
World Transit Research

9-1-2011

Modelling the ability of fare to spread AM peak passenger loads using rooftops

Neil J. Douglas

Liesel Henn

Keith Sloan

Follow this and additional works at: <http://www.worldtransitresearch.info/research>

Recommended Citation

Douglas, N.J., Henn, L., & Sloan, K. (2011). Modelling the ability of fare to spread AM peak passenger loads using rooftops. Conference paper delivered at the 34th Australasian Transport Research Forum (ATRF) Proceedings held on 28 - 30 September 2011 in Adelaide, Australia.

This Conference Paper is brought to you for free and open access by World Transit Research. It has been accepted for inclusion in World Transit Research by an authorized administrator of World Transit Research. For more information, please contact pauline.forbes@eng.monash.edu.au.

Modelling the ability of fare to spread AM peak passenger loads using rooftops

By Douglas N.J.¹ Henn L.² and Sloan K.³

Contact author Neil Douglas email: DouglasEconomics@ihug.co.nz

¹ Neil Douglas is Manager of Douglas Economics.

² Liesel Henn is a Researcher at Southern Cross University, Lismore NSW

³ Keith Sloan is Associate Professor, Southern Cross Business School, Southern Cross University, Lismore NSW.

Abstract

'Rooftops' originates from theoretical work by Hotelling into location choice. In the 1970s, Hotelling's ideas were applied to passengers' choice of intercity trains which gave rise to the name 'rooftops' since the graphs resembled streets of rooftops. Rooftop models have focused on time but including fare is not difficult requiring 'values of time' to convert fare into minutes.

As a demonstration, a rooftops model was applied to a rail corridor to assess the effect of discounts and surcharges on passenger's choice of AM peak trains. The demand parameters such as the value of time and displacement were estimated by Stated Preference market research. Dollar for dollar, the sensitivity to a fare discount was less than for a surcharge and this difference carried through to the value of onboard time. Passengers also valued late displacement higher than early displacement.

The model predictions were compared with observed counts of train loads with calibration factors introduced to bring the predicted loads closer to the observed loads. The calibrated model was then used to predict the impact of fare discounts and surcharges. A peak hour surcharge was forecast to reduce peak hour loads more than discounts offered on early and late peak trains. Discounting early peak trains was also forecast to be more effective than discounting late peak trains.

Acknowledgements This study was undertaken as part of Project R1.107 Urban Rail Demand Management Strategies funded by the CRC for Rail Innovation (established and supported under the Australian Government's Cooperative Research Centres program).

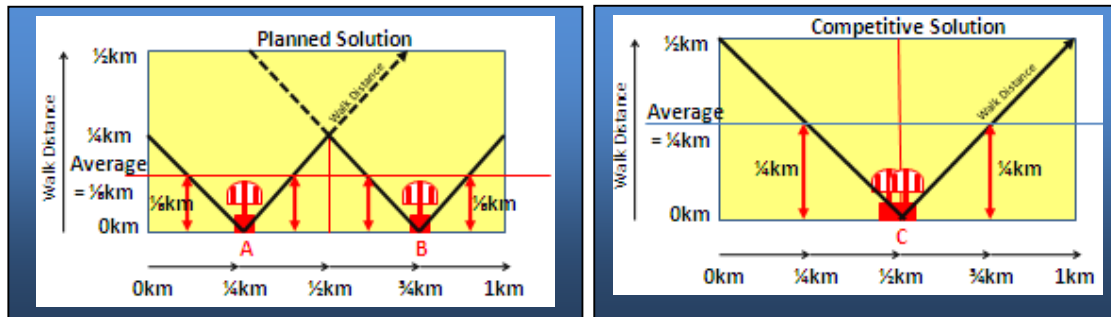
The authors would like to acknowledge the assistance of George Karpouzis, Atiqur Rahman, Kerrie Tandy, Trevor Puckering and Tim Robinson of the Economic and Financial Analysis Unit of RailCorp and Michael Doggett and Mark Guthrie of Market Development & Research Unit, RailCorp.

1. Rooftops

1.1 The origins of 'Rooftops'

The 'rooftops' approach originates from work in spatial economics by Hotelling in the 1920s (Hotelling, 1929). Hotelling analysed where companies should locate. Figure 1 uses Hotelling's approach to examine where two ice cream sellers should locate on a one kilometre long beach. Two solutions are compared: a planned solution in the left box and a competitive solution in the right box.

