level. When the model analyses the road infrastructure at the lane level of detail, the analysis is known to be at the microscopic level, with the mesoscopic level analysis sitting somewhere in between where analysis is lane-specific with some constraints imposed compared to the microscopic level (Chiu et al., 2011, Ferrara et al., 2018b, Ferrara et al., 2018a, He et al., 2010, Liu et al., 2006).

Considering the lane-specific nature of analysis at the microscopic and mesoscopic levels, it is not uncommon to see them combined with the simulated behaviour of individual vehicles, resulting in traffic simulation models at microscopic and/or mesoscopic levels.

While in principle, from the traffic demand perspective, both flat demands and profiled demands can be used to inform either a macroscopic traffic assignment or mesoscopic/microscopic traffic simulation model, it is a common practice for macroscopic assignments to be informed by flat model period demands. It is also true for mesoscopic and microscopic traffic simulation models to be informed by profiled demands. For this reason, while essentially it is not an appropriate or recommended application, the terms “static traffic assignment” and “macroscopic traffic assignment” are sometimes used interchangeably. Likewise, it is not uncommon to see the terms “dynamic traffic assignment” and “mesoscopic/microscopic traffic simulation” used freely in place of one another.

In this paper, we limit the types of combinations among the classes of models, categorised from different perspectives as explained above, to those most commonly used and leave the less commonly used combinations for future research.

2.1. Static macroscopic traffic assignment models

As discussed earlier, the underlying assumption for all static models is the flat nature of the demand for the entire analysis period. With respect to allocating the demand on the roads between each OD pair, traffic assignment methodologies can be classified into 'All or Nothing' Assignment, Stochastic Traffic Assignment, Capacity Restrained Assignment, Incremental Assignment, User Equilibrium Assignment, System Optimum Assignment (Saw et al., 2015).

As also previously discussed, macroscopic traffic assignments are link-based and are supported by mathematical models to reproduce the average behaviour of vehicles. In this respect, the generalised cost for routes between each OD pair will determine the route choice. While a proxy for the delay experienced due to congestion, signals or movement priorities is taken into account by functions such as Volume Delay Function (VDF), Turn Penalty Function (TPF) and Junction Delay Function (JDF), assignment of traffic demand to a road is not constrained by the capacity of the road, meaning that the assigned volume during an analysis period can be more than the actual capacity of the road, i.e. possible to have volume/capacity >1.

While exploring all assignment methodologies named earlier is not within the scope of this paper, due to their extensive applications in static macroscopic traffic assignment, we will further discuss the 'all or nothing' and the 'user equilibrium' assignments.

2.1.1. All or Nothing (AoN) assignment

The simplest form of allocating the demand between a pair of Origin-Destination is the assignment of the entire demand to the route with the lowest generalised cost, in other words, the least resistance (Ortúzar et al., 2011a, Saw et al., 2015). As in many cases, it equates to the shortest path between the OD pairs, this method is sometimes referred to as the shortest path/route method (Saw et al., 2015). While this assumption appears unrealistic, particularly for congested urban networks with alternative routes to choose, its main application is that it acts as a building block for the implementation of other types of assignment methodologies (Mathew and Rao, 2006).

2.1.2. User equilibrium assignment

User equilibrium assignment cannot be named without referring to the work of Frank Knight in the 1920s and later John Nash and his game theory in the 1950s. In the same decade, John Wardrop (cited in Krylatov et al., 2020) stated that the journey times in all routes used between a given OD pair are equal and less than those experienced by a single vehicle on any unused route. This statement, known as Wardrop's first principle, is the underlying assumption for all user equilibrium assignment models (Krylatov et al., 2020).

Mathew and Rao (2006) argue that the user equilibrium assignment methodology is built on the pillars of three assumptions:

1. The user has perfect knowledge of the network and the associated cost of each path,
2. Travel time on a given link is a function of the flow on that link only, and
3. Travel time functions are positive and increasing.

Different methodologies have since been proposed and evolved to implement Wardrop's first principle. The two most frequently used methods are discussed in more detail in this paper while discussing all available methods is out of the scope of this article.

a. Frank and Wolfe

The Frank-Wolfe Algorithm (FWA), also known as the Conditional Gradient Method, is an optimisation algorithm that is commonly used to solve convex optimisation problems (Frank and Wolfe, 1956). The FWA was first proposed by Marguerite Frank and Philip Wolfe in 1956 and has since been widely applied in various fields, including transport modelling, where FWA is used as a traffic assignment method to find the user equilibrium (UE) conditions in transportation networks.

The FWA is an iterative algorithm that starts with an initial set of path flows and finds the direction of the steepest descent, minimising the difference between the current path flows, and the UE flows. The UE flows are the path flows that satisfy Wardrop's first principle, which states that all travellers in the network choose the lowest perceived travel cost route between an origin-destination pair.

The FWA algorithm updates the path flows in each iteration by taking a step towards the UE solution along the direction of the steepest descent. The size of the step is controlled by a parameter known as the step size or the line search parameter. The step size parameter determines the rate at which the path flows converge to the UE solution. A smaller step size parameter leads to a slower convergence but produces a more stable solution, while a larger step size parameter leads to a faster convergence but can result in oscillations and instability.

