TRANSIT ASSIGNMENT: WHY LOGIT BASED METHODS ARE REQUIRED FOR MODELLING SOUTH AFRICAN TRANSIT NETWORKS

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ABSTRACT

Transit assignment has become an important component of transportation modelling as planners seek to evaluate the passenger demand and fare revenues for improvements to existing and new transit schemes. Transit assignment attempts to solve a complicated problem, with complexities arising from both the transit network definition as well as the human decision-making process. Acknowledged shortcomings in commonly used assignment approaches have been highlighted in the literature. The application of universal traveller decision rules in transit assignment are not necessarily compatible with traveller preference and choice behaviour, especially with the advent of smartphone-based, real-time transit operations information. This paper investigates the potential for transit line patronage distortion in South African metropolitan areas when using standard frequency-based transit assignment based on optimal strategies. These distortions arise from the dense transit networks in metropolitan areas, the high number of competing lines, as well as the behavioural assumptions made in the process. The potential distortions in assigned transit line patronage volumes make link-based passenger volume validation difficult to achieve. Moreover, the use of these models to forecast the demand for new transit schemes could result in misleading estimates of demand and fare revenue. This paper suggests that more advanced transit assignment techniques are required to more accurately reflect traveller choice and demand in dense transit networks. It is proposed that a logit-based trip allocation approach in transit assignment is necessary to achieve satisfactory assignment validation.

1. INTRODUCTION

In multi-modal environments, transportation planners commonly use transit assignment to load aggregate zone-based transit trip matrices (often segmented by trip purpose and/or

income) onto the transit network as the last step in the four-step modelling processes. The outputs of this process provide aggregate network performance measures such as passenger-hours and passenger-kilometres for use in economic analyses, as well as disaggregate measures such as passenger link flows, the passenger demand profiles on individual lines, and boarding and alighting volumes at stations and stops for system design and operational planning.

Transit assignment is also used to 'skim' transit network minimum time and cost matrices used in gravity-based trip distribution models and mode choice models. The most commonly used assignment technique is the optimal strategy approach (also known as the headway or frequency-based approach), or the optimal strategy approach with capacity constraint developed in the 1990's (Annu, Hannu, & Pursula, 1997).

These static, headway-based models do not accurately reflect the complexities of the information based multi-modal complexities of modern networks (Nokel & Wekeck, 2007; Kucirek, 2012). Time-table or schedule-based transit assignment, despite its technical advantages, is little used in South Africa due mainly to the unscheduled nature of the minibus taxi mode. However, it is also vulnerable to the same single-strategy distortions. Newer agent-based microsimulation transportation models offer individually based modelling methodology that offer improved solutions (Huynh, et al., 2011). However, while road based vehicle models have been developed in South Africa (Wevell, 2011; Neumann, Roder, & Joubert, 2015) mode choice simulation with these models have had no practical applications in South Africa.

The problems arising from the application of optimal strategy based assignment in environments with high frequency, dense transit networks, often with several competing routes (or common lines) are widely known. The estimation of optimal strategies requires the use of Linear Programming (LP) methods, and this can result in extreme solutions (Florian & Constantin, 2011). This is potentially the case with the taxi mode in South African urban transit networks. Large zones exacerbate the problem, as several centroid connectors may be required for zonal (walk) access and egress to the taxi network. Significant difficulties will be encountered when validating the transit assignment outputs with observed transit data using goodness-of-fit criteria (UK Department for Transport, 2014).

The traveller decision rules made in optimal strategy algorithms can distort the allocation of trips to individual lines in dense transit networks, and not reflect the choice preference of alternative lines as would be estimated by a discrete choice model such as the multinomial logit model (MNL). The most fundamental decision rule is that the traveller chooses a set of paths between O-D (with the paths making up a strategy) that minimises their overall generalised transit cost or time. (Generalised costs are a linear combination of time, cost and transfer penalties). The full demand is assigned to this minimum cost strategy, and higher cost paths offering services between O-D are ignored. Therefore, the accurate estimation of the alternative line costs is important for this stage.

A second assumption is that the traveller boards the first transit vehicle to arrive when making a trip between origin and destination (O-D) (Florian & Spiess, 1989). Lines in the strategy with higher frequencies between O-D will thus get chosen more often, and proportionally have more trips assigned to them, irrespective of their perceived cost. This decision rule could therefore also introduce trip allocation distortions.