Figure 1: Ice cream stalls on 'Hotelling' beach



In the planned solution, seller 1 locates a $\frac{1}{4}$ kilometre along the beach at A and seller 2 locates $\frac{3}{4}$ kilometres along the beach at B. Assuming the same flavours and prices, all the customers on the left hand side of the beach would walk to seller A and all customers on the right would walk to B. People sunbathing at either end (0 or 1 kms) or in the middle of the beach ($\frac{1}{2}$ kms) would have the longest walk of a $\frac{1}{4}$ kilometre whereas a person sunbathing next to the stall would have a 0 kilometre walk. The average walk, assuming sunbathers distribute evenly along the beach, would be a $\frac{1}{8}$ kilometre. The diagonal lines show how the walk distance increases from each stall. The threshold delimiting the two catchments is where the two inward lines intersect at the centre of the beach.

Competitively, there would be a tendency for the ice cream sellers to shuffle towards the centre of the beach to capture more of the market. Seller 1 would capture $\frac{5}{8}$ of the beach if he moved to the centre of the beach so long as seller 2 remained at B. In fact, only when both sellers shuffled to the centre of the beach at C would a competitively stable solution be reached. However, this competitive solution increases the average walk to a $\frac{1}{4}$ kilometre which is a $\frac{1}{8}$ kilometre more than the 'planned' solution.

This paper effectively extends Hotelling's approach to situations where different ice creams are offered, crowds develop at the centre of the beach and queues develop at the ice cream stalls. Should the popular ice cream seller raise prices or the unpopular seller offer discounts to reduce queuing? However, rather than addressing a spatial problem, the paper uses Hotelling's approach to look at the temporal problem of crowding on trains over the AM peak.

Hotelling's technique was first applied temporally in the 1970s to assess passengers' choice of intercity trains in the UK by Tyler and Hassard (1970). The technique was given the name 'Roof-tops' because, as will be shown, the train choice graphs look like streets of rooftops. The technique was successful in explaining and predicting passenger choice particularly for irregular services and became the basis for modelling intercity train timetables (UK Passenger Demand Forecasting Council, 2002).

Other applications of Rooftops include Harrell who used the approach to assess lightly used rail services (Harrell, 1987). In Australia, Ashley and McPherson used rooftops to model fast

regional rail services in Victoria (Ashley, 2004). In Sydney, Douglas Economics in association with Trainbrain developed a train choice model for the Independent Transport Reliability and Safety Regulator to assess the impact of CityRail timetables on AM and PM peak train passenger loads, (Douglas Economics, 2009).

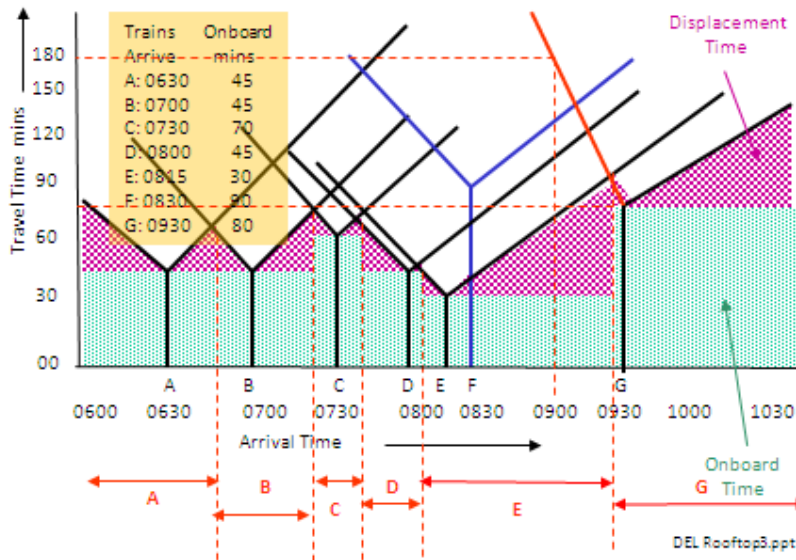
All the Rooftops applications listed above have focussed on travel time and frequency and have not included fare. However as will be demonstrated, augmenting Rooftops to include fare is relatively straightforward and by doing so, it is possible to model the effect of differential fares such as discounts and surcharges on passenger loads.

1.2 The 'Rooftops' approach

The basic Rooftops approach compares the travel time of different train services to passengers wanting to travel at different times. Figure 2 presents the rooftops approach.

Seven trains are shown. Train A arrives at 0630, train B at 0700 and train C at 0730. Train E, is an 'express' train taking 30 minutes. There are three limited stop trains A, B and D that take 45 minutes. There is also a slower 'limited stop' train C taking 70 minutes and two 'all stop' services F and G that take 90 and 80 minutes respectively.

Figure 2: 'Rooftops' Train Choice Model



The vertical axis shows the total travel time which comprises two elements: (1) the time spent on the train and (2) the displacement time. The displacement time represents the difference between when passengers want to arrive and when the timetable allows them to arrive and is measured on the horizontal axis as well as the vertical axis (both axis have the same scale). Displacement is shown as the sloping lines that fork in opposite directions from the arrival time and their look gave rise to the name 'rooftops'. The left hand line from each train's arrival time measures late displacement time; the right hand line measures early displacement time.

