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Impact of Capacity, Crowding, and Vehicle Arrival Adherence on Public Transport Ridership: Los Angeles and Sydney Experience and Forecasting Approach

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Abstract

This paper describes innovative aspects in the development of regional travel models for both Sydney and Los Angeles. The overall approach was to incorporate the effects of capacity, crowding, and delayed vehicle arrivals in the network supply, mode choice, and assignment modules. Capacity and crowding modules were first developed and applied in Sydney. The Los Angeles effort has built upon that work and will also consider variations in vehicle arrivals.

Most travel models ignore the fact that transit vehicles have limited capacity. The most behaviorally realistic way to implement this feature was through extra weight functions applied at the boarding station. A method was also developed to take into account crowding as a negative factor in the user perception of transit service quality**.** The work revealed that the probability of having a seat should be reflected in the segment in-vehicle time weight. There is a strong indication, from existing research and the Stated Preference surveys undertaken in Sydney, that in-vehicle time for a standing passenger should be weighted more onerously compared to a seating passenger.

Ridership in heavily congested corridors in Los Angeles has been adversely impacted by delays in vehicle arrivals and severe bunching. Estimated wait and in-vehicle time functions will be incorporated in an integrated mode choice model and assignment procedures as part of the work reported in this paper. These methods can be used by modelers dealing with urban transport systems that have reached, or will reach, capacity and experience serious congestion related delays.

1. Introduction

Most major cities have strategic transport models which are used for planning and forecasting purposes. In most cases the strategic models are developed to be fit for these purposes without requiring excessive detail and complexity. The strategic models are often used in the early stages of planning and assessing new transport infrastructure projects. However they do not always include the necessary level of detail or functionality for providing project demand forecasts for design, investment and procurement purposes. As an example; crowding, which is a source of major concern to many passengers and a lot of surveys have put it close to the top of the list of priorities, is not considered in most strategic models.

This paper first describes the Sydney experience in developing a public transport project modelling capability. It shows how by relying on several worthwhile studies, which have been done since the late 1980s, the Metro Network Transport Model (MNTM) was developed to ensure the best use of existing data and tools while overcoming the understandable limitations in the STM– the NSW Government's Strategic Travel Model (STM). MNTM is a behavioural choice model, the structure of which was originally developed for assessing transit projects in Los Angeles, During 2009 the model was refined and calibrated to meet the model platform objectives for metro forecasting in Sydney.

The overall approach is to break transit trips into access/main mode(s)/egress stages. A railway journey is almost always part of a journey 'chain' that includes a journey to, and later from, the railway station by different modes of transport. MNTM integrates all the cost components of each journey before allocating demand between rail and alternative modes. Such integration depends very much on the extent to which the interchange between transport modes and services is viable. Cost of getting to the rail stations or from them is an important part of a rail journey utility calculation in MNTM, the structure of which is based on accessibility and capacity of each station.

The Capacity and Crowding module in the MNTM is a synthesis of various previous attempts to incorporate capacity constraints and crowding factors in not only transit assignment but also mode choice models. The paper concludes by outlining the on-going work in Los Angeles to incorporate capacity and crowding, along with modelling delays in vehicle arrivals at stops or stations.

2. Background

The STM is a proven and reliable tool for strategic level forecasting of planning and infrastructure in the Sydney Greater Metropolitan Area. However, the fact that it relies on EMME and its strategy based algorithm in transit assignment, limits it's ability to appraise public transport projects at a sufficient level of detail. The inherent limitations of strategy based algorithm, especially when the network is congested, are well addressed in the literature. In addition the STM lacks station choice for the access/egress legs. The STM train assignment, which has the highest hierarchy, is based on assuming more (double) speed for higher modes in the hierarchy table. This could lead to illogical station choices and inconsistency between mode choice and transit assignment.

A multi-disciplinary demand forecasting team, led by PB, was appointed in February 2009 to develop an enhanced modelling platform for transit project appraisal. The modelling platform was to be referred to as the Metro Network Transport Model (MNTM). It was a prerequisite to develop an approach which would capture the complex behavioural choices that people make when using an integrated transport system such as exists in Sydney. The existing Sydney rail system (CityRail) carries almost a million trips each weekday. More than half of these trips use at least one other mode of motorised transport.

This requirement provided an early signpost that the behavioural choice model would need to include both mode choice and some level of path choice (through the transport networks).

For calibration purposes, the NSW Transport Data Centre's continuous Household Travel Survey (HTS) provided the most comprehensive record of travel by residents of Sydney. The HTS dataset is based on a sample of approximately 3,000 households per year. It was also recognised that only around 30% of home-based work (HBW) trips in the HTS are by public transport. In order to increase the 'richness' of observed public transport travel in the dataset nine years of the HTS data was pooled.

3. Overall modelling approach

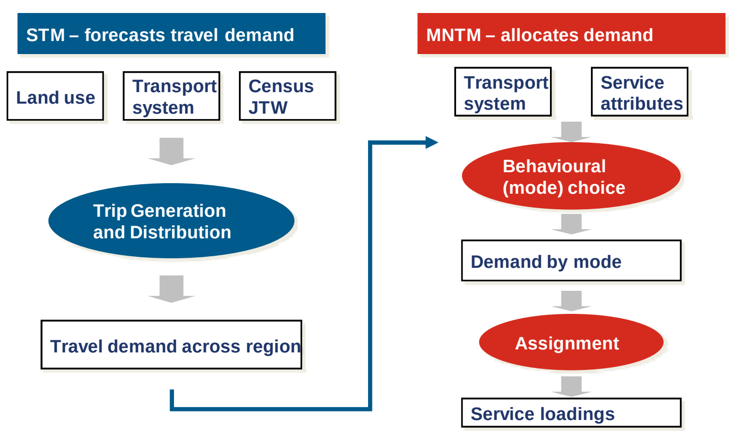
The accepted baseline in developing MNTM was that STM is reliable for the trip generation and distribution stages of the four stage process. The PB US behavioural choice model offers the opportunity to enhance the mode and path choice through a new behavioural choice model.