One of the advantages of the FWA is that it can handle non-linear and non-convex functions that arise from the non-linear relationship between travel costs and flows. Additionally, the FWA can be more computationally efficient than other user equilibrium traffic assignment methods, such as the Method of Successive Averages (MSA), which can be computationally expensive for large-scale transportation networks.

b. Method of Successive Averages (MSA)

The Method of Successive Averages (MSA) is an iterative process that aims to converge to a solution in which all travellers in the network are assumed to select the path with the lowest cost with respect to their perceived travel cost. The MSA method uses a set of equations that describe the relationship between the travel costs of all the paths between an origin-destination pair and the flows that use each path.

Essentially, MSA and FWA follow the same principles. The main difference is the step size, which is determined by minimising the objective function in FWA, while in the case of MSA, the step size is 1/k, where k is the number of iterations (Bezembinder et al., 2016).

It is also to be noted that a generalised form of MSA is called “Volume Averaging” where the step size is any fixed value (Muijlwijk, 2012).

2.2. Dynamic traffic simulation models

As discussed earlier, considering the dynamic nature of demand over a model period, it is a common practice to see the profiled demand combined with the simulated behaviour of individual vehicles, resulting in a dynamic traffic simulation model.

Car-following model is known to be the backbone of traffic simulation algorithms. Referring to the work of researchers before him, Gipps (1981) describes the general form of the car following model as:

$$a_n(t+\tau) = l_n \frac{[v_{n-1}(t) - v_n(t)]^k}{[x_{n-1}(t) - x_n(t)]^m}$$

Equation 1: General form of Car Following Model (Gipps, 1981)

Where vehicle $n-1$ is followed immediately by vehicle n, and τ is the reaction time, $x_n(t)$ is the location of vehicle n at time t, $v_n(t)$ is the speed of vehicle n at time t, $a_n(t+\tau)$ is the acceleration of vehicle n at time $t+\tau$, and $l_n, k\ and\ m$ are parameters that need to be estimated.

By referring to the work of Seddon (1972), Gipps (1981) argues that while models derived from the general form of car-following model work acceptedly in most cases, "it is desirable for the interval between successive recalculations of acceleration, speed and location to be a fraction of the reaction time" and that it requires the storage of a considerable quantity of historical data when using the model in a simulation program. Gipps (1981) also discusses the issues with the parameters $l_n, k, and\ m$ and that these parameters have "no obvious connection with identifiable characteristics of driver or vehicle."

Gipps (1981) accordingly proposed the model presented in Equation 2, which addresses the shortcomings of its preceding car-following models in that:

a) the model mimics the behaviours of real traffic,
b) the parameters in the model correspond to obvious characteristics of drivers and vehicles, and
c) the model performs well when the interval between successive recalculations of speed and position is the same as the reaction time.

$$v_n(t+\tau) = \min\left\{v_n(t) + 2.5a_n\tau\left(\frac{1-v_n(t)}{V_n}\right)\left(0.025+\frac{v_n(t)}{V_n}\right)^{1/2},\ b_n\tau + \sqrt{(b_n^2\tau^2 - b_n[2[x_{n-1}(t) - s_{n-1} - x_n(t)] - v_n(t)\tau - v_{n-1}(t)^2/\hat{b}])}\right\}$$

Equation 2: Gipps car-following model (Gipps, 1981)

where,
vehicle $n-1$ is followed immediately by vehicle n,
a_n is the maximum acceleration which the driver of vehicle *n* wishes to undertake,
b_n is the most severe braking that the driver of vehicle *n* wishes to undertake (b_n<0),
$\hat{b}$ is the estimate for the most severe braking that driver of vehicle *n-1* wishes to undertake,
s_n is the effective size of vehicle *n*,
V_n is the speed at which the driver of vehicle *n* wishes to travel,
$x_{n(t)}$ is the location of the front of vehicle *n* at time *t*,
$v_n(t)$ is the speed of vehicle *n* at time *t*, and
τ is the apparent reaction time, a constant for all vehicles.

Traffic simulation models can, therefore, also be classified based on the interval between successive recalculations of acceleration, speed and location of each individual vehicle in the next with respect to the vehicle in front. This classification determines whether simulation is at the mesoscopic or microscopic level.

2.2.1. Dynamic microscopic traffic simulation models

Simulation at the microscopic level addresses the desirable part of Gipps' expectation of a car-following model, that is, for the interval between successive recalculations of acceleration, speed and location to be a fraction of the reaction time (Gipps, 1981). In microscopic simulation, this interval between successive recalculations of acceleration, speed and location

is what is known as the simulation step, with reaction time (at stop and at traffic lights) being determined by applying factors greater than 1 (Aimsun, 2022, DIT, 2022).

