Forecasting Passenger Congestion in Rail Networks

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ABSTRACT

Just as traffic congestion constrains the efficient movement of people and goods on the road system, passenger congestion on the rail network affects the on-time running of trains and operation of stations. In Melbourne, population growth, fare policy changes and fuel price instability have contributed to unprecedented growth in public transport patronage in recent years, leading to significant crowding issues in parts of the rail network. This paper describes a new approach to the forecasting of passenger congestion on rail networks using simulation to predict crowding on trains and in stations. The simulation technique models the choices of individual passengers as they select their departure time, train service, interchange points and walking paths through stations. The position of each passenger is then mapped in time and space to determine when and where crowding may occur. The model has been successfully applied in Melbourne to test changes to the train timetable and to estimate when congestion mitigation measures may be required in central city stations. It is hoped that this approach will help planners make better use of existing infrastructure before costly capital works are required.

1 INTRODUCTION

Just as traffic congestion constrains the efficient movement of people and goods on the road system, passenger congestion on the rail network affects the on-time running of trains and operation of stations. In Melbourne, train patronage has grown by about 40% over the last three years, leading to significant crowding issues in parts of the rail network (Herald Sun 2009).

To develop solutions to overcrowding on the rail network, the Victorian Department of Transport (DoT) commissioned a study in 2007 to evaluate the capacity of Melbourne's inner city stations and train services. The City Loop and Inner Core (CLIC) study's objectives included the following:

- determine how train loads might be affected by alternative train timetables, including different combinations of through and direct services;
- forecast pedestrian throughput at each inner-city station and identify capacity constraints;
- forecast the number of passengers transferring between rail services, taking into account the ease of transfer (e.g. cross-platform versus subways/bridges);
- handle unconstrained or capacity-constrained rolling stock loadings;
- incorporate peak spreading, that is, the re-timing of trips in response to crowding;
- calculate the proportion of standing and sitting passengers; and
- produce detailed passenger travel time outputs for economic evaluation purposes.

To address these objectives, it was clear that some form of model was required to forecast passenger demands and to test the effects of new rail services and infrastructure. However, the study managers realised that a traditional four-step strategic transport modelling approach was not going to be sufficiently detailed to answer the questions posed by the study. A new, more detailed model was needed.

This paper describes the new rail network model that was developed for the CLIC study. Working hand-in-hand with a strategic model, the ClicSim model not only forecasts crowding levels on individual trains but also simulates pedestrian movements through stations. Unlike other train loading models, the new model uses a behavioural choice component to represent passengers' decision-making processes, and integrates this with an agent-based simulation to model dynamic congestion levels on trains and in stations.

Section 2 of this paper reviews some of the common techniques for forecasting train loads and station congestion, and which approaches was adopted by the ClicSim model. Section 3 describes the structure of the model and Sections 4 and 5 demonstrate the practical outcomes and conclusions from the model's development.

2 PASSENGER CONGESTION FORECASTING TECHNIQUES

This section reviews some of the common forecasting techniques used for train load estimation and pedestrian flow modelling.

2.1 Train Loads

2.1.1 Averaging Techniques

At the simplest level, estimates of train loads can be determined by taking the total number of passengers using a rail line at a given location and dividing by the number of trains available during the time period. Passenger volumes can be determined directly from passenger counts (boardings and alightings) or derived from a strategic model. Usually a location is chosen in the network where train loads are known to be at a maximum (e.g. immediately outside major city stations or interchange points).

While this technique gives an estimate of average train loads, it does not take into account the relative attractiveness of express and stopping services, nor does it allow for variability in train frequencies[1]. To better represent these effects, a more sophisticated passenger decision-making model, such as the Rooftop Model, may be more appropriate.

2.1.2 The Rooftop Model

The Rooftop Model was originally developed by British Rail in the 1970s to estimate the relative passenger loads on fast and slow train services (Tyler and Hassard 1973, Shilton 1982). Since then, it has been applied in Australia to predict train loads for the Victorian Regional Fast Rail project (McPherson and Ashley 2004).

The Rooftop Model takes into account each passenger's desired departure time and allocates passengers to available trains by minimising the train travel time and "schedule delay" (i.e. the difference between the passenger's desired and actual times of departure). By selecting suitable penalty factors for the schedule delay, the model is able to differentiate the loads on express and stopping services more effectively than the simple averaging methods described earlier.

While the Rooftop Model is quite effective in corridor studies (McPherson and Ashley 2004), it is difficult to apply in complex urban rail networks with frequent trains, branching and looping lines, and passengers interchanging between services. To allow for these complexities, a process that considers a broader representation of train choice attributes is needed.

2.1.3 Choice Models

Passenger train choice models are a further generalisation of the averaging and Rooftop Model allocation techniques described above. In essence, choice models determine a set of feasible train journey alternatives for each passenger and determine the probability of each

[1] Assuming that passengers enter a station at a constant rate during a particular time period, one could assume that boarding volumes will be proportional to the time between successive trains (all other conditions being equal).

alternative being chosen. Each alternative has a certain utility (or attractiveness) which is typically based on attributes such as travel time, number of interchanges, waiting time and schedule delay. Using common discrete choice model formulations such as logit or probit models (see for example, Train 2003), the proportion of passengers choosing each alternative can be estimated.

A choice-based modelling framework provides a flexible way of representing the explanatory variables that govern passenger train choices. One of the main difficulties in applying these techniques is the need to enumerate all of the feasible train paths for each passenger. In a large urban rail network such as Melbourne or Sydney, the enumeration of alternatives can rapidly lead to combinatorial “overload” if there are frequent services and multiple interchange points.

The ClicSim model solves this problem by using a culling process to avoid combinatorial overload. The method is based on a branch-and-bound approach proposed by Friedrich, Hofsäß and Wekeck (2001). Section 3 of this paper describes the approach in more detail.

2.2 Station Capacity

To identify capacity constraints and congestion “hot spots” in a railway station, planners will often use some form of pedestrian model. Pedestrian models simulate the progression of passengers through platforms, ticket barriers, walkways, stairs and escalators.