In order to support this premise the 24 hour STM tour matrices were validated against the Sydney Household Travel Survey (HTS). This validation included the comparison of the matrices against HTS at Statistical Sub-Division (SSD) level as well as trip length distribution comparisons and sensitivity tests.

3.1. MNTM is an enhanced behavioural choice module for STM

In this hybrid modelling approach, STM performs trip generation and distribution stages and MNTM performs mode and path choice. In this context the 'transit path' is defined by the key interchanges that are used on a public transport journey. Post-MNTM assignments, undertaken in EMME, provide the detail of routes chosen between these interchanges. The overall modelling process is illustrated in Figure 1.

Figure 1: STM/MNTM modelling system



3.2. STM provides MNTM with all-mode demand matrices

The 'handover' data between STM and MNTM therefore consists of a set of all-mode, 24 hour tour matrices and a vehicle trip table (for highway skims). The tour matrices are segmented in two dimensions:

- by the six home-based purposes available in STM, and
- market segments which reflect four levels of household car availability.

The 24 demand segments are derived by aggregating the 128 segments that are used in STM. Prior to input to MNTM, however, the 8 MNTM demand segments are further aggregated as shown by the shaded blocks in Table 1.

Table 1: Demand segmentation

	No HH car	No licence 1+ HH Cars	Competition for car	No competition for car
HBWork	✓	✓	✓	✓
HBBusiness	✓	✓	✓	✓
HBEducation(P)	✓	✓		
HBEducation(S)	✓	✓		
HBEducation(T)	✓	✓	✓	✓
HBShopping	✓	✓	✓	✓
HBOther	✓	✓	✓	✓

HB – Home Based
HH - Household
Shaded areas illustrate further aggregation during processing for MNTM

The most important refinements to the matrices during the input stage for MNTM are:

1. convert tours to trips (maintaining Production-Attraction, format)
2. control the matrix trip totals to the HTS calibration data set (using global factors for each purpose and market segment)
3. split matrices into peak and off-peak (using global factors for each purpose, market segment, and CBD/non-CBD attraction)
4. combine 'Other' and 'Shopping' purposes as illustrated by the shading in table 1
5. combine the first two market segments (lowest levels of car availability) as illustrated by the shading in table 1

3.3. STM and MNTM are discrete steps in the modelling process

Early in the model development the potential for feeding costs and demand back from MNTM to STM was considered. It was concluded that this would be very complex to implement due to inconsistencies between the models. It was also considered that this feedback would not be guaranteed to provide more accurate 24 hour tour matrices.

As a result the principle adopted for the modelling process is that STM should complete the analysis of trip generation and distribution using its own mode choice and assignment stages. All mode matrices would be produced by re-combining the modal matrices. In other words, STM should be cycled until it meets equilibrium requirements for that scenario.

The matrices that exist at the 'handover' point are therefore assumed to be complete and sufficiently reliable to allow MNTM mode and path choice to be completed without the need to repeat generation and distribution stages in STM.

The all-mode demand matrices produced by STM (once processed for MNTM) are therefore fixed for all further analysis stages. This is true for both the all-mode demand matrices and the vehicle trip tables (used only for MNTM highway skims).

The only exception to the fixed matrix approach within MNTM is in the routine for calculating non-user (highway) benefits. In this routine the vehicle trip tables are updated using MNTM output. The updated vehicle trip tables are assigned in EMME to estimate changes in congestion that arise from the project. This step does not involve the STM.

4. Behavioural choice model specification

The behavioural nested logit choice model is the core of the MNTM. For each origin-destination pair, the model allocates demand by mode and, in the case of rail-based public transport, by access/egress options. The choice model is one step within a 'macro routine', or framework, which contains inner and outer loops to model the effects of station parking capacity and train crowding. This routine is described in more detail in Section 5.

4.1. Choice between multi-modal route options

One of the defining features of the MNTM behavioural model is that travel choice is not simply between main modes (car, rail, bus etc). In MNTM the choice is between a range of multi-modal options and routes.

For example, a person faced with a journey between Western Sydney and the CBD might consider the following options:

- walk to one of the two nearest CityRail stations / train to CBD / walk to destination
- bus to one of two nearby stations where there are faster trains / train to CBD / walk to destination
- drive or get a lift to one of four stations with different rail service options / train to CBD / walk to destination.

In MNTM, these (and other) multi-modal route options are constructed and the relative 'costs' compared in the choice model. The probability of choosing each option is then used to allocate the total demand between options for that OD pair.

In many transport models (including STM) the various route and multi-modal options in the above example would be represented as a single CityRail option (chosen by a model pathbuilder). This may be a reasonable simplification where the priority is to allocate demand between rail and car, for example. However this approach would provide very little detail about how people with a broad range of different preferences might actually use a new rail facility.

Critically, the simplified model approach could potentially provide unreliable forecasting for a new rail facility which is in competition with an existing one. The modelling would be characterised by 'lumpy' switching between the competing options.

By modelling access mode and station choice, the MNTM approach ensures that the switching between competing rail options would be 'smooth' as relative attributes are varied. In this model formulation, people behave as individuals with their own preferences, changing behavioural choices in a probabilistic manner. This logic underpinned the design of the MNTM choice model structure for forecasting demand on major rail projects.