2.2.2. Dynamic mesoscopic traffic simulation models

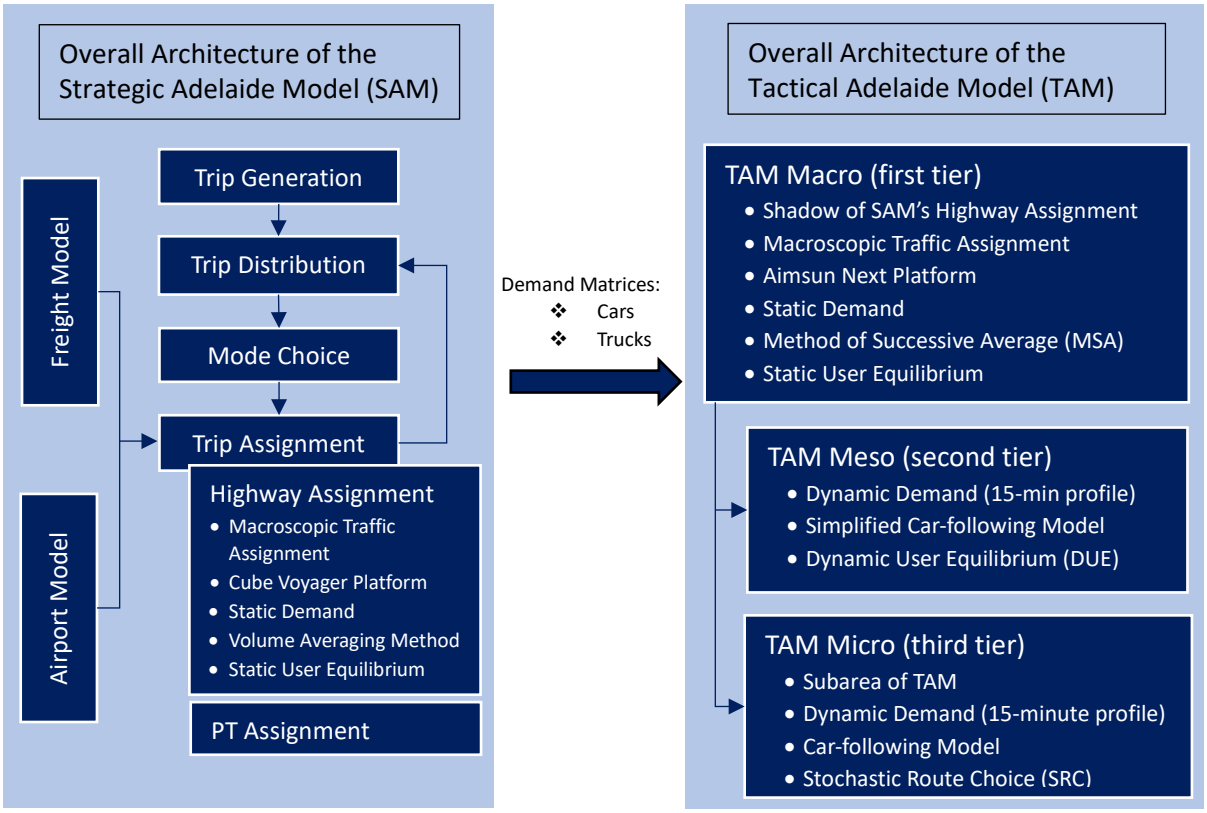
While mesoscopic traffic simulation models also have the car-following algorithm in their engines, the main difference to a microscopic level simulation is Gipps' desirable component of a car-following model. In other words, the interval between successive recalculations of acceleration, speed and location does not need to be a fraction of the reaction time. In other words, the interval is defined by an event, and the next event for a vehicle is when the vehicle enters or leaves a section or node (Aimsun, 2022, DIT, 2022).

3. Tactical Adelaide Model (TAM): A multi-tiered traffic modelling framework

Transport and traffic modelling is a term with a wide spectrum of applications. It encompasses strategic travel demand models as well as traffic assignment models at the macroscopic, mesoscopic and microscopic levels (Chiu et al., 2011, Mathew and Rao, 2006, Ortúzar et al., 2011b).

In South Australia, the Strategic Adelaide Model (SAM) and the Tactical Adelaide Model (TAM) are the main components of the transport and traffic modelling realm (DIT, 2022). At its core, SAM follows the four-step trip-based travel demand modelling methodology and is used to provide travel demand forecasts for the Greater Adelaide area. TAM is, however, a multi-tiered traffic assignment modelling framework. Figure 1 shows the overall architecture of SAM and TAM as well as the interaction between the two.

Figure 1: Overall Architecture of SAM and TAM



3.1. Tactical Adelaide Model (TAM) in a nutshell

The need for a traffic assignment modelling framework, to complete the integrated modelling framework for Adelaide metropolitan area, has been identified since the early 2010s. The Metropolitan Adelaide Traffic Simulation and Assessment Model (MATSAM) was the first attempt in South Australia to develop a multi-tiered traffic assignment model.

A bottom-up approach, adopted for MATSAM, intended to consolidate discrete subarea models, developed by different traffic modelling service providers for a variety of planning studies, to build a working metropolitan-wide traffic assignment model at the macroscopic and mesoscopic levels. This proved challenging due to factors such as inconsistency in the quality of models built for each subarea, difficulty in subarea demand integration with the metropolitan-wide network, and connection to the strategic travel demand model.