Harney (2002) provides an overview of various techniques used to model pedestrian flows. Most of these modelling techniques fall into two broad categories: **flow propagation models** and **simulation models**.

2.2.1 Flow Propagation Models

Flow propagation models consider the flow rates of pedestrians through each part of the network using relationships between crowd density and travel times. Densities and flows are calculated in discrete area units (or “blocks”). The models also take into account average walking speeds and constraints such as ticket barriers and escalators. Such models calculate pedestrian levels of service, travel times and the dynamic propagation of queues through the network.

One of the popular flow propagation models used since the 1990s is PEDROUTE (Buckman and Leather 1994). PEDROUTE, developed by Halcrow in association with London Underground and the British Airport Authority, enables planners to conduct rapid capacity assessments of stations and airports. Although not as complex as simulation models, flow propagation models are relatively quick to set up and simple to use, and are still favoured for high-level capacity studies.

2.2.2 Pedestrian Simulation Models

In the last decade, a new class of pedestrian models has gained popularity in research and industry. Agent-based simulation models simulate the goals, behaviours and movement of individual pedestrians (or agents), allowing a much more detailed representation of crowd behaviour and congestion effects.

Many of the popular commercial modelling software applications (e.g. Legion, SimWalk, Paramics and VISSIM[2]) use this approach.

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[2] See http://www.legion.com, http://www.simwalk.com, http://www.paramics-online.com, http://www.ptvag.com

3 THE CLICSIM PASSENGER SIMULATION MODEL

3.1 Overview

The ClicSim model uses a choice-based train allocation technique in conjunction with a custom-built agent-based pedestrian model. This integrated approach provides a great deal of flexibility for planners:

- the complete journey of each passenger on the rail system is modelled – both the train component and station (walking) component;
- accurate transfer penalties (that take into account the walking time between platforms) are automatically calculated;
- the peaks in pedestrian congestion caused by trains arriving simultaneously at a station can be simulated;
- crowding on trains will cause some retiming of passenger journeys, simulating the peak spreading effect; and
- outputs from the model are available at the individual passenger level, allowing planners to diagnose why certain trains are overloaded.

3.2 Inputs and Outputs

The main inputs to the model are:

- forecast passenger flow patterns expressed in a station-to-station origin-destination (OD) matrix;
- the train timetable;
- a specification of the rail network; and
- a specification of the pedestrian networks within each station (i.e. platforms, walkways, escalators and exits).

In the Melbourne implementation, the passenger OD matrix was derived from an extensive passenger interview survey. Future passenger flows were then generated by applying growth factors to the observed matrix. Growth factors would typically be calculated by a strategic transport model or similar forecasting models.

The rail network and internal station pedestrian networks are represented hierarchically within an XML file. The XML format allows modellers a great deal of flexibility in specifying the networks, transparent version control and auditing, and the ability to interface with spreadsheets or other models. An example of the XML coding is shown in **Error! Reference source not found.**.

The main outputs from the model are:

- boardings and alightings by train, station, platform and time of day;
- train loads by train, line section and time of day;
- numbers of passenger transfers by station, trains, platforms and time of day;
- pedestrian congestion measures (level of service and area occupancy) by station, location within the station, and time of day;
- passenger travel times (comprising walking time, in-vehicle time and transfer time); and
- animated outputs showing the movement of trains and dynamic pedestrian densities within stations.

All outputs can be disaggregated to the level of the individual pedestrian if required, providing a powerful way of interrogating the model.

```xml
<stations>
  <station nodeID="1" name="Flagstaff" code="FGS" transferpenalty="16" >
    <walknodes>
      <walknode nodeID="3" name="Unpaid concourse 1" area="60"
       traveltime="00:00:09" coordinateX="800" coordinateY="400" />
    </walknodes>
    <exits>
      <exit nodeID="1" name="La Trobe Street Exit" entryproportion="0.17"
       exitproportion="0.3" area="75" coordinateX="600" coordinateY="200"/>
    </exits>
    <platforms>
      <platform name="1">
        <waitingarea nodeID="6" boardproportion="0.25"
         alightproportion="0.25" />
      </platform>
    </platforms>
    <walklinks>
      <walklink startnode="3" endnode="4" exittype="queued"
       servicepoints="2" queueservicetime="00:02.4" bidirectional="false"/>
    </walklinks>
```