4.2. The choice model was transferred from US applications

The MNTM choice model structure is similar to the Los Angeles model system. This model was developed by PB US for the Los Angeles County Metropolitan Transportation Authority and has been used to estimate ridership for:

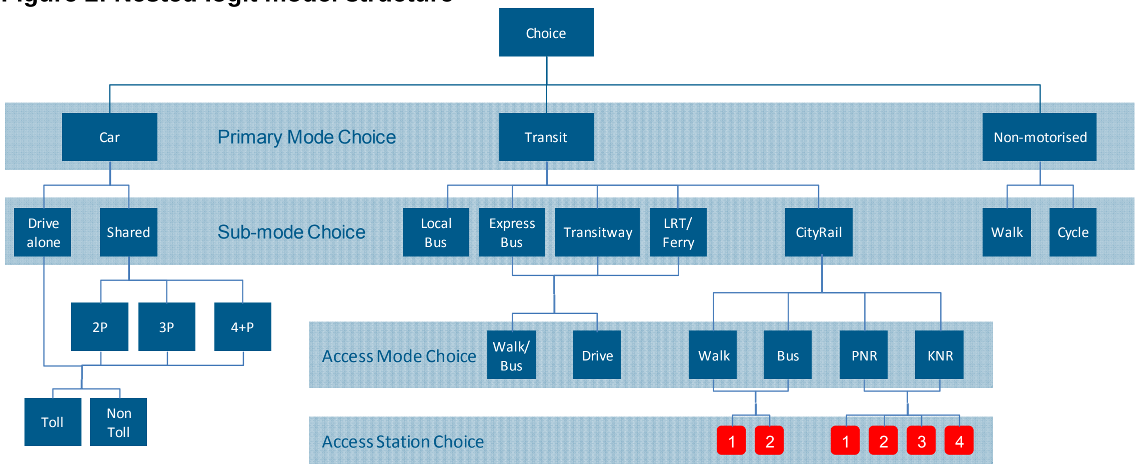
- existing Metro lines - Red, Purple, Blue, Green, and Gold
- an extension of the Gold Line to East Los Angeles
- four new lines - a northern extension of the Gold Line, a second line through the heart of the CBD, the Exposition Line, and a western extension of the Red Line to Santa Monica.

This model formulation represents best practice in the United States and is comparable to models developed for New York, San Francisco, Washington DC, and Chicago.

4.3. A nested logit formulation is used

The behavioural choice model is illustrated in Figure 2. This nested logit structure includes choices of 'main modes', 'sub-modes' and access/egress station for public transport as illustrated.

Figure 2: Nested logit model structure



This choice model is different from that used in STM which effectively has one level of mode choice. This single level allocates demand between the 'main mode' options for a journey. In this context the main modes are defined as a hierarchy and include rail, bus, car etc.

4.4. In MNTM most transit choices are transferred to the logit model

One of the key decisions about public transport model structure is whether sub-modes or sub-choices are handled in the mode choice model, or in assignment (see UK WebTAG guidance for example). In the STM, main mode (and destination) is modelled within the choice model and sub-mode and station choice is modelled in assignment.

The decision to use the MNTM choice structure was based around rationalising this question within the context of Sydney's integrated transport network.

The key advantages of including the sub-choices in the nested logit structure are:

- logit choice models are more stable providing smooth transfers of demand as relative attributes of options change
- logit models provide greater transparency than assignment models
- logit models provide a better platform for including car as an access mode to public transport – assignment models are poor at handling mixed car and public transport journeys (which are a significant proportion of Sydney's rail demand).

Against these advantages the decision also took into account the implications of increased complexity of including sub-choices in the model. This is particularly the case where elements of both route (or station) choice as well as mode choice are included. However, given the first hand experience of use of MNTM model structure in the US, and the depth of analytic capability in Sydney, it was concluded that this choice structure would be appropriate.

4.5. The choice model response is controlled by coefficients and constants

There are three key sets of values that need to be established to define the response of the choice model in Figure 2. These are:

- model coefficients used in the utility expressions – coefficients applied to level of service and other variables used to compute utility for a route option between origin and destination
- model constants which capture the overall effect of any significant variables that are missing or unexplained in the utility expressions
- logsum coefficients used to ‘scale’ utility up through the nested logit tree.

4.5.1. Model coefficients used in utility expressions

The model coefficients are used in the computation of utility for each route/mode option. The utility expression for a trip option (mode and route) is made up of a range of variable types such as time, cost and number of transfers involved.

The coefficients used in the MNTM were initially asserted on the basis of previous applications of this model structure. During calibration process there were some minor adjustments to the coefficients.

The CityRail station choice (non-price) coefficients are based on results from the Chicago model estimation and relate to commuter rail in that model application which serves a similar function in Chicago to the CityRail network in Sydney. These coefficients are used to build utility for the CityRail access options. The coefficient values are scaled to be applicable at the station choice level of the nested logit tree.

The general model coefficients are based on a broader range of international benchmarks. These are used to build utilities for all other transit sub-modes as well as car and non-motorised nests. These coefficient values are scaled to the primary mode level of the nested logit tree as they are applicable across all three primary nests. They therefore need to be scaled down through the various levels of each tree prior to use for building utility at the lower level.

4.5.2 Model constants reflect non-included attributes

The model constants represent the non-included or non-measured attributes. In calibration they are used as a ‘residual’ to explain the difference between the observed data and the results of the model’s attempt to represent the choices made by people. So, for example, people often demonstrate a preference for train over bus which cannot be explained by travel times and costs alone.