This paper presents the results of an investigation into these complexities from a theoretical and practical point of view. Firstly, the practical difficulties of simulating mode choice in South African urban areas are briefly highlighted. The paper then presents the various decision rule assumptions made in transit assignment algorithms with the emphasis on the frequency-based optimal strategy methodology that is most commonly used. Two alternative transit assignment methods are discussed, and practical examples are shown to illustrate the improvement of the assignment results.

2. HIGHLIGHTING TRANSPORTATION MODELLING COMPLEXITIES IN SOUTH AFRICA

In South Africa, it is evident that the necessary input data sets for mode choice modelling and transit assignment are often not supported by the required Stated Preference (SP) and/or Revealed Preference (RP) primary data sets (Venter & Hayes, 2017). In part, this reflects the complexity of the four-step multi-modal transport modelling process in metropolitan areas. The complexity results from the large income disparities in South African society; relatively low car-ownership levels; the apartheid-based spatial patterns; and the development of the minibus taxi industry. In Gauteng, over the last three decades, minibus taxis have captured the highest mode share in urban areas, e.g. 36.4% of motorised public transport trips in Gauteng (Transport, 2014), followed by bus and Bus Rapid Transit (BRT) at 11% combined.

From a technical perspective, the complexity is four-fold. Firstly, for improved model accuracy, there is the need for travel market segmentation by trip purpose, income group and car ownership to reflect public transport captivity. Secondly, there is the multi-modal nature of commuter transport. For example, in the Tshwane, Ekurhuleni and Johannesburg metropolitan areas there are a total of six motorised modes, i.e. minibus taxi, car, train, bus, BRT and Gautrain. This excludes the feeder and distribution bus and park and ride and drop-off access options. Thirdly, each public transport mode has its own fare structure, and in some cases, there are different fare structures for the same mode, for example different fare structures for the Johannesburg Metrobus and PUTCO bus services.

Finally, the dense public transport routes and services for the minibus taxi mode are also difficult to observe in-situ and hence define in a model, especially with large zones. The high number of routes (some on minor road links not included in the model) and high frequencies are difficult to define and code. The taxi routes offer commuters several trip options between origin and destination and are hence competitive both amongst themselves (known as the common line problem), (Brands, de Romph, Veitch, & Cook,

2013; Fu, Liu, & Hess, 2012), as well as with other modes. This has important implications for practitioners using frequency-based transit assignment.

Given these complexities, it is important for practitioners to understand the use of Discrete Choice Models (DCM) & their utility equations; the use of the DCM attribute weightings in transit assignment; and the transit assignment method used.

3. DISCRETE CHOICE MODELS (DCM)

The interaction between mode choice and transit assignment is shown in the following figure (excluding non-motorised modes). Most commonly, the primary mode choice, i.e. between the available motorised modes) is undertaken using a DCM, e.g. a multinomial logit (MNL) or multinomial mixed logit model (MML). The secondary split, i.e. between the lines of a specific mode, is estimated using transit assignment. The modelling of access modes requires the use of nested models.
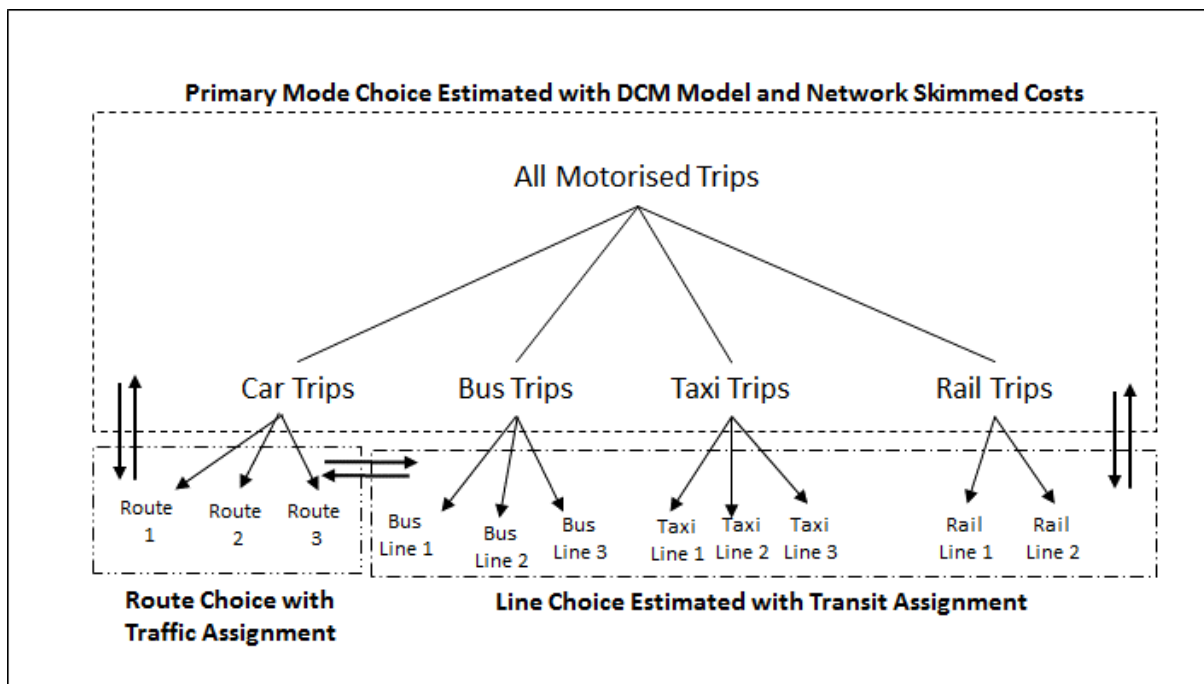