Figure 1: XML snippets showing the structure of the network input file

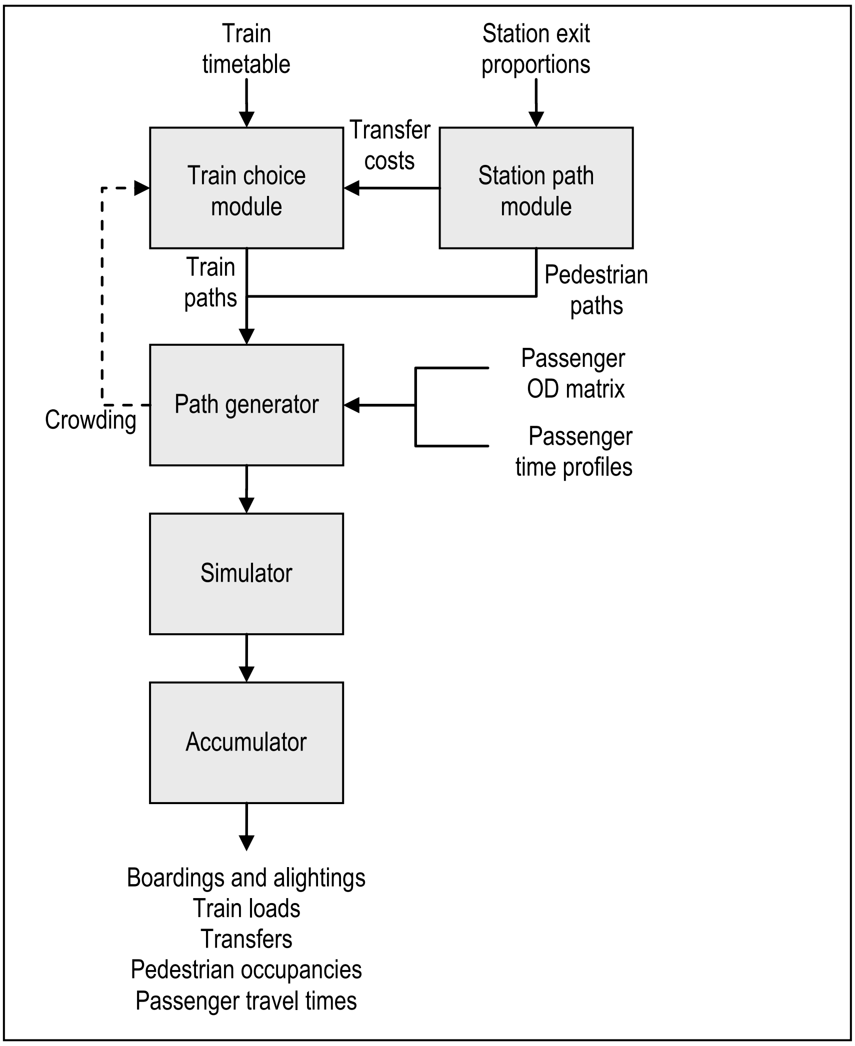

Figure 2: Structure of the ClicSim Model

3.3 Model Structure

The main components of the model are shown in
Figure 2 and described below.

3.3.1 Train Choice Module

The train choice module uses a branch-and-bound public transport assignment technique based on the work of Friedrich et al (2001). The module was implemented in the following way for each cell in the passenger origin-destination (OD) matrix:

1) **Split demand into time intervals** – the passenger volume between each pair of stations is apportioned to a set of 15-minute intervals during the peak period. The proportion of travel allocated to each interval is based on the observed arrival and departure profiles at each end of the trip.

2) **Enumerate all possible train combinations** – all train combinations between the chosen origin and destination are determined. These include all possible departure times and interchange combinations. Because the number of combinations would be prohibitively large for a typical trip (literally tens of thousands of paths), limitations are placed on the total number of interchanges made by each passenger and the stations at which interchanges are permitted. The set of train paths is represented in a connection tree as described by Friedrich et al (2001).

3) **Cull infeasible combinations** – the connection tree is “pruned” to remove any infeasible combinations. Infeasible combinations include those where:

   - passengers alight, then immediately reboard, the same train;
   - for a given origin-destination pair, a train departs earlier and arrives later than the preferred train[3] (in this case, the train departing earlier will be culled from the selection set);
   - interchange times are shorter than the minimum calculated walking time between platforms; or
   - transfer times are greater than a predefined maximum allowable transfer time (in the Melbourne model, this was nominally set at one hour to allow for infrequent country trains).

4) **Calculate the perceived travel cost for each combination**.

   The perceived cost C (in minutes) is given by:

$$C = \left(IVT + c_{transfer} + t_{access} + t_{egress}\right) F_{crowd} + F_{time}$$

   where:

   - IVT is the in-vehicle time (in minutes);
   - $c_{transfer}$ is the total transfer cost (see below);
   - t_{access} is the walking time between the origin station entrance and boarding platform;
   - t_{egress} is the walking time between the alighting platform and destination station exit;
   - F_{crowd} is a crowding penalty factor (see below); and

[3] In practice, a small travel time tolerance is used so that if a train is one or two minutes earlier, it would still be considered. This allows for variability in train running times and passengers’ perceptions of travel times.

- F_{time} is a departure/arrival time penalty factor (see below).

The total transfer cost is the sum of individual transfer costs at each station s in the set of transfer stations S on the passenger's journey. The total transfer cost is given by:

$$c_{transfer} = \sum_{s \in S} \left(a_s \cdot t_s + b_s \right)$$

where:

- t_s is the transfer time (in minutes) at station *s*;
- a_s is a station-specific waiting time coefficient; and
- b_s is a station-specific constant travel time penalty.

The crowding penalty factor F_{crowd} represents the relative attractiveness of seated, standing and crush conditions on a train. The model calculated the value of F_{crowd} from the piecewise linear relationship depicted in Figure 3.

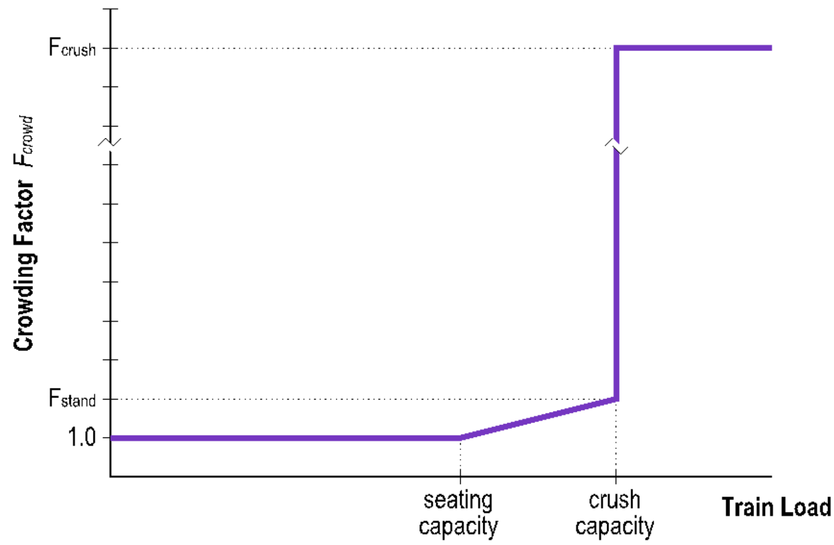

Figure 3: Crowding penalty factor calculation

In this figure:

- F_{stand} is the standing penalty factor;
- F_{crush} is the crush loading penalty factor; and
- the train load is the departure load modelled <u>at the boarding point</u> on the passenger's journey.

In the Melbourne application, the crush loading penalty factor was set to an arbitrarily high value (10,000) to prevent passengers from travelling on overloaded trains.

The time penalty factor F_{time} is calculated as shown in Figure 4.