A displacement line at 45 degrees (as for train A) implies that a minute of displacement is valued equal to a minute of onboard train time. Steeper slopes would weight displacement time more heavily and flatter slopes would weight displacement time relatively less than onboard train time.

In essence, the train service offering the lowest total or generalised time (onboard plus displacement) is chosen and this depends on when passenger wants to arrive. Where the displacement slopes for two train services intersect the two trains have the same generalised time. The intersection points are referred to as thresholds.

In Figure 2, a person who wants to arrive at 0630 would use train A. This train gets the passenger to the destination exactly when they want and imposes zero displacement time. The generalised time would therefore be just the 30 minutes time spent on the train. A person who wanted to arrive at 0640 would arrive ten minutes earlier than desired if they used train A or twenty minutes later if they used train B. With early and later displacement valued equally and also the same as onboard time (i.e. with the 45° slopes shown) the passenger would have a generalised time of forty minutes (30 + 10 minutes early displacement) using train A and fifty minutes (30 + 20 late displacement) using train B. Train A would therefore be ten minutes less than train B and so would be selected. In fact, Train 'A' would 'capture' all passengers wanting to arrive before 0645. After 0645, train B would take less time and passengers would choose train B until 0720. The catchment 'watershed' for trains A and B is therefore 0645.

Train F is a slow train and by taking 90 minutes fails to capture any trips since passengers would be better off travelling earlier on train E or later on train G.

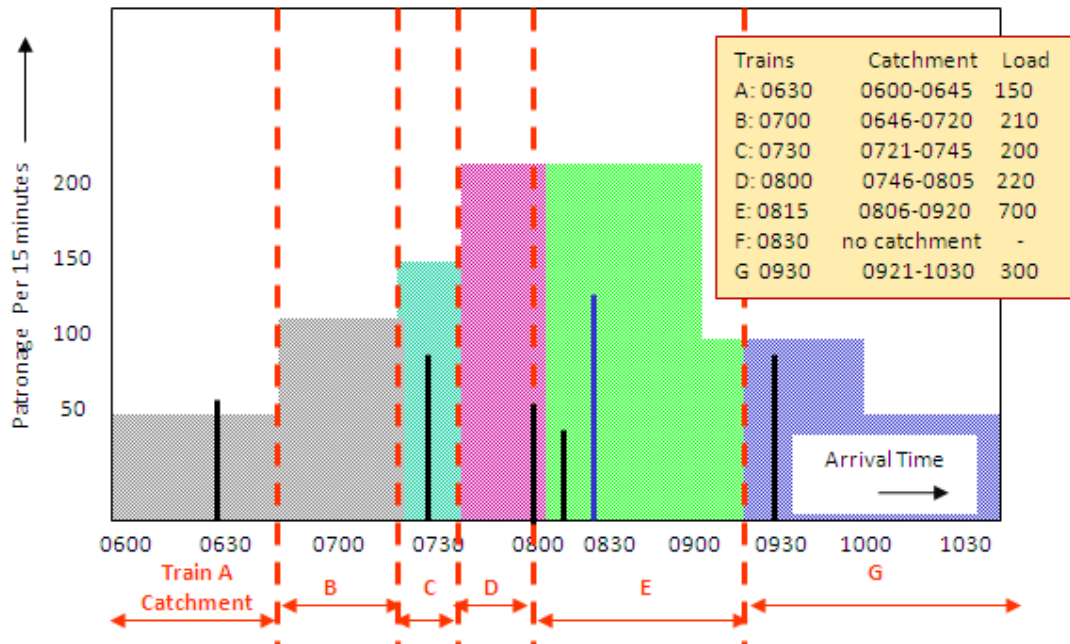
Train G illustrates the situation where late displacement is valued more than onboard time. The late displacement line, shown in red, is steeper than 45°. A person wanting to arrive at 9am would be 30 minutes 'later' than desired using train G and with the late displacement line shown, the 30 minutes displacement would add 100 minutes to the onboard travel time to give a generalised time of 180 minutes. Late displacement is therefore valued at 100/30 or 3.3 times onboard rail time and the steeper slope restricts train G's catchment to post 09:25.

It is also possible to calculate the 'service level' over the travel period by adding the green shaded areas (representing the onboard train time) to the maroon shaded area (representing the displacement time).