Figure 1: Interaction between Mode Choice Modelling and Line Choice with Transit Assignment.

Traveller (behavioural) trip utility attribute coefficients for primary mode choice simulation are most commonly estimated using discrete choice models (DCM'S), based on Random Utility Maximisation (RUM). Representative utility equations are estimated for each market segment with an Alternative Specific Constant (ASC) for the alternative mode. The ASC (typically normalised to zero for the travellers current mode) provides an estimate of the travellers unobserved factors of utility, for example, comfort, reliability, safety and security.

Both multinomial logit (MNL) and mixed multinomial logit (MML) models have been applied in South Africa. Commonly, these models are developed using data sets obtained from traveller Stated Preference (SP) surveys, and in some cases this is combined with traveller

Revealed Preference (RP) data (Johannesburg, 2014). However, the design of SP and/or RP surveys is not straight forward. An analysis (Venter & Hayes, 2017) of four SP surveys undertaken by South African metropolitan planning authorities found deficiencies in all the questionnaires. These included non-orthogonal choice set designs; the absence of critical utility attributes; the presentation of unrealistic attribute values in the choice sets; and the use of conjoint methods when these have clear disadvantages over DCM methods (Louviere, Flynn, & Carson, 2010).

The trip utility attributes and their associated weightings together with the ASC's are then applied in the aggregated, zone based transit assignment skim process to estimate the market segment utility. This is done by multiplying the weighting coefficients and the corresponding skimmed cost or time matrices, and summing these matrices to obtain the representative, zone-based trip utility estimates. This process assumes an aggregation of the individual choice preferences reflected in the DCM model to the full population reflected by the zone demographic segmentation and network-based transportation model. A further complication is the need to convert monetary costs (e.g. fares) into equivalent time units in the model using the value of travel time savings (VTTS) derived from the DCM willingness to pay. Transportation software platforms use generalised time units to perform vehicle and transit assignments.

4. FREQUENCY BASED TRANSIT ASSIGNMENT

Frequency-based optimal strategy assignment is well understood and extensively used (Florian & Spiess, 1989) and is standard in software platforms such as EMME and VISUM. A strategy is defined as a set of attractive lines at each boarding-decision point encountered by the traveller. An optimal strategy minimises the travellers perceived travel generalised cost (Liu, Bunker, & Ferreira, 2010). Strategies are developed based on a set of decision rules that it is assumed a traveller uses to reach their destination. The strategy can become more complex when there are multiple routes and services, and there is the opportunity for transferring between services to reduce the overall generalised cost of the trip. The basis for the development of optimal strategies is the assumption that the only network knowledge the traveller has is the arrival of the services at their first (boarding) stop. This gives rise to the concept of expected waiting time, and the allocation of trips onto the lines in the optimal strategy on a weighted frequency basis.