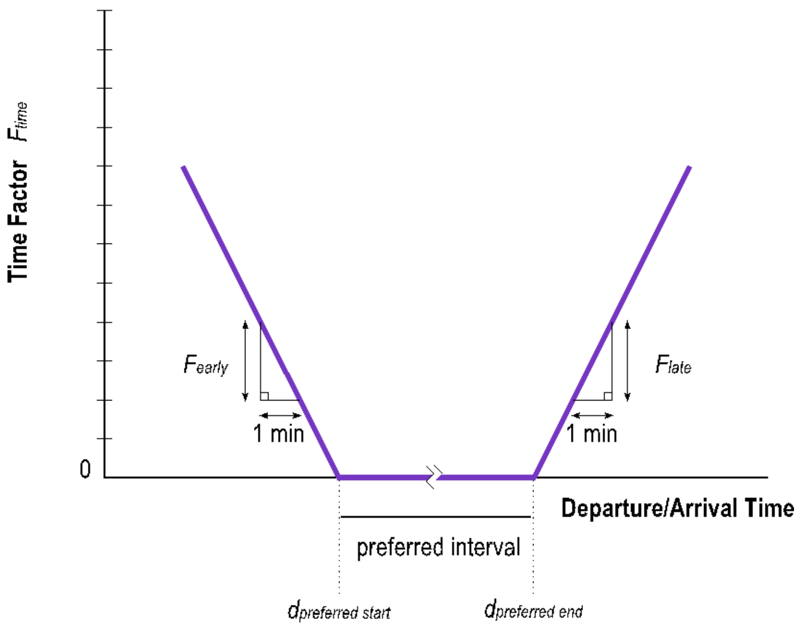

Figure 4: Time penalty factor calculation

In this figure:

- the preferred interval is the current time interval being modelled (see step 2);
- F_{early} is the penalty multiplier applied to arrival or departure times d_{actual} before the start of the passenger's preferred time interval $d_{preferred\ start}$

$$F_{time} = F_{early}\left(d_{preferred\,start} - d_{actual}\right) \qquad d_{actual} < d_{preferred\,start}$$

- F_{late} is the penalty multiplier applied to arrival or departure times d_{actual} after the end of the passenger's preferred time interval $d_{preferred\ end}$

$$F_{time} = F_{late}\left(d_{actual} - d_{preferred\,end}\right) \qquad d_{actual} > d_{preferred\,end}$$

In the Melbourne model, 15-minute time intervals were adopted.

5) **Calculate the probability of using each train path –** a multinomial logit model is used to allocate passengers to each train path from each station:

$$p_t = \frac{\exp(-\lambda C_t)}{\sum_{i \in S} \exp(-\lambda C_i)}$$

where:

- p_t is the proportion of passengers allocated to train path t;
- S is the set of all feasible train combinations between the origin and destination;
- C_i is the perceived cost of travel on train path i (see step 4); and
- λ is a model sensitivity parameter.

In the Melbourne model, the model sensitivity parameter λ was determined through sensitivity tests. The final value of λ=0.3 gave a realistic distribution of passengers to express and stopping trains.

The apportionment of passengers is carried out for each origin-destination pair and each time interval.

3.3.2 Station Path Module

The station path module determines the walking paths of pedestrians between platforms, and also between platforms and station exits.

- **Platform-to-platform paths** are used to calculate realistic transfer times and penalties between platforms (e.g. a cross-platform transfer will have a lower cost than a transfer using a subway or over-bridge). The transfer costs are used by the train choice module in the determination of train path probabilities. Platform-to-platform paths are also used by the simulation module to simulate pedestrians transferring between platforms.
- **Platform-to-exit paths** are used to determine the routes that pedestrians use for platform access and egress. The simulator uses these paths to determine the minute-by-minute locations of pedestrians within each station. The proportions of pedestrians using each route are determined from surveys of passenger volumes at each station exit.

3.3.3 Path Generator Module

The path generator module compiles the train paths and pedestrian paths into a composite path for each pedestrian. A separate path is generated for each passenger trip in the origin-destination matrix.

3.3.4 The Simulator

The simulator is responsible for tracking the positions of individual passengers in the train and pedestrian networks. The simulator updates the position of each passenger during each time step of the simulation (typically at half-second intervals). The progress of each passenger through the network depends on train arrival and departure times, average walking speeds and queues within stations.

3.3.5 The Accumulator

The accumulator takes the time and space data output from the simulator and determines the total numbers of passengers in each part of the network at any given instant. Train loads calculated in the accumulation step are fed back to the train choice module so that crowding can be taken into account in passengers' choice of trains.

3.3.6 Crowding Increments

The simulation model does not "know" which trains are crowded until after it has assigned passengers to trains. Therefore, the model uses an incremental feedback process whereby it assigns a small number of passengers at a time from the OD matrix and progressively monitors the level of crowding on each train as each passenger path is calculated.

The incremental crowding method generally works well, but will still occasionally allow trains to be filled beyond capacity[4]. Train overcrowding may also occur in the extreme case where all trains departing from a particular station are already crowded. In this case, passengers have no choice but to travel on an already-crowded train. Model results showing this type of crowding behaviour usually indicate an insufficient number of trains in the timetable.

[4] In the Melbourne model, this was due to the size of the increment chosen. A more sophisticated algorithm that selectively assigns passengers in smaller increments could avoid this problem.

3.4 Model Validation

The ClicSim model was validated for Melbourne conditions by comparing modelled passenger loads on trains with observed loads from surveys. Figure 5 and Figure 6 show the modelled and observed numbers of passengers on incoming trains at Richmond Station in the morning peak. Richmond Station, located just outside the Melbourne CBD, was chosen because eastern suburban trains are usually most heavily loaded at this point.