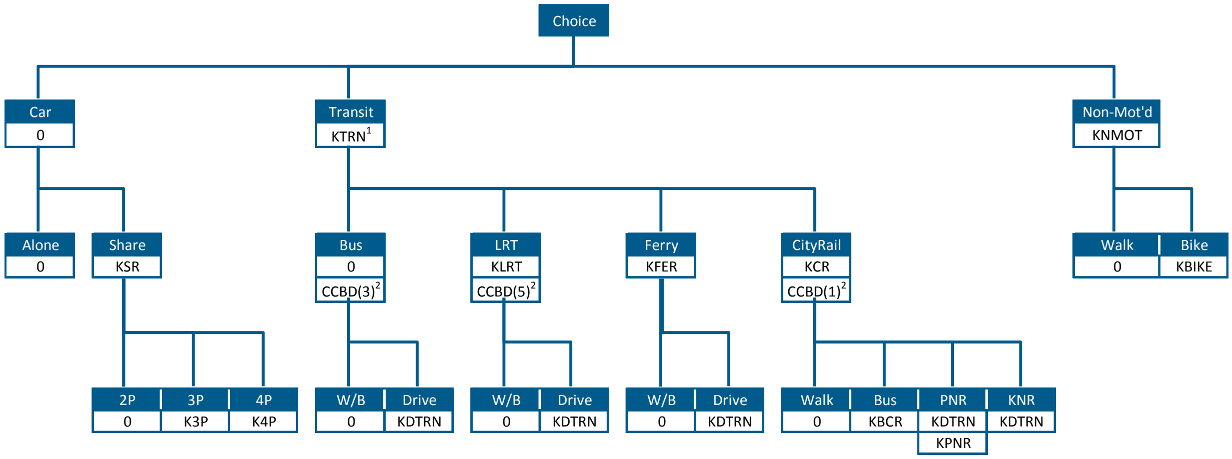
In reality these ‘non-included’ attributes are often made up of factors like comfort, security, reliability and amenity value. Ferry travel is frequently chosen over other options for travel despite being considerably slower and more expensive. In many cases this is because people attached an amenity value to being on the water. For commuters it can be a lifestyle choice.

The model calibration focuses on deriving these constant values through an iterative approach. This involves estimating travel choices and then matching them to the observed data (calibration target values). For each iteration the constant values are adjusted incrementally until adjustments fall below a threshold.

In the nested logit tree structure the choice utilities at each level of each nest are adjusted by constants to ‘force’ a distribution of choices close to that observed. For each nest one choice is assigned a zero. So for example, at the sub-mode choice, there is no bus constant.

Constants are available for all other options (CityRail, LRT and Ferry) and these will explain the un-included reasons why people are observed to choose the mode that they do at this level. The application of constants in the choice tree is illustrated in figure 3.

Figure 3: Definition and location of constants in nested logit tree



[1] Stratified by trip length
[2] For trips with CBD attractions

4.5.3. Logsum coefficients scale utility up the nested logit tree

For each option at each level of the tree a 'composite' of the utilities in the nest below is computed to provide the utility at that level of the tree. For example, in Figure 2 the utility at the 'primary mode' level for 'transit' is a composite of all the utilities at the 'sub-mode' level. This composite is then used to allocate demand between transit and car.

The composite utility is derived from the logsum of the next level utilities. A logsum coefficient is applied to the logsum to scale the amount of utility that is passed up the tree. These coefficients effectively control the 'vertical sensitivity' of the model.

In a model such as MNTM it is important that changes which affect the lower levels of the tree do not have too big an impact at the top of the tree. It is intuitive that an improvement to walk access to rail should alter the existing diversion between walk, bus and drive access more than the primary mode choice between transit and car.

The logsum coefficients used in MNTM are set on the basis of experience elsewhere. The coefficients increase from 0.3 at the lowest level of the tree up to 0.75 between primary and sub-mode levels.

4.6. Trip cost inputs (skims) are produced in EMME

The trip cost inputs to MNTM are the elements which are used make up the utilities by all the various trip options for an OD pair. These levels of service inputs include:

- walk time - to/from and between transit modes, (minutes)
- wait time - for transit modes, (minutes)
- in-vehicle time (IVT) for all modes, (minutes)
- price of travel (transit fares, vehicle operating costs, toll costs and parking costs), (dollars)
- number of interchanges between various modes.

EMME is used to provide the level of service inputs for MNTM in the form of skim tables. Skims are prepared for each of the above level of service attributes, by mode, for the various trip stages:

- Zone to Station/Interchange (for all transit modes)
- Station to Station (for CityRail, LRT and Ferry)
- Station/Interchange to Zone (for all transit modes)
- Zone to Zone (for all modes).

MNTM then uses the skim tables to build utilities for the various paths that go into the choice set. It should be noted that no 'generalised costs' are transferred from EMME to MNTM. Only the demand weighted times, costs and numbers of interchanges are passed over.

4.7. MNTM calculation process for allocating demand

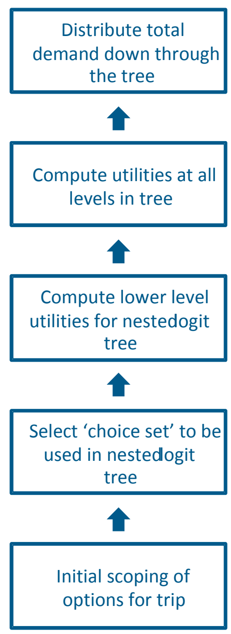
In practice the MNTM nested logit model calculations follow a 'bottom-up' process. This process is illustrated in Figure 4. The process starts with an initial scoping of trip options. These are then refined to make up the choice set for the nested logit model calculations.

For example, ten CityRail car (PNR/KNR) access stations are initially scoped, based on proximity to origin. These are then reduced to the four in the choice set by comparing utilities for the whole-trip options. MNTM selects the stations which have the least utility. This calculation occurs twice - once for PNR and once for KNR. Therefore, it is possible to select different PNR stations from KNR stations.

For each of the options in the choice set (defined by the lowest level of the tree) utilities are calculated from the various skim values for time and costs.

The composite utilities for each level of the tree are calculated using the logsum coefficients and by applying the appropriate constants. These composite utilities provide the basis for the allocation of the demand back down through the tree.

Figure 4: MNTM choice model process for each origin-destination pair



4.8. Limitations of the model structure

A key feature of this type of nested logit model is the need to manage the number of permutations of multi-modal trips. If every possible combination was included in the choice model it would become too cumbersome. It is therefore important to identify the key markets that need to be explicitly modelled and leave the less important markets to be handled in assignment.