With lessons learned from MATSAM, the Tactical Adelaide Model (TAM) was designed with the top to bottom approach, starting with the Greater Adelaide Area (GAA) wide static macroscopic model, which accordingly informs the two lower tiers of GAA-wide mesoscopic and subarea microscopic model, making TAM a multi-tiered traffic assignment model. The overall architecture of TAM is shown in Figure 1.

3.2. TAM Macro: A shadow of the highway assignment sub-model of Adelaide's strategic travel demand model (Strategic Adelaide Model)

Through the development process of the Tactical Adelaide Model (TAM), a need has been identified to close the gap between SAM and TAM, the two main components of DIT's integrated modelling framework, with regard to the outputs of the static macroscopic assignment. In other words, since TAM inherits its OD demand matrices from SAM (as shown in Figure 1), it is paramount that SAM and TAM produce similar results for static macroscopic assignment outputs. It provides greater confidence that the models are generally in agreement and that the differences can be isolated to specific known limitations of the modelling tools and approaches. Hence, TAM's macroscopic assignment outputs can be used instead of SAM's highway assignment model, hence the name "SAM Shadow". Conversely, it is also recognised that step changes to some of these inputs are necessary as the model is transitioning from a strategic macro demand model to an operational dynamic simulation model, requiring greater detail.

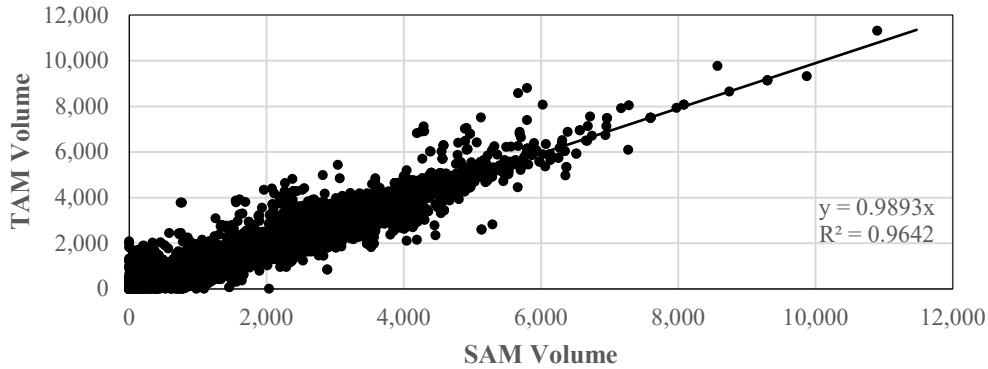
The first step of closing the gap between the two models has, therefore, been the alignment of the inputs and assumptions used in the two models. These include:

1. Geometry (the location and connectivity of nodes and links)
2. Centroid geometry (the location of centroids and centroid connectors for loading the demand into the network)
3. Network attributes (such as section speed limit, road type and capacity)
4. Cost functions (for centroid connectors, links, and turns)
5. Traffic demands for base and future years.

While the ultimate objective of the exercise has been for the SAM and TAM cost functions to produce similar generalised costs, in order to remove the uncertainty associated with the outputs of cost functions related to turns in each of the models, at the start of the exercise, fixed turn costs, extracted from the final iteration of SAM assignment, were used to inform TAM macroscopic assignment. In other words, the purpose of the direct importation was to establish a baseline that accounts for the differences between the two software packages, as specified in Figure 1, that cannot be reconciled.

Figure 2 shows the regression analysis results comparing the assigned volume on each link in SAM highway assignment model and TAM macroscopic assignment with directly imported turn costs. The importation yielded a slope of 0.9893 and a coefficient of correlation (R^2) of 0.9642, which indicates a strong correlation between the two data sets. The direct importation represents the "closest possible" realisation of SAM within the Aimsun Next platform.

Figure 2: Baseline Link Volume Comparison (SAM HWY Assignment vs TAM Macroscopic Assignment)

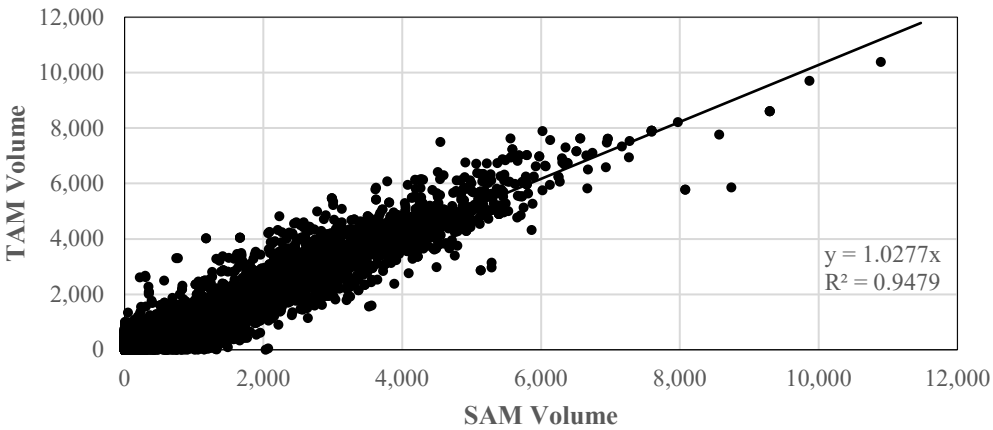


In the second iteration of the exercise, while SAM and TAM have principally been kept geometrically aligned by ensuring that the modelled road network in TAM contained at least all the same links as SAM and that the centroid connectivity was replicated, because TAM serves the purpose to be used as a platform for a dynamic traffic assignment, many components are modelled in greater detail in TAM than SAM. The key differences between the models are:

- More detailed signal timing in TAM based on historical data
- Different calculation of turn costs between the two models
- Costs are applied at all turns at signalised and unsignalised intersections in TAM, while SAM has costs incorporated for turns of signalised intersections and a selected number of unsignalised intersections.
- Network discrepancies, for example, turn bans that have not been modelled in SAM
- More links in TAM, resulting in a greater route choice

Figure 3 shows the regression analysis results comparing the assigned volume on each link in SAM and TAM. This yielded a slope of 1.0277 and an R^2 of 0.9479. There is a slightly lower correlation in this scenario compared to the direct importation which is attributable to the methodology differences described above.

Figure 3: Final Link Volume Comparison (SAM HWY Assignment vs TAM Macroscopic Assignment)

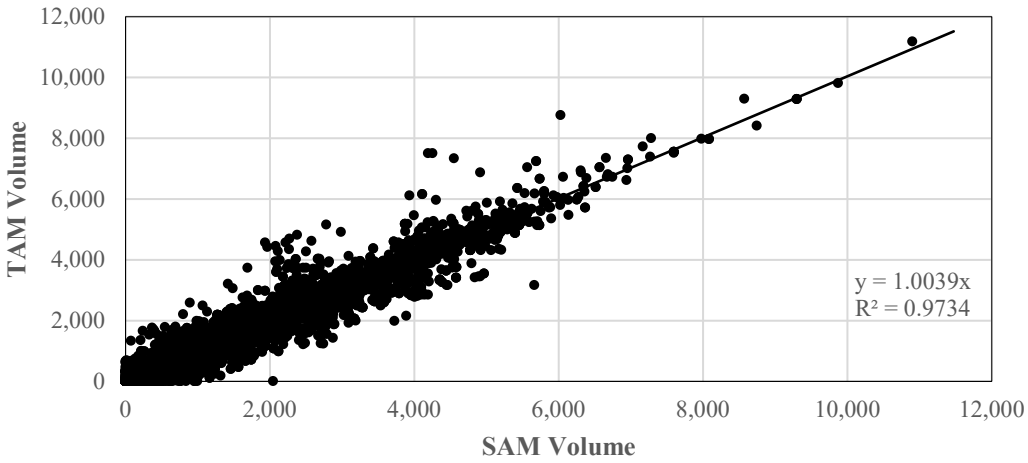


The methodological differences were the subject of sensitivity tests to establish how much they were influencing the overall results. The sensitivity tests included:

- Excluding the additional links present in TAM but not in SAM
- Using link capacities and speeds imported from SAM rather than those in TAM
- Importing fixed delays at all junctions from the final iteration of the SAM assignment

The impacts of these changes were assessed individually and in conjunction with each other. Figure 4 shows the regression analysis results comparing the assignment volume on each link in SAM and TAM from the final sensitivity test, which incorporated all the changes listed above.

Figure 4: Link volume comparison between SAM and TAM with the use of non-SAM links excluded, link capacities and speeds directly imported from SAM, and fixed delays at all junctions from the final SAM assignment iteration



3.2.1. Assignment engine in TAM Macro

As discussed in the previous section, different implementation methodologies have evolved since user equilibrium traffic assignment was proposed and supported by Wardop's first principle in the 1950s. Method of successive averages (MSA) and Frank-Wolfe have been explored from the available methodologies for implementation in TAM. While due to using gradient and interpolation methods to make incremental steps towards maximising the objective solution, Frank-Wolfe gained popularity and is implemented widely for static macroscopic traffic assignment models, it should be noted that the methodology works based on a critical assumption that the routes to choose from between each origin-destination pair are completely independent of each other. This assumption may not be realised for networks with intersections at which different competing paths influence each other (Bezembinder et al., 2016).

The alternative method, known as the method of successive averages (MSA), has also been explored. Unlike the Frank-Wolfe Algorithm, which calculates step size at each iteration to minimise the objective function, MSA uses a fixed step size per iteration, which is determined by $1/k$, where k is the number of iterations. Although MSA may not be as efficient, and in some cases achieves slower convergence as the number of iterations is fixed, MSA weights the flow of each iteration equally. With the fixed step size and the equal weighting approach, MSA is considered a more suitable assignment approach for considering the interaction of traffic movements at signalised intersections in the process of determining the OD routes. Additionally, with a higher number of iterations (e.g., 100 iterations), MSA assignment approach is generally observed to generate results in line with Wardrop's principle. Additionally, an investigation of the algorithms for MSA and the 'Volume Averaging' method,

which is used in SAM's Highway Assignment Model, indicates that the methods of MSA and Volume Averaging are more similar from the methodological perspective. As discussed in earlier sections of this paper, the Volume Averaging method is, in fact, a generalised form of MSA. As TAM Macro is intended to be a shadow of SAM's Highway Assignment Model, a closer matched assignment methodology can help achieve better alignment between the two models.