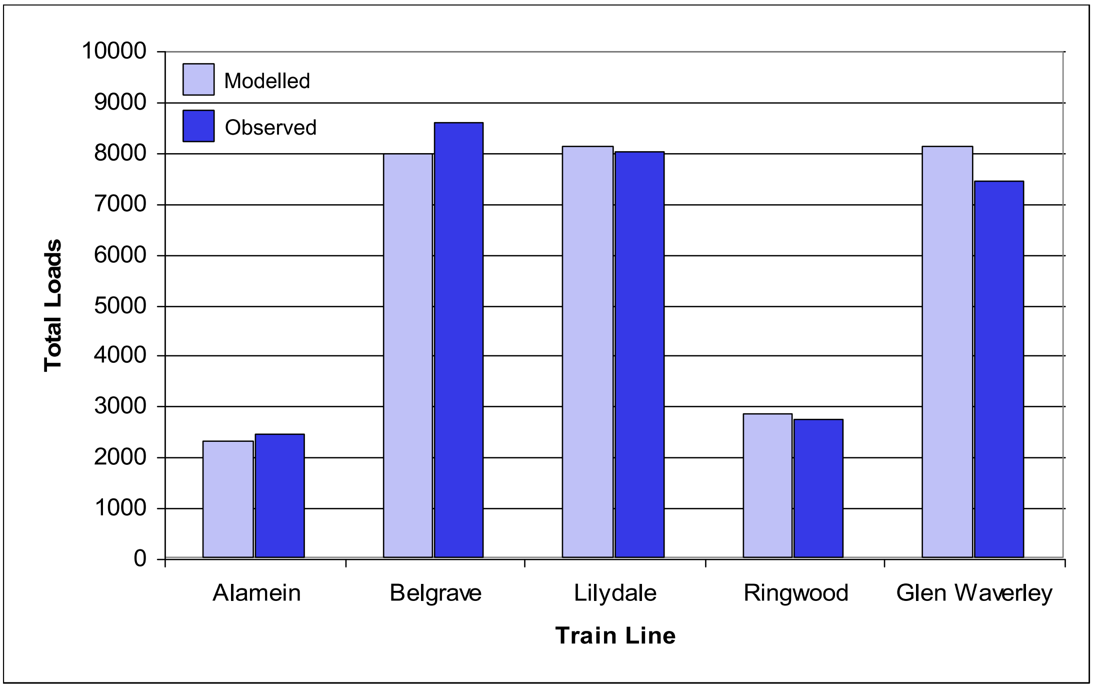

Figure 5: Modelled and observed AM peak line volumes at Richmond for Burnley Group lines, Melbourne. Observed data: 2007 Load Standards Survey, Victorian Department of Transport.

The Belgrave, Lilydale and Glen Waverley lines have a larger catchment area and higher proportion of express trains than the Alamein and Ringwood lines, and therefore attract more passengers. Figure 5 shows that the model allocates passengers to each line to within 10% of the observed total.

At the individual train load level (Figure 6), the model reproduces the general pattern of express and stopping train loads quite well, though the error on individual train services is higher than at the total line level. Given that the model assumes that all trains are running on time (which does not always happen in practice), this was considered to be an acceptable result.

Figure 7 shows the modelled pedestrian densities during the busiest half hour at Flinders Street, Melbourne's busiest station. This plot was checked by station operations staff and confirmed to accurately represent the locations where congestion is most apparent.

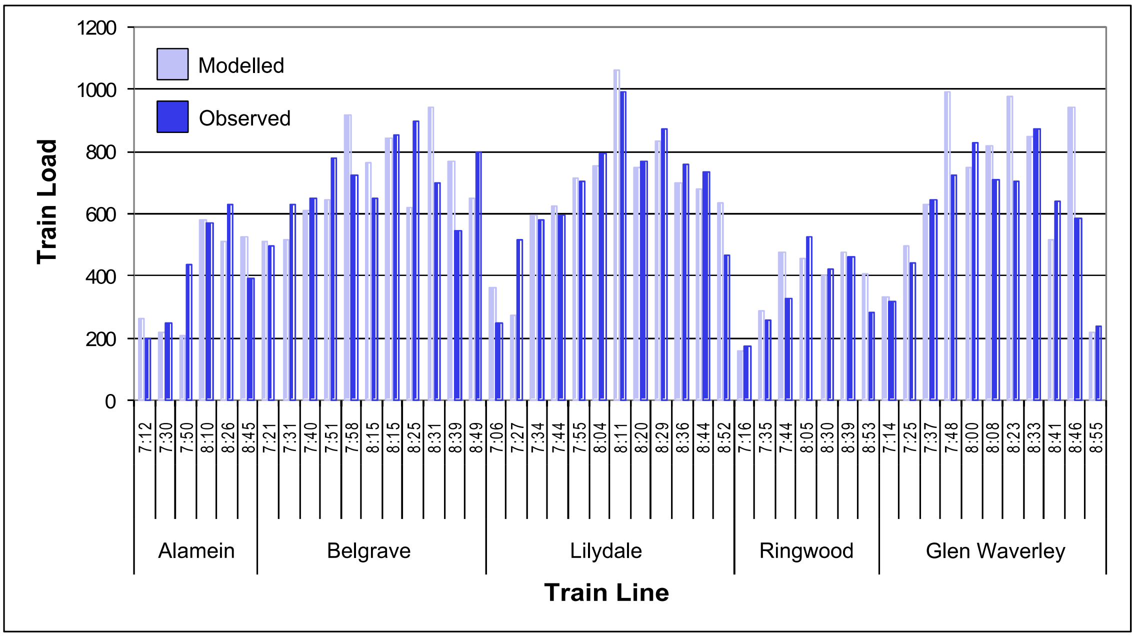

Figure 6: Modelled and observed train loads at Richmond for Burnley Group lines, Melbourne. Observed data: 2007 Load Standards Survey, Victorian Department of Transport.