The following simplified example demonstrates the development of optimal strategies. Total travel time has been used to develop the optimal strategy. It is assumed that an origin zone i is connected to three minibus taxi routes with two centroid connectors (walk mode) of equal length. The total travel times are shown in the table alongside. The demand (after primary mode choice) is 100 minibus taxi passenger trips between i and j. Careful note should be taken of:

- The position and number of centroid connectors. More than one centroid connector from a zone results in some lines not being included in the optimal strategy;

- Taxi line 3 is the only line included in the optimal strategy based on the trip costs, and all 100 passengers are assigned to this line. This is clearly not an appropriate solution, and demonstrates the limitations of frequency-based strategy assignment;

- The total line generalised costs must be estimated using the weighted travel times and costs, with the weights being derived from the MNL or MML utility definitions for the minibus taxi mode;

- Validation (i.e. goodness-of-fit between the observed and modelled passenger flows) of this simplified example using link volumes would not be possible.
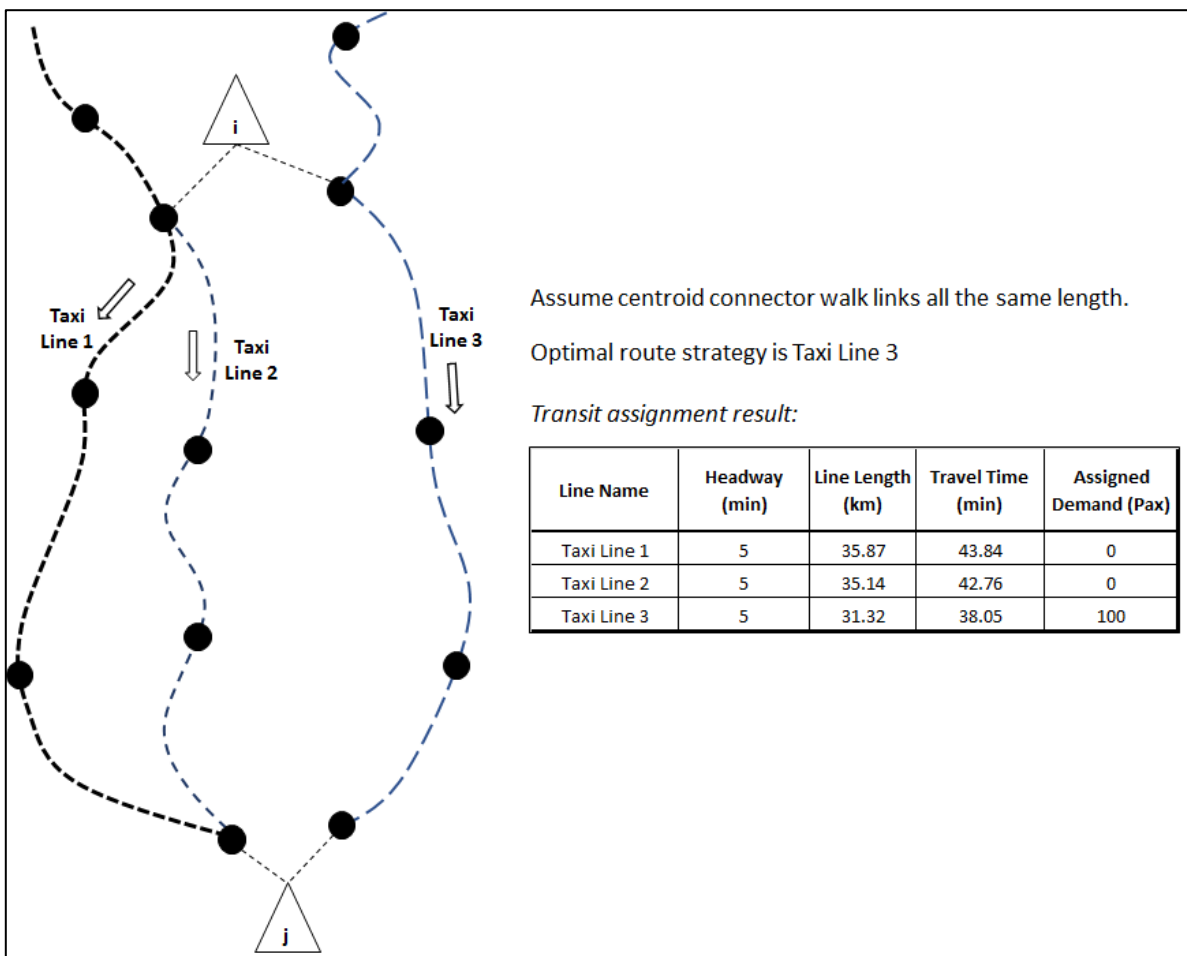

Assume centroid connector walk links all the same length.