5. MNTM Model framework

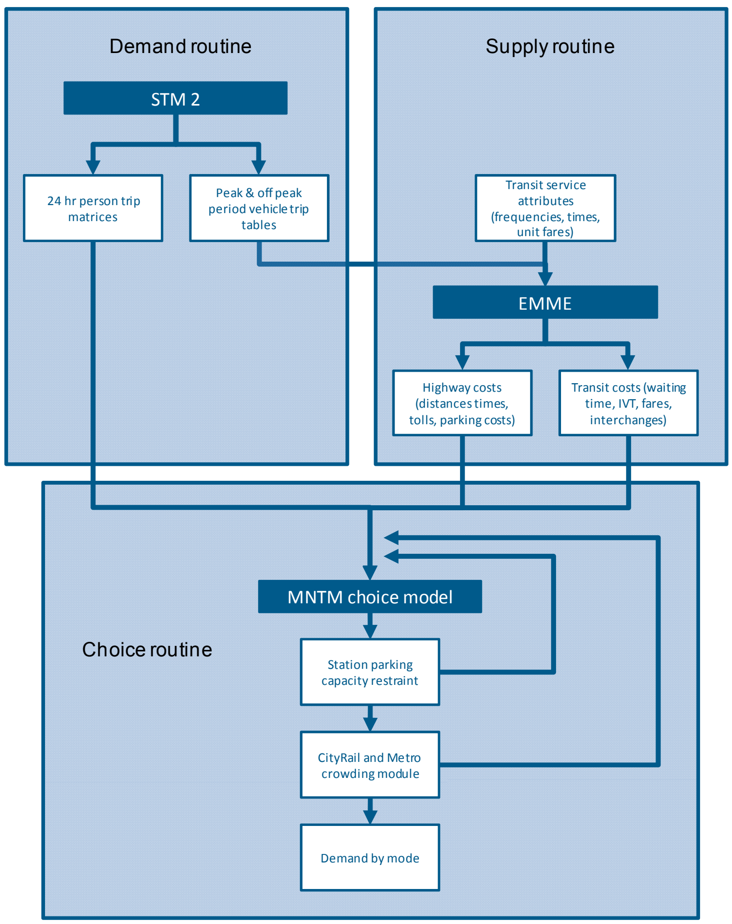
The MNTM choice model, described in Section 4, allocates demand between modes of transport and transit routes (as defined by stations or interchanges). For every origin destination pair the choice model performs this allocation for each market segment and each journey purpose.

The framework within which the MNTM choice model operates is shown in Figure 5. This framework is made up of three sub-routines:

- the demand routine which produces the 24 hour tour matrices and vehicle trip table - STM
- the supply routine which produces the highway and transit cost skims for use in the MNTM – carried out using EMME
- the choice routine which allocates the demand.

The choice routine involves running the MNTM choice model within inner and outer 'loops'. These loops were set up to provide additional functionality to the overall model for station parking restraint and transit crowding. The principles behind these additional functionalities are described below.

Figure 5: MNTM model framework



5.1. Parking restraint to influence access station choice

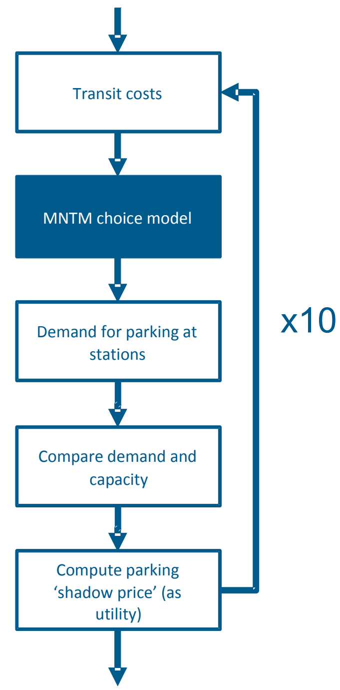
As station car parks reach capacity, people experience inconvenience. They have several immediate options around access modes and station choice:

- park further away from the station and accept greater inconvenience
- switch to another station where there is more parking availability
- switch to walk or bus, as access modes to that station (or another station).

These options are all represented at the lower levels in the nested logit tree. As the scale of this inconvenience increases people might consider switching sub-mode or even primary mode, and drive all the way, for example. These are responses which are represented higher up the tree (it should be noted that people might also switch their destination or time of travel. It was not attempted to model these higher order effects in MNTM).

The modelling framework provides the potential functionality to model these effects through the parking restraint loop. The inconvenience is represented by a reduction in utility which is derived from the ratio of parking demand to parking capacity at a station (parking capacity is provided in the MNTM station file).

Figure 6: Parking restraint procedure



The parking restraint implementation is shown in Figure 6. The reduction in utility for using a station (i) due to parking constraint is calculated using the function:

$$\begin{cases} U_i = \text{LN}\,(V_i/C_i) & \text{for } V/C > 1.05 \\ U_i = 0 & \text{for } V/C <= 1.05 \end{cases}$$

Where:

- U_i is the utility increment due to parking constraint at station i
- V_i is the demand for parking at a station i
- C_i is the available parking capacity at station i.

In this calculation, utility can be converted to price using the coefficient of parking at the station choice level. The form of the function has been directly transferred from the Los Angeles application.

The procedure in Figure 6 is carried out for home based work (peak period) purpose first. The residual parking availability for each station is then passed to each of the non-work purposes (peak period). This residual availability is then treated as available capacity and the procedure repeated for all other purposes.