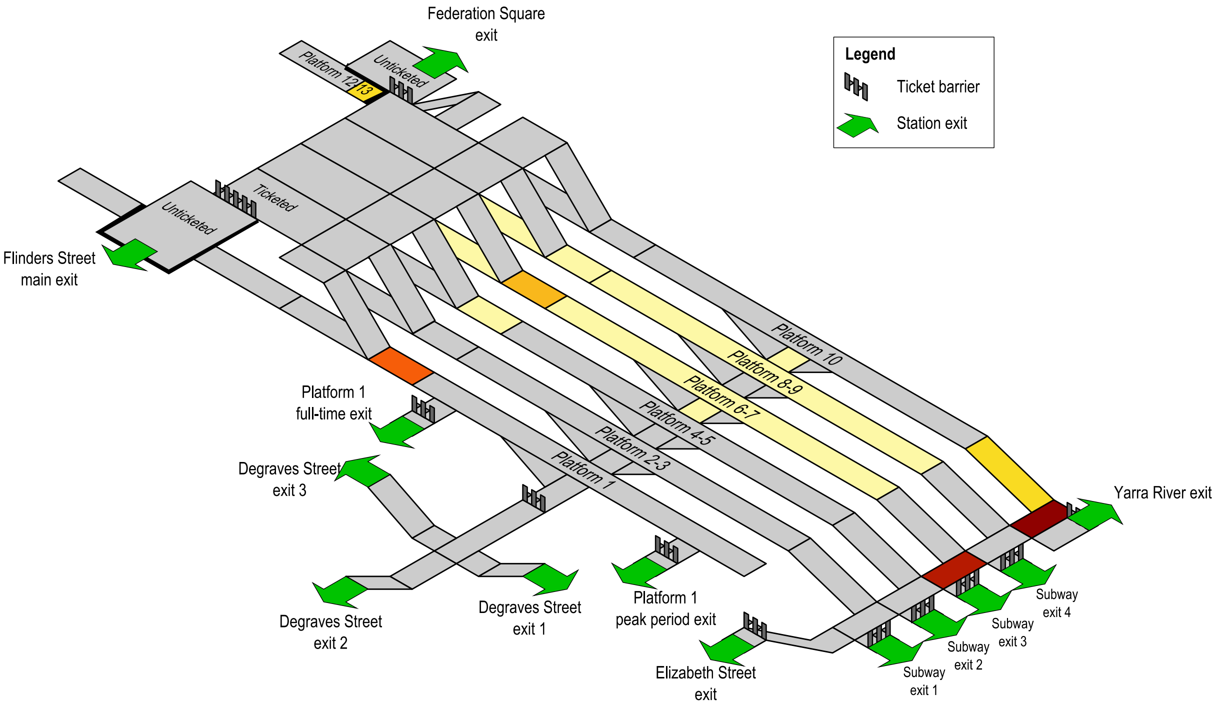

Figure 7: Pedestrian densities at Flinders Street Station, Melbourne (AM peak busiest half hour, 2008). Warm colours (reds and oranges) represent the most congested locations.

4 MODEL APPLICATION

The ClicSim model has been used to simulate passenger movements across the entire Melbourne metropolitan rail network. In the AM peak, over 200,000 passengers, 1,800 trains and 200 stations were simulated. The internal station networks were modelled for the ten inner-city stations under consideration in the CLIC study. At other stations, a simplified set of platforms and walking links were used.

Using a half-second simulation time step, the train choice calculations (i.e. passenger assignment) took about two hours to process and the spatial-temporal simulation of passenger movements about five minutes.

Figure 8 shows the user interface of the ClicSim software. The simulation is displayed as an interactive animation showing the progression of trains and pedestrian movements. The animation uses different colours to represent the loading levels on trains, allowing modellers to readily identify the times and locations in the network where train loads become critical.

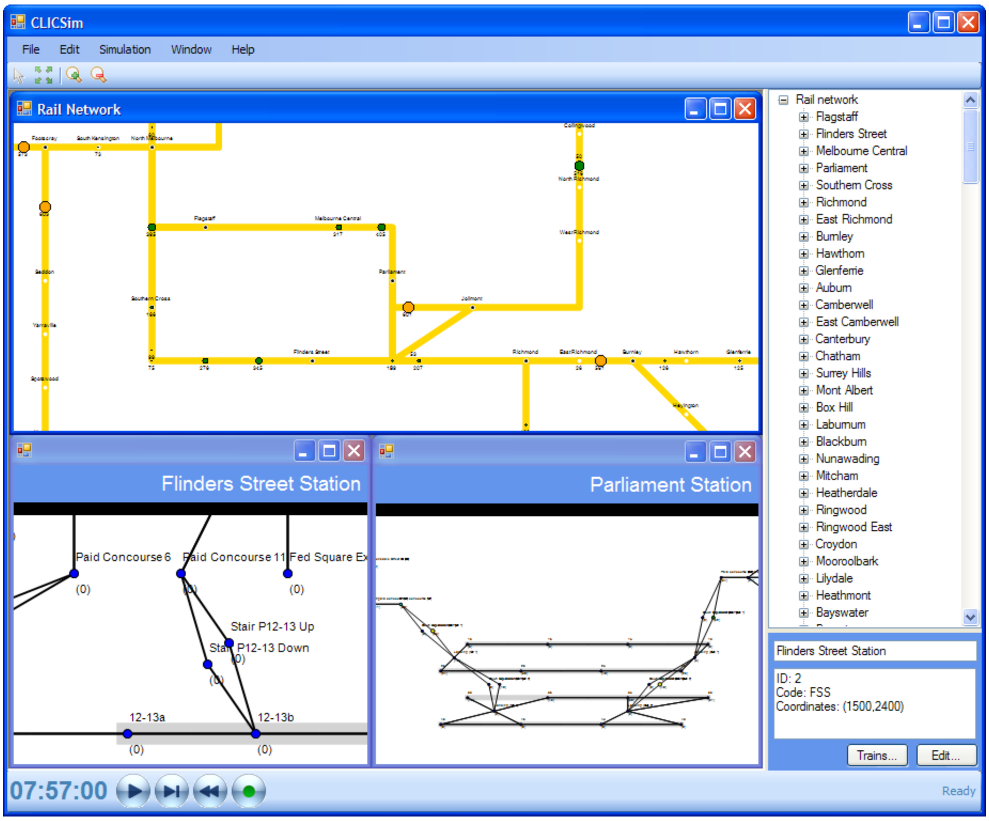

Figure 8: ClicSim user interface showing animation of trains (top pane) and internal station networks for two stations (lower panes).