Optimal route strategy is Taxi Line 3

Transit assignment result:

Line Name	Headway (min)	Line Length (km)	Travel Time (min)	Assigned Demand (Pax)
Taxi Line 1	5	35.87	43.84	0
Taxi Line 2	5	35.14	42.76	0
Taxi Line 3	5	31.32	38.05	100

Figure 2: Simplified Example of Frequency-Based Taxi Transit Assignment Strategy

Capacity constrained strategy assignment algorithms were developed in the 1990's and 2000's (Blain, 2000; Liu, Bunker, & Ferreira, 2010; Hamdouch, Ho, Sumalee, & Wang, 2011). These algorithms are more suited to timetable-based assignment, as individual time-based vehicle capacities are considered, and additional waiting times can be calculated accurately. If passenger demand exceeds available service capacity (seated and standing), travellers may either opt to wait for the next service that has spare capacity (and hence incur an additional waiting time), or choose another mode.

Boarding failures due to line capacity constraints therefore increases total waiting time and hence total trip cost, and consequently affects the primary mode choice. The concept of overall network equilibrium thus needs to be considered, and an iterative process undertaken to achieve this. Defining the minibus taxi line frequency and line capacity in South African metropolitan transit networks is difficult to quantify accurately.

5. ALTERNATIVE ASSIGNMENT APPROACHES

Alternative transit assignment methods have been developed to overcome the shortcomings of standard frequency-based methods, especially the distribution of trips to common lines. Two alternative approaches to transit assignment that are available on transportation planning platforms are discussed. Both attempt to overcome the problem of trip allocation to common lines.

5.1 Variant Transit Assignment:

Several approaches to variant assignment have been developed. They all require the estimation of multiple optimal strategies. Trips are allocated to the competing strategies according to a logit model formulation utilising the total strategy trip generalised costs. Two important considerations must be taken into account:

- To enable the calibration of the distribution of trips between competing strategies between O-D, a logit scale parameter θ must be introduced. This parameter allows the adjustment of trip proportions, and varies between 0 and 1. A value of 1 will minimise the distribution of trips and a value of 0 will maximise the distribution of trips. The form of the logit equation for line i amongst n lines is from zone x is:

$$P(line\ i) = \frac{exp^{-\theta_x(Util\ i)}}{\sum_{n=1}^{n} exp^{-\theta_x(Util\ n)}}$$

    Where:
    - P(line i) is the likelihood of a traveller choosing line i;
    - Θ_x is the unique scale factor for zone x;
    - n is the number of lines between O-D included in the strategy;
    - (Util i) is the trip utility of line i between O-D.

- A trip cost cut-off parameter that limits the number of competing strategies included in the solution. A value of 0 will include all strategies and a value of 1 will include only the cheapest strategy

The previous example of three taxi lines has been re-estimated using the transit assignment variant. In this case, all three taxi lines are included as separate strategies and are included in the assignment. A logit model with scale parameter θ=0.20 and cut-off value of 0.0 was used. The following table summarises the taxi line costs and assigned volumes. Taxi line 3 is still the most attractive line and has 59 assigned trips. Taxi line 1 is the costliest line, and has 18 assigned trips. The analyst would vary the scale factor θ by

zone to obtain the best fit with observed data. The estimation of the zonal scale factors can be automated.

Table 1: Result of Logit Based Transit Assignment

Line Name	Headway (min)	Line Length (km)	Travel Time (min)	Assigned Demand (Pax)
Taxi Line 1	5	35.87	43.84	18
Taxi Line 2	5	35.14	42.76	23
Taxi Line 3	5	31.32	38.05	59