Train passenger loads can be calculated by assigning passengers to trains. If the desired travel time profile was constant (i.e. as many people want to travel at 0615 as at 0830) train loadings would be determined by the time period share captured by each train multiplied by the patronage over the period. In Figure 2, train A's catchment was the 45 minute period 6am to 6.45am which would be 16.7% of the 270 minute period 6am-10.30am. If 1,000 passengers wanted to travel in the whole period, train A would obtain a load of 167 passengers. However, the desired travel time profile is highly unlikely to be constant. Rather it is likely to be 'bell shaped' with more people wanting to arrive in the city between 0800 and 0900 than between 0600 and 0700.

Figure 3 on the following page shows the calculation of train load when the passenger arrival profile varies over time. In this situation, the train catchments need to be multiplied by the number of passengers wanting to travel (the vertical axis) at that time. Thus train A, which has a catchment from 0600-0645, obtains a load of 150 people (three 15 minute periods of 50 passengers each).

Figure 3: Train Service 'Catchments'



1.3 Extending the Rooftops approach to include fare

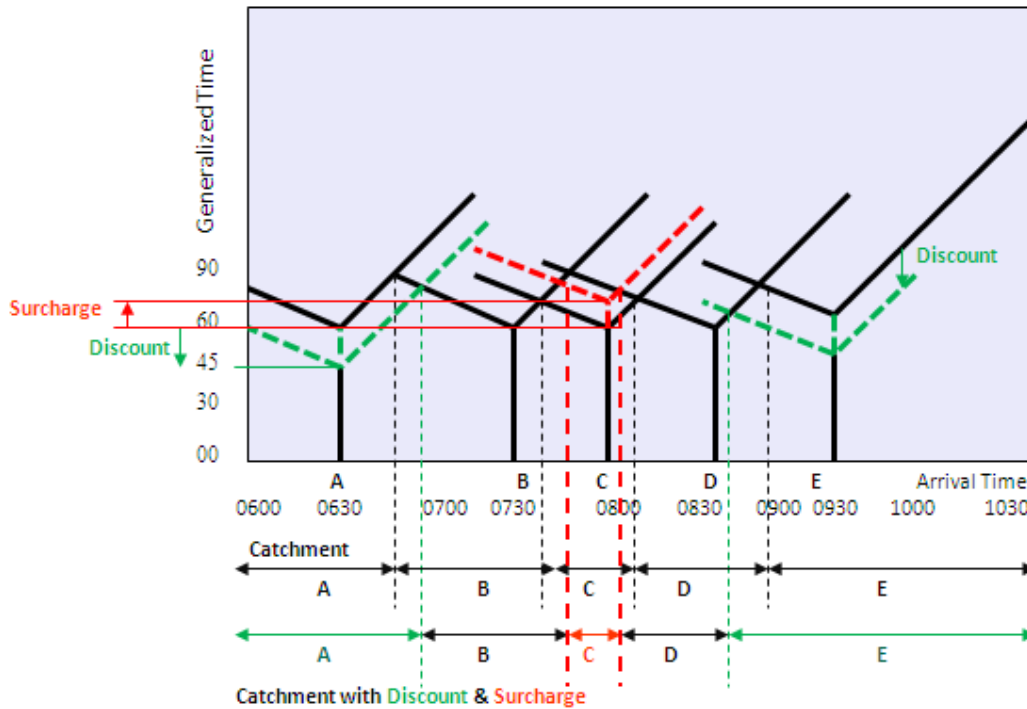
So far the rooftops model has considered onboard train time and arrival time. This is fine when the same fares are charged on all services but if different fares are charged, omitting fare will produce prediction errors since catchments should widen for trains offering discounts and narrow for trains offering surcharges.

The aim of this study was to forecast the effect of fare discounts on early and late trains and surcharges on peak hour trains. Extending the rooftops model to assess fare was not difficult. To assess a fare discount, the equivalent travel time reduction was calculated and subtracted from the onboard time of 'valid' services. For a fare surcharge, the equivalent travel time was added. Detailed analysis of the fares paid by individual passengers was avoided by assuming that the discount and the surcharge would apply equally to all passengers (except school children). Figure 4 on the next page shows the impact of a discount and a surcharge on the choice of trains by passengers. Four train services are shown A, B, C and D. The situation before the fares are introduced is shown with black rooftops and black catchments.

Fare discounts, shown as dashed green lines are introduced onto 'early' train A which arrives at 0630 and on 'late' train D which arrives at 0930. The discounts reduce the vertical height of the rooftop by an equivalent amount of travel time. If the discount was 50 cents per trip and passengers valued onboard train time at \$10/hour, the discount would be equivalent to a 15 minute reduction in onboard train time. As a result, the catchment for train A extends outwards from 0645 to 0650 so that passengers who would previously have chosen train B now switch to train A.

The imposition of a surcharge on train C arriving at 0800 is shown as a dashed red line. The surcharge has the opposite effect of a fare discount and raises the rooftop by an equivalent amount of train time determined by the value of time. The increase in generalised time narrows the train's catchment so that train C loses patronage to train's B and D.