The software produces a comprehensive set of spreadsheet reports that provide modellers with a complete coverage of boardings and alightings, train loads, travel times, transfer behaviour, congestion levels and pedestrian flows. The following figures provide examples of the types of outputs that can be produced by the model.

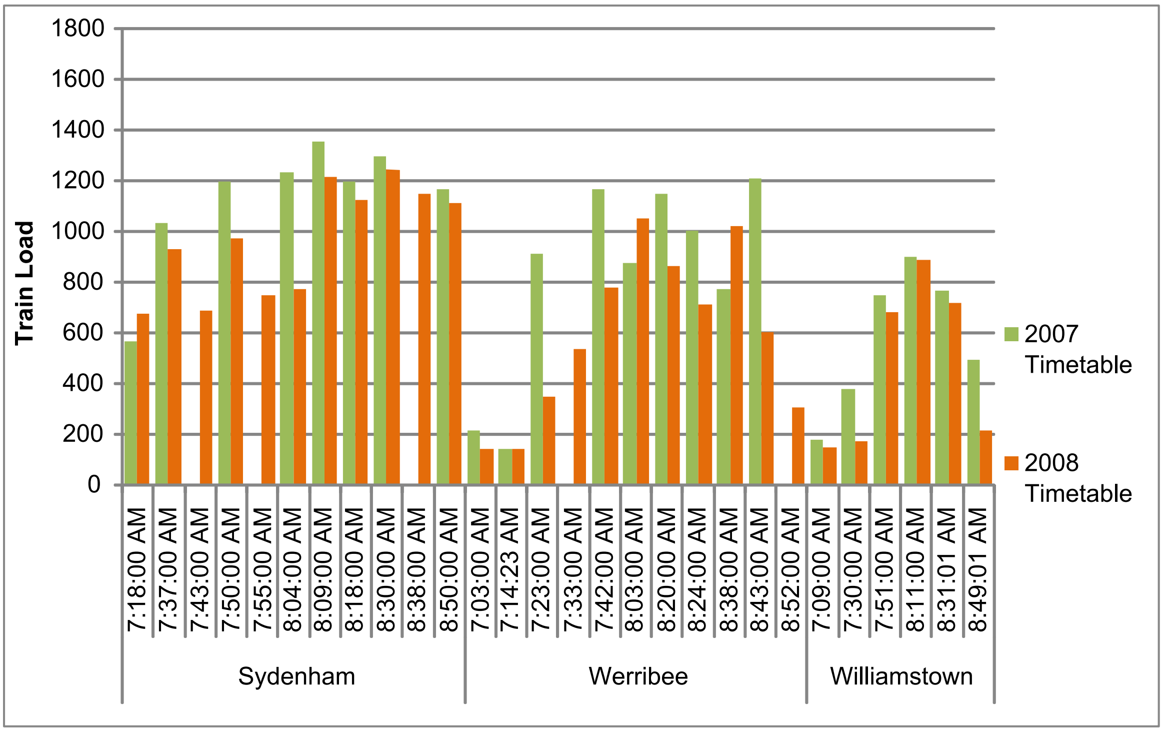

Figure 9: Comparison of train loads with two alternative timetables. The addition of more trains causes a reduction in loads, although these are mostly early in the peak.

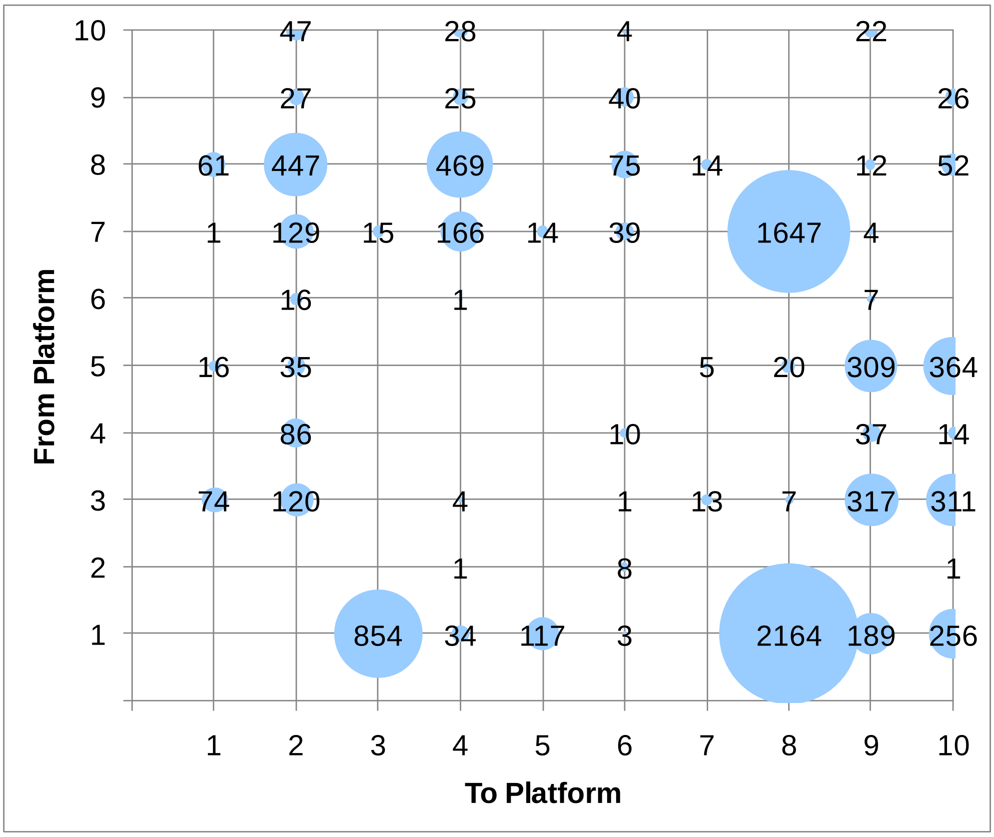

Figure 10: Volumes of transferring passengers between platforms at Richmond Station. The vertical axis represents the origin platform and the horizontal axis represents the destination platform. Platforms 7 and 8 represent a cross-platform interchange, whereas Platforms 1 to 8 do not. This type of diagram can be used to diagnose inefficient train presentation patterns at multi-platform stations.