5.2. CityRail and Metro crowding to influence choice

On busier parts of the rail network, particularly in peak periods, passengers experience the effects of crowding on public transport services. Effects include:

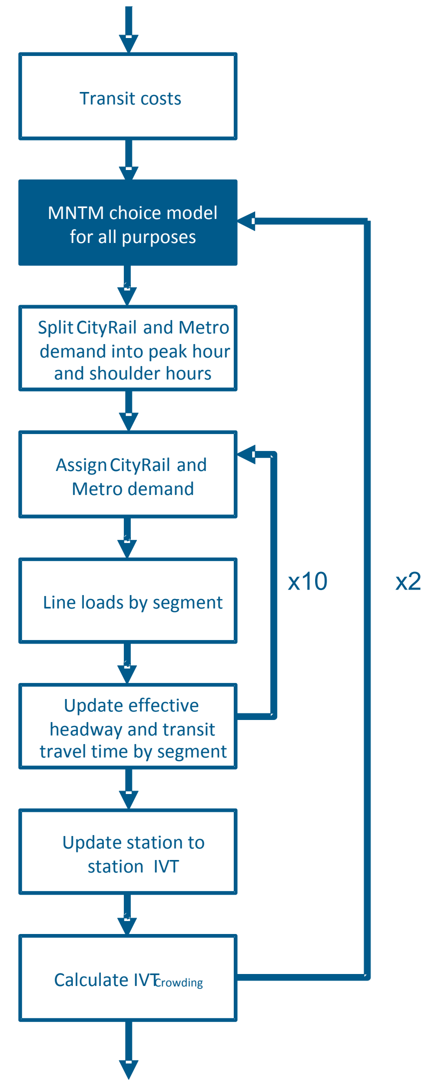
- inability to get a seat (or get to a seat) and therefore having to stand for part or all of a journey
- unpleasantness of having to stand in crowded vestibules or aisles
- inability to get onto train due to extreme crowding.

In response people might switch to using another station (for rail) or switch to another mode. These responses for CityRail (and Metro) are included in the crowding version of the model.

In reality people will also consider travelling at other times or to other destinations. Although consideration was given to a peak spreading module, this was not implemented due to the significant increase in complexity and the lack of suitable calibration data.

The procedure implemented within the MNTM model framework is shown in simplified form in Figure 7. The key output from the crowding analysis is the incremental In-Vehicle Time due to crowding effects ($\text{IVT}_{\text{Crowding}}$).

Figure 7: Crowding procedure



It should be noted that the version of the modelling framework used in application on metro projects used this procedure without the feedback of $\text{IVT}_{\text{Crowding}}$ to transit costs. Although crowding levels were measured there was no behavioural response modelled. $\text{IVT}_{\text{Crowding}}$ could then be used to value the change in crowding between a base case and build case. This version of the model was calibrated in the base year specifically to operate without the feedback.

A crowding factor function provides the basis for updating travel times by segment. The typical form of the function used in preliminary model calibration (with behavioural response) and testing is shown in Figure 8.

Metro car configurations were assumed to be 50 seated capacity with a total car capacity of 213. CityRail is assumed to have 105 seated capacity and 187 total car capacity. The configurations of the cars are assumed to be different with metro having a more open style designed for standing with high passenger turnovers at stations.

The shape of the crowding functions has been set on the basis of international comparisons and judgements about how the CityRail and Metro car configurations compare. It is intuitive that people would experience more discomfort standing in a car which is primarily configured for seating. Even so it would be necessary to undertake further investigation of the perceptions to the car configurations under different loadings for new applications of MNTM with crowding response.

Crowding factor is implemented in EMME using a segment-specific in-vehicle time multiplier in the TTF function (segment extra attribute) to add a shadow price to real in-vehicle time. Shadow price brings the demand under capacity in transit assignment. In practice, shadow prices are calculated iteratively according to the following algorithm:

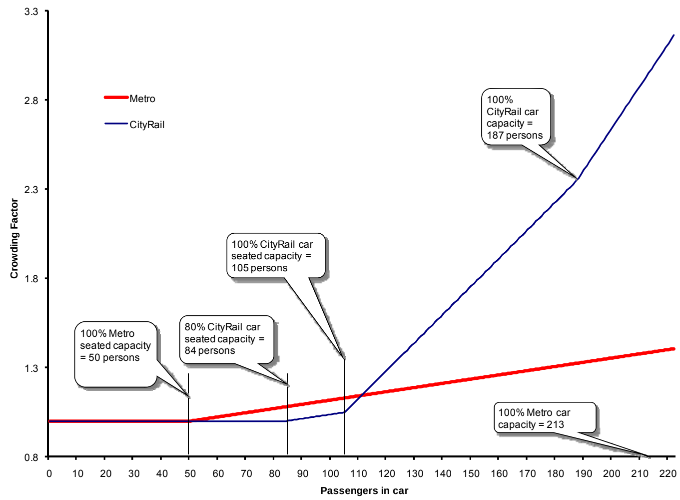
1. Set iteration counter $i = 1$ and initial shadow price $S_0 = 0$

2. Run the simulation procedure to obtain volumes $V_i = \varphi(S_{i-1}, C)$

3. Recalculate shadow price by formula $S_i = S_{i-1} + f(V_i, C)$

4. Set iteration counter $i = i + 1$ and go to Step 2 until the convergence has been reached. At convergence we assume that $S_i = S_{i-1}$ since $f(V_i, C) = 0$ (i.e. the shadow prices are stabilized and volumes correspond to the capacities). Consequently $V_i = V_i - 1$ (the volumes are stabilized). Note that an incremental calculation of shadow prices is essential for getting the volumes under capacities (feasible solution).