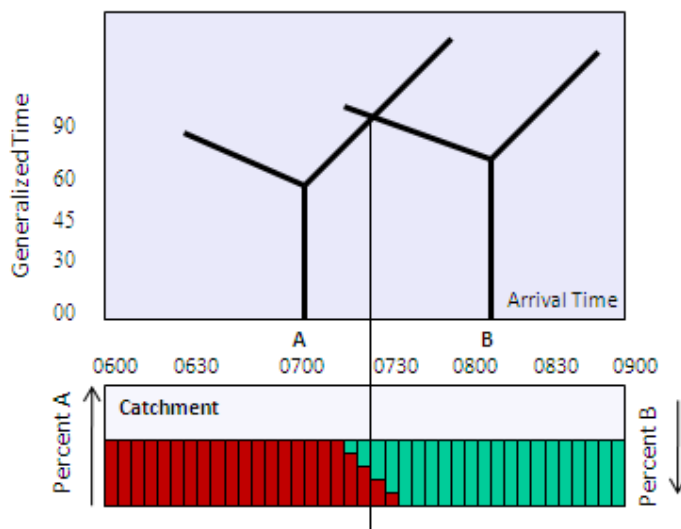
Figure 4: Impact of Fare Discounts & Surcharges



1.4 Probabilistic train assignment

Most 'rooftops' models have used 'all or nothing' assignment which means that a train one minute quicker would capture all patronage but a minute slower would capture none. An alternative approach is probabilistic assignment. Probabilistic assignment calculates the chance of a passenger choosing a train based on the relative generalised time to other trains. The result is a shaded (fuzzy) gradation demarking train competitiveness instead of vertical lines. Figure 5 shows the assignment as a set of percentage bands choosing train A that vary from 0% to 100% (the mirror image for train B).

Figure 5: Probabilistic Assignment



Mathematically, the probability of choosing the train i for time 'slot' j ($\Pr(T_{ij})$) was determined by its travel time (GT_{ij}) compared to all other trains, equation 1. The separation parameter β governs the fuzziness and introduces a proxy for variations in the value of time and displacement between passengers: the lower the value of β (ignoring sign) the less clear cut are the train catchment boundaries.

$$\Pr(T_{ij}) = \frac{\exp\{-\beta(GT_{ij})\}}{\sum_i \exp\{-\beta(GT_{ij})\}} \quad \dots(1)$$

The total patronage for train i in time slot j was calculated by multiplying the number of passengers wanting to travel in time slot j by the probability ($\Pr(T_{ij})$). Summing over all time slots j gave the patronage for each train service for station pair k (Q_{ij}), equation 2:

$$Q_{ik} = \sum_j \Pr(ij) \cdot Q_j \quad \dots(2)$$

Summing over all station pairs (k) gave the total load per train (Q_i), equation 3:

$$Q_i = \sum_k Q_{ik} \quad \dots(3)$$

2. Case example

The Illawarra line including South Coast intercity services was used as a case study.¹ The Illawarra suburban line is particularly highly loaded and achieved the highest AM Peak passenger loading across the Sydney network with loads reaching 135% of seat capacity based on load surveys at cordon stations undertaken by RailCorp in March 2010. The suburban line carries 32,000 passengers in the 3.5 hour AM Peak 0600-0930. South Coast intercity services from Bomaderry, Port Kembla and Wollongong carry a further 8,000 passengers. Table 1 presents the loading figures for suburban and intercity services.

**Table 1: Average Loads on Morning Peak Illawarra Trains to Sydney CBD
RailCorp Loading Surveys March 2010**

Line		One Hour Peak 0800-0859 (Central Time)				3.5 hr Peak 0600-0930 (Sydenham Time)			
(Survey Station)	Service	Trains	Seats	Pax	LF	Trains	Seats	Pax	LF
Illawarra	Cronulla	4	3,520	5,120	145%	12	10,586	11,590	110%
(Sydenham)	Waterfall/Thirroul/S'land	6	5,088	7,355	145%	13	11,086	12,490	115%
	Hurstville/Mortdale	4	3,546	4,050	115%	12	10,344	7,425	70%
	Suburban Total	14	12,154	16,525	135%	37	32,016	31,505	100%
Line		One Hour Peak 0729-0828 (Central Time)				3.5 hr Pk 0530-0900 (Helensburgh Time)			
(Survey Station)	Service	Trains	Seats	Pax	LF	Trains	Seats	Pax	LF
South Coast	Kiama/Dapto/P. Kembla	3	2,560	1,410	55%	9	5,520	3,240	60%
(Helensburgh)	Thirroul - Bondi Junction	2	1,704	50	5%	3	2,516	60	0%
	South Coast Total	5	4,264	1,460	35%	12	8,036	3,300	40%