The proportions of trips between the lines for varying values of θ for zone j is shown in the following figure.
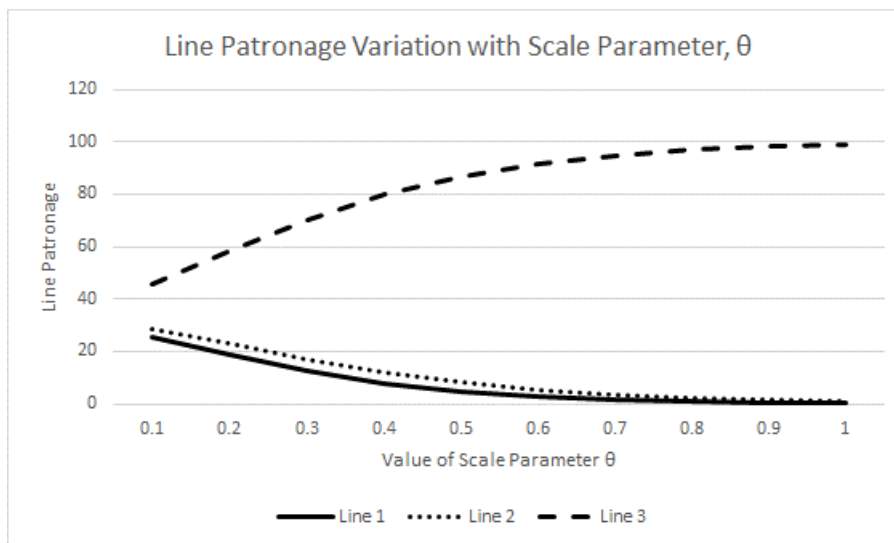

Figure 3: Effect of Variation of Taxi Line Patronage with Variation of Scale Factor

Finally, consideration should be given to using the variant assignment method to estimate the skimmed cost and time matrices used in the primary mode choice trip utility estimation. If the skimmed times and costs are estimated using standard transit assignment, then only the least cost optimal strategy values will be captured. These time and costs skims should be based on the weighted value of the multiple strategies determined in the variant assignment approach.

5.2 The Zenith Method

A similar multi-strategy method was proposed by Brandt (Brands, de Romph, Veitch, & Cook, 2013). In conventional models, the user defines the centroid connectors that provide centroid access and egress. In this approach, called the Zenith method, the assignment algorithm searches for transit line stop locations within a user defined radius around a centroid/s. This requires the definition of a search radius (in kilometres) around the zone centroids for different access and egress modes. The transit line stop locations within the search radius are identified and centroid connectors automatically defined for the appropriate (user defined) mode (e.g. walk, cycle, car). Unique stop-to-stop paths between

O-D are then defined based on the optimal strategy approach. The model has not been applied in South Africa and hence its performance and suitability cannot be assured.

Criteria for accessing the transit network can be different for different access modes as follows:

- A distance radius around the centroid (see example in following figure where two stop nodes have been captured by the distance radius);

- The type of transit system reached, for example that all centroids should have at least one access linkage to a taxi line;

- The type of station to be accessed, e.g. park and ride facility;

- The minimal number of stops accessible from a centroid. This criterion ensures that zones are not isolated (unconnected) in the network.
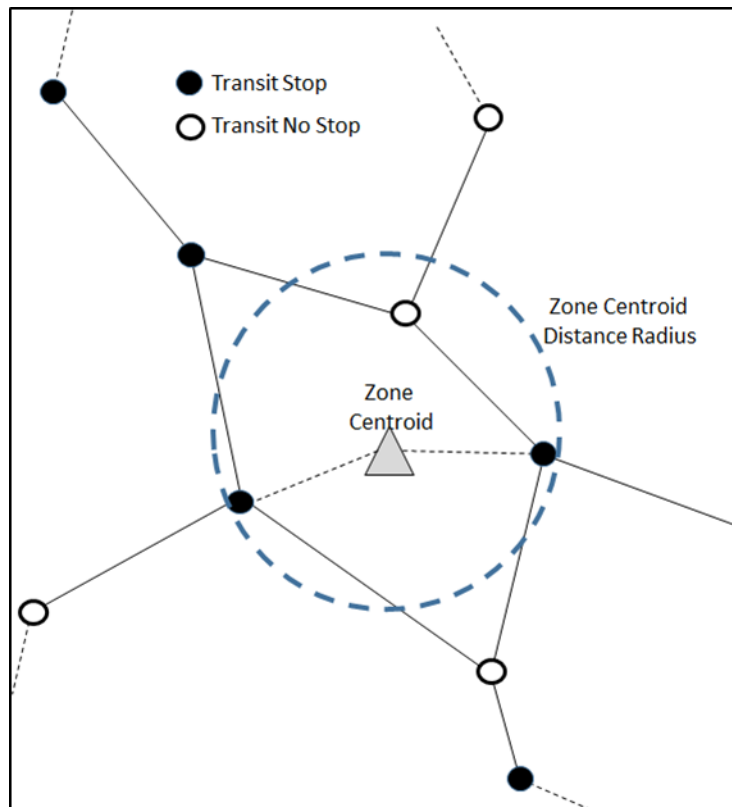