Figure 8: Crowding functions for CityRail and Metro



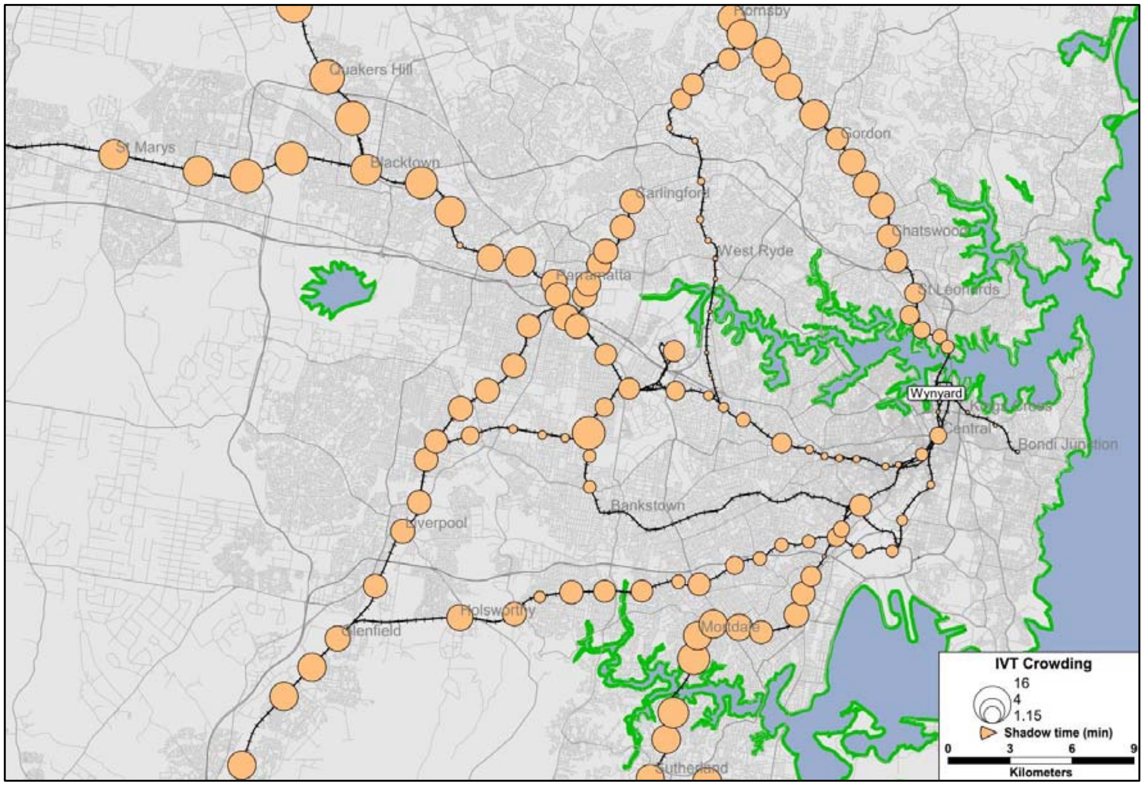
The first purpose of the developed method is to ensure feasibility of transit ridership forecast for each line and segment with respect to the total capacity. This is necessary because EMME transit assignment algorithm does not recognize overcrowding - it does not consider vehicle capacities when assigning passengers and calculating transit times. By applying shadow price, cases where the transit volume exceeds total segment capacity will be penalized until the feasible solution is reached. A feasible solution might not exist especially if a restrictive transit assignment framework with a fixed transit table is employed (i.e. the riders of overcrowded lines can switch to some other lines). However, having feedback to mode choice will solve this problem by diverting trips to other modes.

The second purpose is to capture $IVT_{Crowding}$ matrix and use it as one of the mode choice inputs according to figure 7. From this standpoint, not only exceeding of the total vehicle capacity but also exceeding the seating capacity (or even approaching it) should be penalized since standing is generally considered as a very strong negative factor. The $IVT_{Crowding}$ is based on EMME transit skim calculation to capture the shadow price between CityRail stations. Adjacent to each CityRail station, a dummy centroid is coded to make station−to−station skim calculation possible. Figure 9 depicts a sample result of captured $IVT_{Crowding}$ matrix based on 2006 Sydney base model before any feedback to mode choice when Wynyard station is the destination in one hour AM peak.

It should be noted that circles on figure 9 scaled logarithmically. This figure extracted from a full matrix and for any origin/destination station a similar figure can be prepared. The full matrix as explained has the values converted to equivalent of in vehicle time and it is prepared to be taken into account during mode choice to study behaviour response to the crowding. The matrix captures accumulated values skimmed from a previously calculated segment attribute all the way along from an origin to a destination.

As an example, this figure shows a rail trip from Bondi Junction on the east to the Wynyard station associates with a negligible crowding cost. On the other hand, equivalent of crowding cost for getting from Parramatta station on the west to Wynyard station in CBD is amongst the highest. Passengers from all the stations along north shore line (from Hornsby) to Wynyard also suffer significantly from crowding, while Bankstown line provides the least congested rail service during AM Peak.