Travel time profiles were developed to describe when passengers want to travel. The profiles were based on barrier exit data. Two profiles were developed: one for adult passengers and one for school children. A separate profile was developed for school children, who account for 9% of total journeys, to allow for their more peaked travel profile

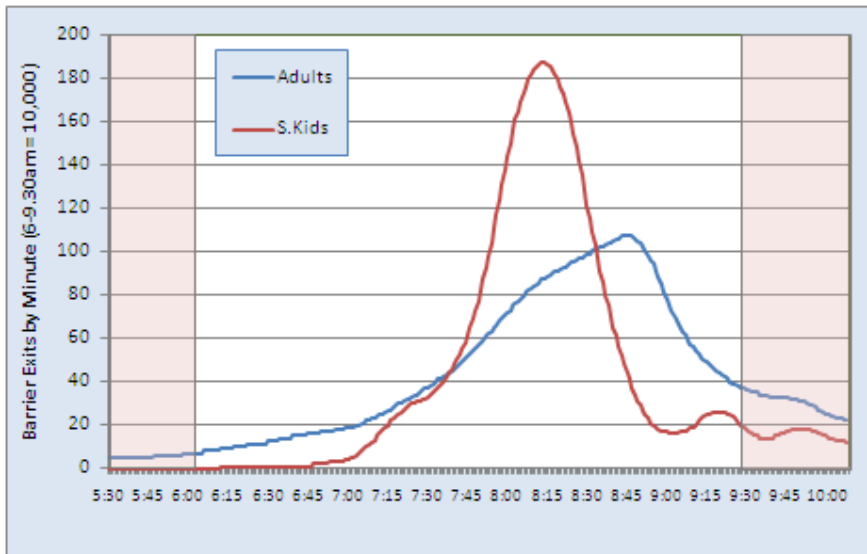
¹ South Coast intercity services were included because their stopping pattern overlaps those of suburban services; all intercity services stop at Hurstville for example.

and also to enable the effect of a fare discount or surcharge to be limited to adult passengers.

Each profile represents the percentage of passengers wanting to exit at their destination station during a particular minute. The two profiles were scaled so that adult and school children each total 10,000 over the 3½ hour period. Thus if the exit profile had been constant, 48 adults would have exited the ticket barrier per minute. The two profiles were then extended over 'buffer periods' which were added to enable forecasts of early and late peak period trains.

It is worth noting that barrier data is only a 'proxy profile' for the ideal travel time of passengers. An associated survey of 1,790 passengers contained questions about the ideal travel time (Henn, Douglas and Sloan, 2011) found that 80% were travelling at the 'ideal time' and a further 17%, were within 15 mins of their ideal time (with 13% preferring a train earlier and 4% a train later). In total, 97% were travelling within 15 minutes of their ideal time and only 3% were travelling outside of 15 minutes of their ideal time.

Figure 6: Barrier Exit Profile in the AM Peak



3. Values of time, displacement and separation

The parameters used in the rooftops model were estimated by passenger surveys carried out in Aug-Dec 2010 across the Sydney metropolitan rail network. Interviewers presented passengers with a series of paired choices and asked passengers which train service they would use out of each pair.

The train services varied in terms of the departure time, time spent on the train and the fare. Figure 7 presents one of the choices. Train A departs 40 minutes earlier than now, takes 10 minutes longer than now and has the same fare as now whereas train B departs as now, takes the same time as now but costs \$4 more. Thus, passengers were effectively being asked whether they would be willing to pay \$4 more to avoid a ten minute longer trip that departs 40 minutes earlier.

Fifty choices were designed to give a statistically controlled experimental design. Each respondent completed a set of eight or nine choices. Five fare 'levels' were included in the experimental design. Three levels specified an increase (or surcharge) of \$2, \$3 or \$5 and two levels specified a decrease (discount) of either \$2 or \$3. It was therefore possible to assess whether passengers were more or less sensitive to a dollar discount as to a dollar surcharge.

The survey was also designed to assess whether passengers valued late displacement more than early displacement. 25 choices featured departing later by 15, 20, 30, 40 or 60 minutes and 25 choices departing earlier.

Onboard time varied around the current time with train B either 5 or 15 minutes faster than now or 10 or 15 minutes quicker.

Figure 7: Stated preference example choice

10	A	B
 Depart	40 mins Earlier than now	 Depart as now
 On train	10 mins Longer	 On train as now
 Fare	as now	 Fare Single \$4 More Weekly \$44 Conc \$2

The survey interviewed 1,119 passengers over the off-peak as well as the peak period. For this study, only peak interviews were included which reduced the sample to 786 interviews.