3.3. TAM Meso: A dynamic traffic assignment model at the mesoscopic simulation level

TAM mesoscopic simulation model is a dynamic traffic assignment (DTA) model. It follows Wardrop's first principle but at a dynamic 15-minute time block level with a simulation-based methodology for the allocation of vehicles between each origin-destination pair. The model runs simulations over several iterations to achieve equilibrium, based on generalised costs, across all the chosen paths.

TAM Meso is calibrated and validated, having achieved the requirements of the "Transport Model Development Guidelines", published by the New Zealand Transport Agency (NZTA, 2019) for category C "Urban Area". Real Dataset (RDS) encompassing 3651 turning movement counts across 581 signalised intersections, 100 turning movement counts at unsignalised intersections, and 101 motorway counts for the Greater Adelaide area as observed in May 2019, was used for TAM Meso calibration.

The model seed demand matrices are prepared by DIT's strategic travel demand model, i.e. Strategic Adelaide Model (SAM). In order to transition from a strategic travel demand model, the peak-hour demand matrices from SAM were used as the initial seed matrices. Due to the nature of the strategic demand model, which has no concept of arrival or departure times, these seed matrices were processed and adjusted in reference to the agreed set of real data set of turn movement counts. They were subsequently profiled using Aimsun Next built-in feature 'Static OD Departure Adjustment'.

Static OD Departure Adjustment is a process developed in Aimsun Next to convert a flat demand from a strategic travel demand model by introducing a complete temporal dimension to a profiled demand. It is a mathematical process that infers the expected departure time based on the estimated travel time between the detector point and a trip's origin in a strategic travel demand model. In reference to Aimsun Next's user manual (Aimsun, 2022), a static OD departure adjustment of the profiled demand, the original static demand is distributed through smaller intervals over the duaration of the modeller period. The objective is to reproduce the observed traffic counts specified in the Real Data Set per interval, staying as close as possible to the original number of OD pair trips for the whole period. It is, therefore, important to start the adjustment with a calibrated demand that has been developed using the same set of detector data over the scope of the model. It is noted that Static OD Departure Adjustment does not calculate/run any new traffic assignment. Technically, the process should take the corresponding fixed paths from a Path Assignment calculated earlier using the calibrated demand.

This method works to overcome the limitation of the conventional approach whereby a dynamic traffic demand is calculated and adjusted by slicing the demand into multiple intervals and adjusted independently. The conventional static OD adjustment process shows a bias in departure time for longer trips as the travel time aspect, which crosses multiple time intervals, is neglected. The static departure adjustment solves this problem by considering the travel time

obtained from the static assignment in calculating the expected departure time, even if it spans across multiple time intervals, for dynamic traffic demand.

Figure 5: Example for Departure Adjustment Calculation (Aimsun, 2022)

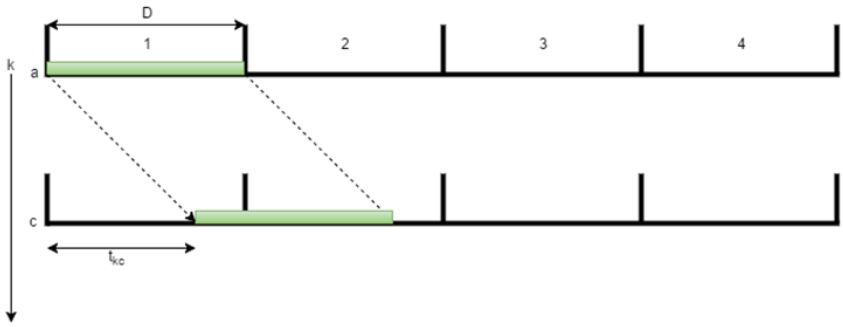


Figure 5 assumes link 'c' is the detection point while link 'a' is the origin. If the travel time from origin 'a' to link 'c' by path 'k' is 't_{kc}', it is expected that 25% of the demand generated from origin 'a' in time interval 1 arrive at the detection point 'c', with the remaining 75% demand, generated from origin 'a', arriving in time interval 2. The same logic is then applied across all origin and detection points to calculate the profiled demand.

GEH statistic has been used to verify model calibration as per NZTA (2019). Wisconsin Department of Transportation (cited in Horowitz et al., 2014) suggests the GEH thresholds and corresponding model acceptability as presented in Table 1. These thresholds are in line with the thresholds of 5, 7.5 and 10 recommended by the New Zealand Transport Agency modelling guidelines (NZTA, 2019), used for TAM meso base year calibration.

$$GEH = \sqrt{\frac{2(m-c)^2}{m+c}}$$

Equation 3: GEH Statistic Formula

where m is the estimated/modelled traffic value, and c is the observed traffic count.