Figure 4: Example of Zenith Method for Zone Centroid Network Access

The allocation of trips to individual transit lines in the strategies is determined by a generalised cost logit model that is weighted by the relative line frequencies. The form of the logit model is as follows:

$$P(line\ i) = \frac{F_i exp^{-\theta x (Cost\ i)}}{\sum_{i=1}^{n} F_n exp^{-\theta x (Cost\ n)}}$$

Where:

- P(line i) is the likelihood of a traveller choosing line i;
- F_i is the frequency of line i;
- Θx is the zonal service choice parameter (i.e. scale factor) for zone x;

- n is the number of lines between O-D;
- (Cost i) is the total trip generalised cost of line i between O-D.

The three-taxi line example with the same scale factor of 0.2 (and equal headways of 5 minutes) will result in the allocation of the same trips to the lines as variant transit assignment. However, if the frequencies are not the same, the proportions can vary significantly as shown in the following figure. In this figure, Taxi Line 3 frequency has been varied between 12 and 5 vehicles per hour, while Line 1 and 2 frequencies have been kept constant at 12 vehicles per hour.
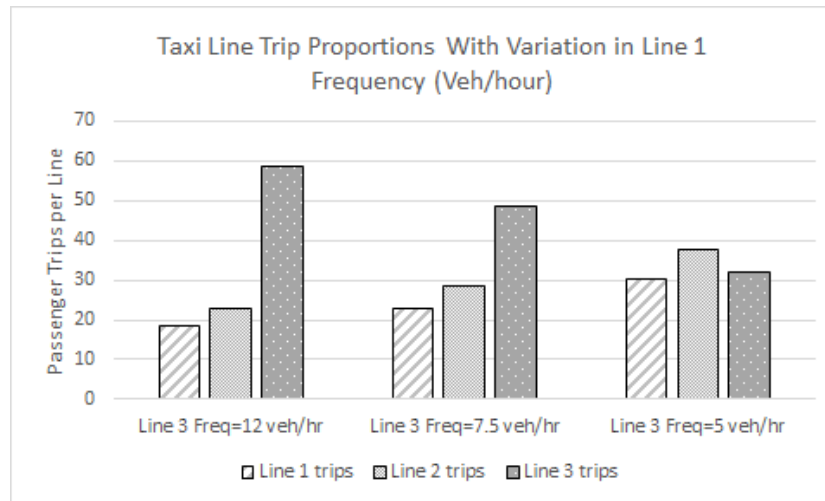

Figure 5: Effect of Frequency Variation using Zenith Method

6. CONCLUSIONS

Several important conclusions can be drawn from the discussion and analysis of this paper. These have implications on the results of transit assignment, and hence on the ability to achieve satisfactory assignment link flow and line validation results:

- Various demographic, operational and network factors present challenges when designing and implementing four-step transportation models in South African metropolitan areas;

- This makes it necessary to carefully design and apply methodologies such as gravity based distribution and mode choice models and standard transit assignment;

- These factors make it necessary to segment the traveller market, and carefully code the various transit networks and associated fares;

- South African metropolitan transit networks are dense, and characterised by high numbers of high frequency taxi routes, with several common lines possible between O's and D's;

- Specifically, the standard frequency-based transit assignment approach using optimal strategies has the potential to materially distort modal link passenger volumes, individual line demands, and stop and terminal passenger boardings and alightings;

- Alternative approaches to transit assignment should therefore be considered and applied by model practitioners, especially to address the common line problem, and the allocation of trips between these lines;

- Several methods are commercially available, but haven't had any application in South Africa;

- The variant transit assignment method is straight forward to use and easily adaptable for model development in South Africa and will significantly assist in the validation of transit demand supply systems;

- It is available on the most commonly used transportation platforms in South Africa, i.e. EMME and VISUM;

- Mode choice and transit assignment with newer methods such as agent-based microsimulation models have not been applied in South Africa. Based on results achieved internationally, these models hold significant potential;

- It is recommended that model practioners consider the application of the variant transit assignment methodology. In addition, consideration should be given to undertaking research into the development and application of mode choice and transit assignment using agent-based models.

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