The average percentage choosing train A was calculated for each fare, travel time and displacement level. Figure 8 shows the relationships. All three graphs slope upwards to the right with more passengers choosing train A, the greater the travel time and fare of train B.

In all three sets of graphs, the percentage choosing train A was higher when train B departed later than when it departed earlier which implies passengers were more averse to travelling later than earlier. The slope was also steeper for late displacement than for early displacement. In terms of sensitivity, the response to the differences in fare was the least sensitive. The fare graph also shows respondents were less sensitive to fare discounts (white filled squares and diamonds) than to surcharges (brown and blue filled squares and diamonds).

A model, similar to equation 1, was fitted using Maximum Likelihood to explain the probability of individuals choosing train A. For fare, discount and surcharge variables were introduced to allow for difference sensitivity. The model was estimated without a constant

since passengers should be indifferent to the two trains when travel times and costs were the same.

Figure 8: Response to the stated preference choices
Percentage choosing train A for each attribute level

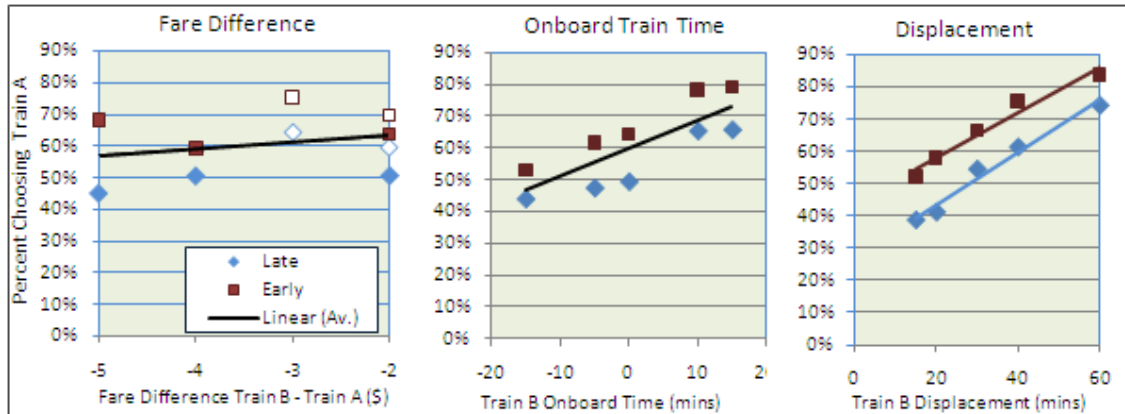


Table 2 presents the parameter estimates. All five parameters were positive as expected, of reasonable magnitude and statistically significant at the 95% confidence level with $|t|$ values greater than 1.96.² The late displacement parameter was the strongest with a t value of 18.5 and the discount fare parameter was the weakest with a t value of 2.7.

Table 2: Stated preference survey parameter estimates

Parameter	β	Std Err	$ t $
Early Displacement	0.021	0.002	10.5
Late Displacement	0.037	0.002	18.5
Ontrain Time	0.040	0.003	13.3
Fare Surcharge	0.177	0.015	11.8
Fare Discount	0.071	0.026	2.7
Observations		6,063	
Interviews		786	
Predicted Choice Correct		67%	

Passengers were more sensitive to late displacement than early displacement which is reflected in parameter estimates of 0.037 and 0.021 respectively. Passengers were also more sensitive to a fare surcharge than to a discount (dollar for dollar). Table 3 presents the relative value of the parameters with early and late displacement expressed relative to onboard train time and onboard time expressed in dollars per hour.

Table 3: Parameter relative values

Relative Valuation	Mean	Std Err	$ t $
Early Displacement / Onboard Time	0.53	0.06	9.4
Late Displacement / Onboard Time	0.93	0.08	11.3
Value of Onboard Time/ Surcharge \$/hr	13.56	1.47	9.2
Value of Onboard Time/ Discount \$/hr	33.80	12.52	2.7

² The t value is the ratio of mean estimate over the standard error. It is noted that statistical packages often output Wald statistics rather than t statistics. Wald statistics are related to the F test of variance and usually give a higher test statistic than the t test.

Onboard train time was valued much higher relative to a fare discount than to a surcharge which reflects the smaller size of the discount sensitivity parameter in Table 2 (the denominator in the value of time). The smaller discount parameter produced a value of time of \$33.80 which was 2.5 times higher than the surcharge value of \$13.56 per hour.