Table 1: GEH Statistic Values and Model/Estimate Acceptability

GEH values and thresholds	Estimate / Model acceptability
GEH < 5	Acceptable fit, probably okay
5 ≤ GEH < 10	Caution: possible model/estimate error or bad data
GEH ≥ 10	Warning: high probability of model/estimate error or bad data

The profiled demand is used as the main demand input for the TAM Dynamic Mesoscopic model together with the supply-side dynamic operational constraints.

While information regarding the number of turning movement counts and motorway counts utilised for model calibration has been presented in preceding paragraphs, it is noteworthy to highlight that travel times across 35 journey routes, broken down into 116 route segments were employed for model validation.

Tables 2 to 5 show that the TAM AM and PM peak period models were calibrated and validated, respectively, as satisfactory to the purpose of category C of NZTA modelling guidelines. The only exception is the validation criteria of ±15% or 1 minute for 5-6 PM and 6-7 PM where the achieved results are lower than the target by 2% and 1% respectively.

Table 2: TAM Meso Base Year (2019 AM) Calibration Results

Traffic Counts Specified NZTA Cat. C Target	Percentage GEH < 5.0 > 80%	Percentage GEH < 7.5 > 85%	Percentage GEH < 10.0 > 90%	Calibration Achieved? (As per NZTA Cat. C)
Turns - All Vehicle 7am to 8am	80%	92%	97%	✓
Turns - All Vehicle 8am to 9am	85%	93%	97%	✓
Turns - All Vehicle 9am to 10am	80%	92%	97%	✓

Table 3: TAM Meso Base Year (2019 AM) Validation Results

Travel Time Validation	Specified NZTA Category C Target	7-10 AM	7-8 AM	8-9 AM	9-10 AM	Validation target achieved?
Within 15% or 1 min difference	>85.0%	89%	91%	88%	86%	✓
Within 25% or 1.5 mins difference	>90.0%	96%	99%	95%	93%	✓

Table 4: TAM Meso Base Year (2019 PM) Calibration and Validation Results

Traffic Counts Specified NZTA Cat. C Target	Percentage GEH < 5.0 > 80%	Percentage GEH < 7.5 > 85%	Percentage GEH < 10.0 > 90%	Calibration Achieved? (As per NZTA Cat. C)
Turns - All Vehicle 3pm to 4pm	86%	94%	97%	✓
Turns - All Vehicle 4pm to 5pm	89%	95%	98%	✓
Turns - All Vehicle 5pm to 6pm	87%	94%	97%	✓
Turns - All Vehicle 6pm to 7pm	81%	91%	97%	✓

Table 5: TAM Meso Base Year (2019 PM) Validation Results

Travel Time Validation	Specified NZTA Category C Target	3-7 PM	3-4 PM	4-5 PM	5-6 PM	6-7 PM	Validation target achieved?
Within 15% or 1 min difference	>85.0%	91%	95%	89%	83%	84%	X
Within 25% or 1.5 mins difference	>90.0%	95%	99%	97%	91%	90%	✓

With respect to the future demand, future nominal peak hour seed matrices from the strategic travel demand model, i.e. Strategic Adelaide Model (SAM), have been used to inform a pivoting process, which at its simplest explanation, compares the adjusted base year matrices with their corresponding base year seed matrices from the strategic model. The difference between the two forms the basis for any pivoting exercise to adjust the future forecast demand (Daly et al., 2011, Manheim, 1979, Transportation Research Board, 1982).

Our experience with different models has demonstrated that there is no "one-size-fits-all" approach to developing future year matrices for dynamic traffic assignment models that use flat demand matrices from a strategic travel demand model, even though the concept of future demand adjustment (pivoting) appears straightforward to implement. The primary shortcoming that may be experienced during this process are:

a. Adjusted demand is in excess of the network capacity for the specific simulation period, potentially causing gridlock;
b. Profiled demand exceeds the physical capacity of the network for a specific simulation period, resulting in excessive delay; and
c. Uneven growth, and uneven adjusted demand, potentially causing excessive localised congestion.

Following comprehensive research and consultation with subject matter experts in both areas of strategic travel demand modelling and dynamic traffic assignment modelling about the available, previously implemented, and innovative methods, a process known as the sectorised method has been adopted for TAM future year demand preparation. Noting that the detailed discussions of the sectorised method and its implementation in the Tactical Adelaide Model (TAM) is not within the scope of this paper and is aimed to be published in a separate article, we suffice to briefly mention that the process involves the aggregation of base year TAM meso demands at large zones, called sectors, determining the sector-aggregated future demands by applying the growth determined by the strategic travel demand model and disaggregating the future sector-aggregated demands to the zones of the base year calibrated model.

One of the shortcomings of this method, which is the subject of further research and improvements for TAM, is the future year demand profiling based on the base year model departure time. This limitation imposes constraints on the model's responsiveness to any change in departure time, and therefore, not predicting any peak-spreading.