Figure 9: Crowding Shadow Time in one hour 2006 AM peak to Wynyard station



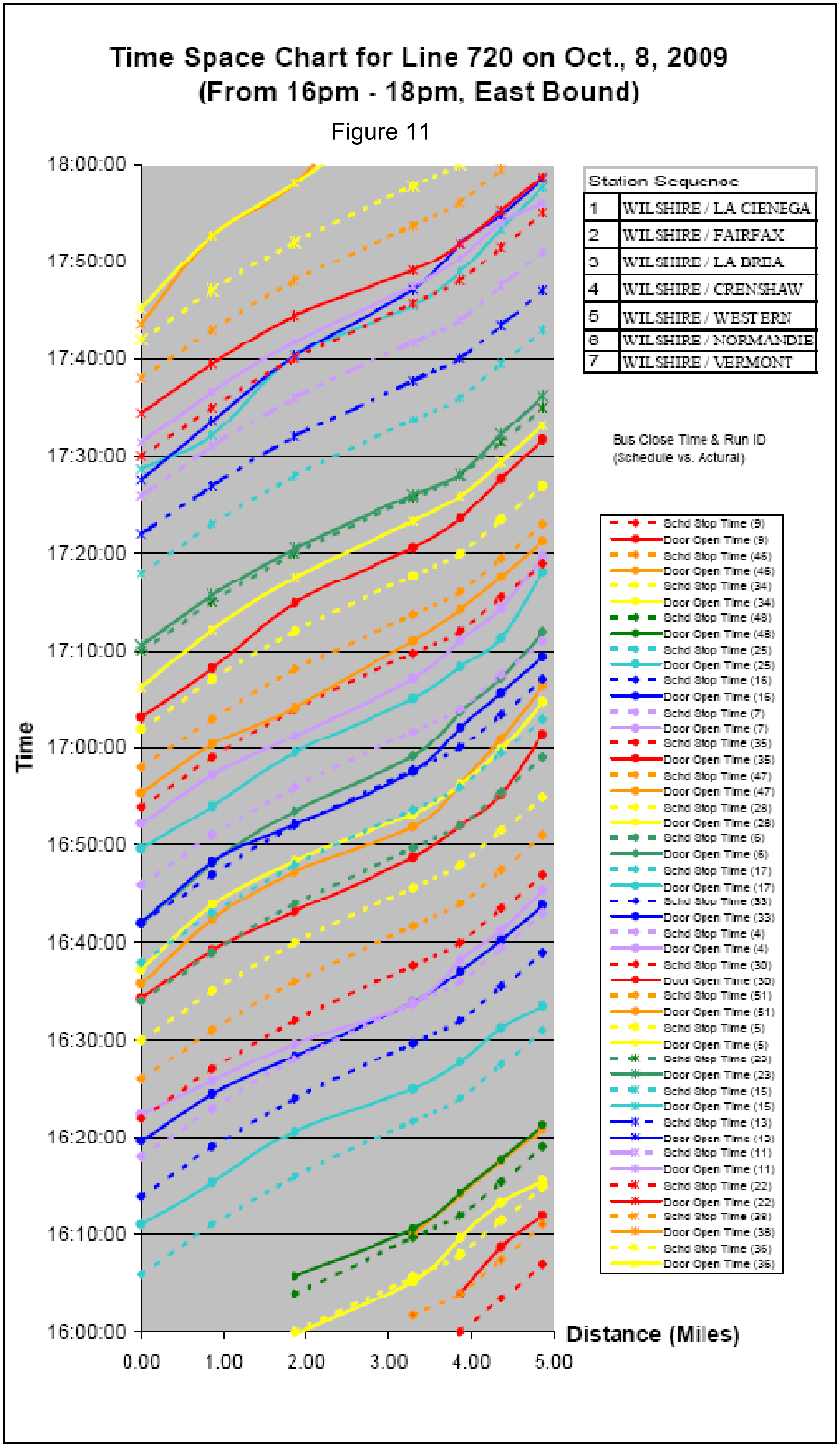
6. Los Angeles

The Westside corridor of the Los Angeles region (Figure 10) is a significant employment center with over 300,000 people traveling into the Westside area every day for work. It is also a very congested area with significant transit ridership, almost one-quarter of Metro's daily boardings are on lines that travel in the Westside corridor. As with any highly congested and highly utilized transit corridor, there are real operational issues that degrade the service quality of the transit mode. However, these operational issues have largely been ignored by the existing travel forecasting model used to date. Thus, the purpose of the new model development work recently underway is to incorporate transit capacity, crowding, and bus bunching delay into the MTA travel forecasting models, building on the work performed in Sydney, in order to provide better and more reliable forecasts as part of the Westside FTA New Starts Analysis.

Figure 10 – Existing Los Angeles Regional Urban Rail System

In addition to capacity and crowding, the Los Angeles model will incorporate measures of bus arrival delays and bunching, the arrival of buses in bunches as opposed to uniform within their headways, which adds additional disutility. These "reliability," or operational components, of transit are significant for the route choice, mode choice, and destination choice components of the travel forecast model. And without these additional components, it means more trips may be forecasted for the corridor than are possible/likely for alternatives which do not increase passenger-carrying capacity.

Figure 11 provides a snapshot view of the typical delays and bunching that occurs on one route in the Westside corridor -- Route 720. Models are being developed which will estimate the level of delay for riders associated with late arriving vehicles.


Time Space Chart for Line 720 on Oct., 8, 2009
(From 16pm - 18pm, East Bound)
Figure 11
Time
18:00:00
17:50:00
17:40:00
17:30:00
17:20:00
17:10:00
17:00:00
16:50:00
16:40:00
16:30:00
16:20:00
16:10:00
16:00:00
0.00
1.00
2.00
3.00
4.00
5.00
Distance (Miles)
Station Sequence
1 WILSHIRE / LA CIENEGA
2 WILSHIRE / FAIRFAX
3 WILSHIRE / LA BREA
4 WILSHIRE / CRENSHAW
5 WILSHIRE / WESTERN
6 WILSHIRE / NORMANDIE
7 WILSHIRE / VERMONT
Bus Close Time & Run ID
(Schedule vs. Actural)
Schd Stop Time (9)
Door Open Time (9)
Schd Stop Time (46)
Door Open Time (46)
Schd Stop Time (34)
Door Open Time (34)
Schd Stop Time (48)
Door Open Time (48)
Schd Stop Time (25)
Door Open Time (25)
Schd Stop Time (16)
Door Open Time (16)
Schd Stop Time (7)
Door Open Time (7)
Schd Stop Time (35)
Door Open Time (35)
Schd Stop Time (47)
Door Open Time (47)
Schd Stop Time (28)
Door Open Time (28)
Schd Stop Time (6)
Door Open Time (6)
Schd Stop Time (17)
Door Open Time (17)
Schd Stop Time (33)
Door Open Time (33)
Schd Stop Time (4)
Door Open Time (4)
Schd Stop Time (30)
Door Open Time (30)
Schd Stop Time (51)
Door Open Time (51)
Schd Stop Time (5)
Door Open Time (5)
Schd Stop Time (23)
Door Open Time (23)
Schd Stop Time (15)
Door Open Time (15)
Schd Stop Time (13)
Door Open Time (13)
Schd Stop Time (11)
Door Open Time (11)
Schd Stop Time (22)
Door Open Time (22)
Schd Stop Time (38)
Door Open Time (38)
Schd Stop Time (36)
Door Open Time (36)

7. Conclusions

Sydney Metro and the Los Angeles Authorities require an improved modelling tool to forecast demand on metro rail projects in both Sydney and Los Angeles. The existing STM model had been used for the early planning and appraisal phases, however several limitations of the Government model meant that a more refined approach was required for the later design, appraisal and procurement phases. To adequately evaluate proposed extensions of the rail system in Los Angeles requires a detailed understanding of the implications of capacity, crowding, and vehicle arrivals if no improvements are made.

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