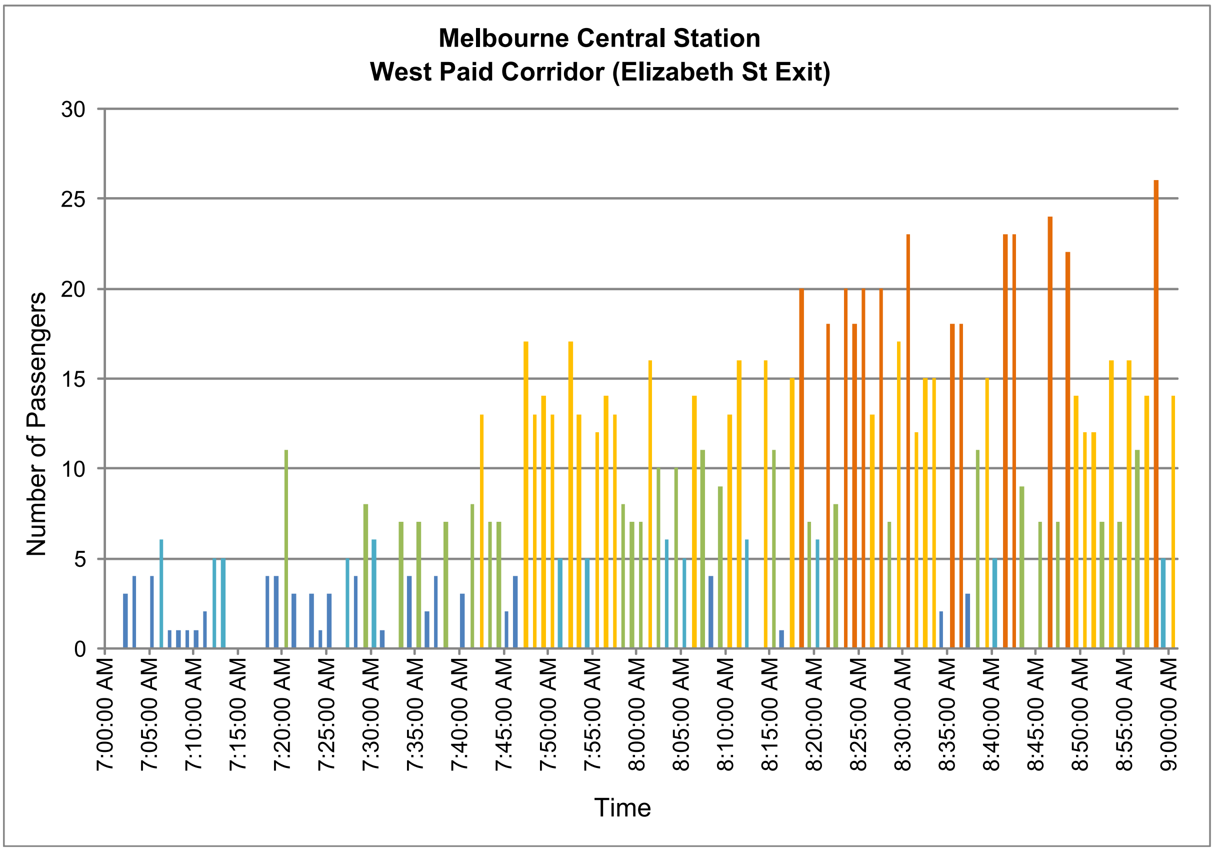

Figure 11: Pedestrian congestion plot showing instantaneous levels of service on a walkway at Melbourne Central Station. Walkway levels of service are defined in Fruin (1971).

5 CONCLUSION

This paper has described a rail network model that uses an agent-based simulation technique to forecast passenger crowding levels on trains and pedestrian movements through stations. The model uses an integrated approach to modelling passenger paths; the train and walk components are both simulated by the model, allowing the position of each passenger to be simulated as they move across the rail system. The use of a discrete choice structure with a branch-and-bound approach enables the model to handle complex urban rail networks and interchange arrangements.

The model has been successfully applied to the Melbourne rail network and shown to reproduce observed train loads and station congestion quite well. It provides a powerful tool for diagnosing crowding issues and assessing the effectiveness of new train timetables and rail infrastructure.

Acknowledgements

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References

Buckman LT and JA Leather (1994), ‘Modelling station congestion the PEDROUTE way’, *Traffic Engineering and Control, 35(6)*, pp 373-377.

Friedrich, M, I Hofsäß and S Wekeck (2001), ‘Timetable-based transit assignment using branch & bound’, *Transportation Research Record 1752*, pp 100-107.

Fruin JJ (1971), *Pedestrian Planning and Design*, Elevator World, Mobile, Alabama.

Harney, D (2002), ‘Pedestrian modelling: current methods and future directions’, *Road & Transport Research,* 11(4), pp 2–12.

Herald Sun (2009), ‘Public transport patronage on the rise amid commuter fury’, *Herald Sun*, March 6, 2009.

McPherson, CD and DJ Ashley (2004), ‘Estimating Passenger Demand for Fast Rail Services With the Rooftop Model’, *27th Australasian Transport Research Forum*, Adelaide.

Shilton, D (1982), Modelling the demand for high speed train services, *Journal of the Operational Research Society 33*, pp 713-722.

Sinclair Knight Merz (2008), *City Loop and Inner Core Patronage Distribution and Station Operations - Model Verification Report*, Final report for Victorian Department of Transport, July 2008.

Train, KE (2003), *Discrete Choice Methods With Simulation*, Cambridge University Press.

Tyler, J and Hassard, R (1973), ‘Gravity/elasticity models for the planning of the inter-urban rail passenger business’, Proceedings of Seminar G, *PTRC Summer Annual Meeting*, University of Sussex.