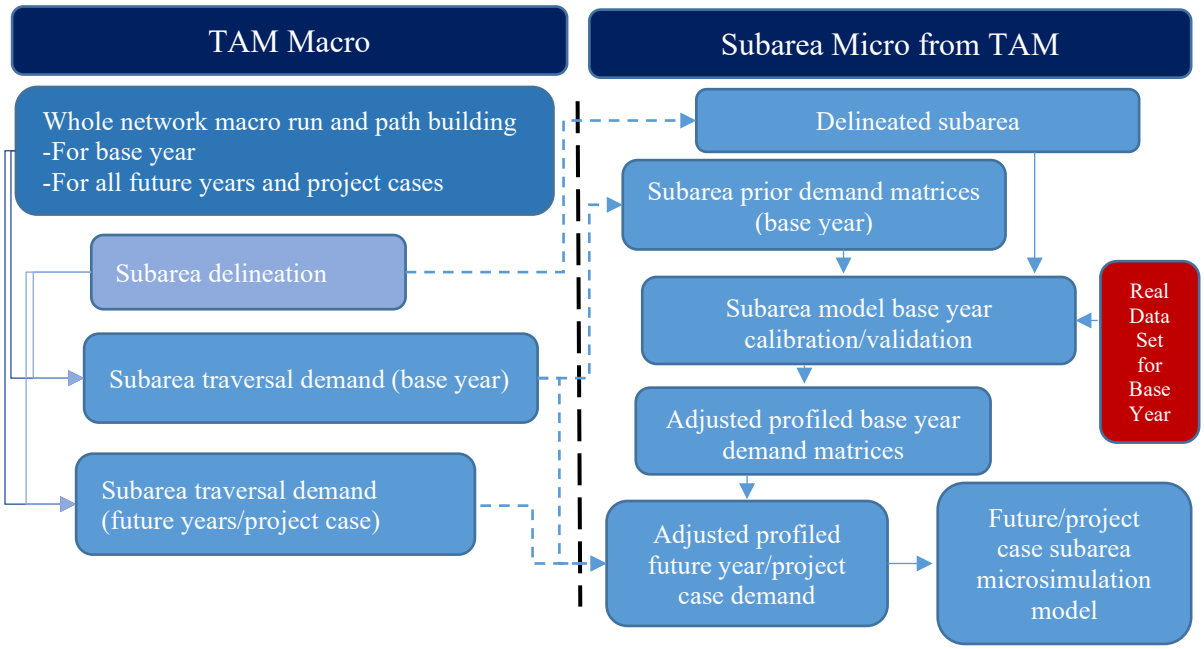
3.4. TAM Micro-Subarea: A dynamic traffic assignment model at the microscopic simulation level

As depicted in Figure 1, TAM provides the platform for building dynamic traffic assignment models at the microscopic simulation level. As these models are a small area of the Greater Adelaide area, which is the whole TAM coverage, they are referred to as subarea models.

TAM's multi-tiered modelling framework facilitates the development of subarea models at microscopic level not just by providing a pre-built network as a starting point for network refinement but also and more importantly, by preparing the subarea demand in the same platfrom through a seamless process.

Figure 6 provides an overview of the modelling architecture for subarea microsimulation model development from TAM and the interaction between TAM Macro and TAM Micro Subarea.

Figure 6: Overview of subarea microsimulation model development architecture from TAM



4. The use case of multi-tiered traffic modelling framework

Opportunities in facilitating different stages of transportation planning exercise because of the availability of multi-tiered traffic assignment models have been recognised by practitioners and researchers in the field of transport and traffic modelling (Aimsun, 2022, DIT, 2022, Ferrara et al., 2018c).

Since its launch in May 2022, different levels of TAM have been used for different transport planning studies, area planning, corridor studies, road and intersection upgrade and design. The smooth transition from one model tier to another in TAM, enabled by the Aimsun Next platform, has proven to be a game changer for supporting planning studies at different stages of their planning and design life.

As a general rule, TAM macro has been used to inform high level planning studies as well as determining subarea demands. TAM meso's predominant application has been to inform planning studies and a long-list to shortlist option testing exercise, while TAM subarea micro is more designed for detailed planning, which are transitioning to the design phase to better inform the design.

5. Summary and conclusions

In this paper, we examined different traffic assignment methodologies and the classification of traffic assignment models from a variety of perspectives. At a high level, static and dynamic models were discussed followed by categorisation based on theoretical concepts of the models to determine whether they are analytical or simulation-based. Details of the supply side analysis to determine if a model is at the macroscopic, microscopic or mesoscopic level were also discussed. Models developed using combinations of these classes were discussed, and the most commonly used combinations were identified to be static macroscopic traffic assignment and dynamic microscopic traffic simulation, as well as dynamic mesoscopic traffic simulation,

which recently gained popularity. The assignment techniques for each of these methods were also discussed.

The Tactical Adelaide Model (TAM) as a multi-tiered traffic assignment modelling framework, developed by the South Australian Department for Infrastructure and Transport (DIT) in collaboration with Aimsun Pty Ltd was also discussed in this paper. This paper aimed to showcase how TAM benefits from different types of traffic assignment methodologies for its various tiers, namely TAM macro, TAM meso, and TAM micro (subarea).

This paper discussed a use case for multi-tiered traffic assignment modelling framework and how TAM, thanks to its multi-tiered nature, is useful for undertaking planning studies at different stages.

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