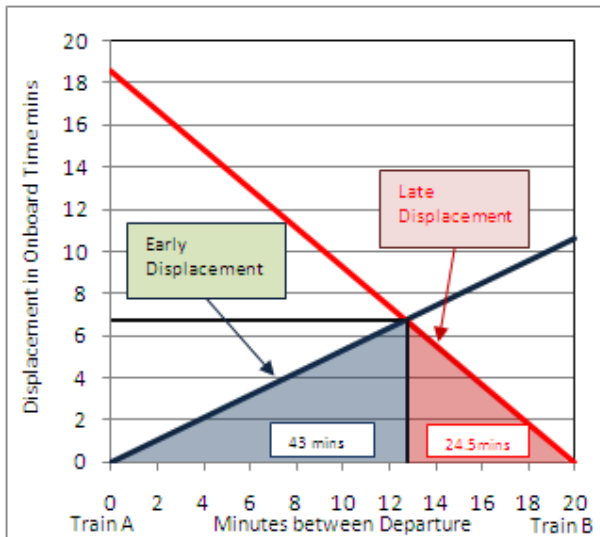
The surcharge value was reasonably close to the value of \$12.85 per hour published in the 2010 CityRail Compendium, RailCorp (2010). The Compendium value was an update of a 2003 market research survey which was similar to the 2010 survey but one where fares were not varied around the passenger's current fare to distinguish between fare discounts and surcharges.

The discount value may be viewed as a 'Willingness to Accept' (WTA) valuation and the surcharge value a 'Willingness to Pay' (WTP) valuation. Some support was found in the literature for WTA valuations of time to diverge from WTP valuations, e.g. Ramjerdi and Dillen (2007).

Travel time displacement was valued lower than onboard train time. Late displacement was valued 93% of onboard time and early displacement 53%. Averaging the early and late values gave a relative value of displacement of 0.73; this value compares with values of 1.29 for work trips and 0.57 for education/other trips estimated by Ashley and McPherson (op cit) for regional fast trains in Victoria. With a 70% work 30% education split, the average value would be just over 1 which is higher than the Sydney value. Ashley and McPherson did not give values for early and late displacement.

Most studies estimate values for service interval rather than displacement. As Figure 9 demonstrates, the two values are not the same. Two trains (A and B) depart at zero and 20 minutes past the hour which gives a service interval or headway between the trains of 20 minutes. The average wait time would be 10 minutes if passengers turned up at random which is 0.5 times the service interval.

Figure 9: Value of displacement and service interval



The early and late valuations obtained from the survey are graphed. The late displacement value of 0.93 is steeper than the early displacement value of 0.53 which extends the catchment of train A to 12.34 minutes and contracts that of train B to capture 7.26 minutes as opposed to an equal ten minute share each.

Total displacement is the area of the two triangles under the displacement lines: early displacement imposes a cost of 43 minutes and late displacement 24.5 minutes. Total displacement was therefore 67.5 minutes with an average displacement of 3.375 minutes (67.5/20). Displacement was valued 0.17 times the service interval (3.375/20).³

CityRail uses a value of 0.77 to measure the time cost of service interval to peak passengers. If passengers turned up at the station at random the average wait would be half the service interval (or headway). If passengers valued waiting time equal to onboard train time, the value of service interval would be 0.5. However, the conventional rule is to value waiting time twice that of onboard train time which would produce a service interval value of 1. At 0.77, the value of service interval is greater than 0.5 and less than 1. Either passengers do not arrive at random or value waiting time less than twice on board time (or both).

The estimated value of displacement at 0.17 is one fifth of the RailCorp service interval valuation. Its relatively low value suggests that waiting time is the dominant component of service frequency for peak passengers rather than travel time displacement.⁴

Four monetary values of displacement were derived from the survey: discount-early displacement, discount-late, surcharge-early and surcharge-late. The values were calculated by multiplying the value of onboard time (discount or surcharge) by the value of displacement (early or late). The highest value was the discount value of late displacement with passengers requiring a fare discount of \$31.43 to travel an hour later. The lowest was the surcharge value of early displacement with passengers willing to pay \$7.19 to avoid travelling an hour earlier. The other two values were a discount value of early displacement of \$17.91 per hour and a surcharge value of late displacement of \$12.61 per hour.

4. Model calibration

RailCorp undertakes regular counts of train passenger loads and reports summaries annually in the “CityRail Compendium”, RailCorp (2010).⁵ The count data enabled the loads predicted by the rooftops model to be compared with observed counts. Ten counts were obtained covering a four year period (2005 – 2009) when the timetable remained largely unchanged. A mean load for each service and a tolerance range was calculated for each service.⁶

The tolerance range was calculated using the lowest and highest counts for each service. The tolerance range is useful since observed train loads vary from day to day and are affected by observation ‘error’. In essence, the modelled loads are being compared against a fuzzy bulls-eye. Figure 10 compares the predicted loads with the 2009 RailCorp observed load.

³ Had both early and late displacement been valued equal to onboard time (i.e. valued at 1), the displacement cost would have been five minutes which is exactly half the average wait and 25% of the 20 minute service interval.

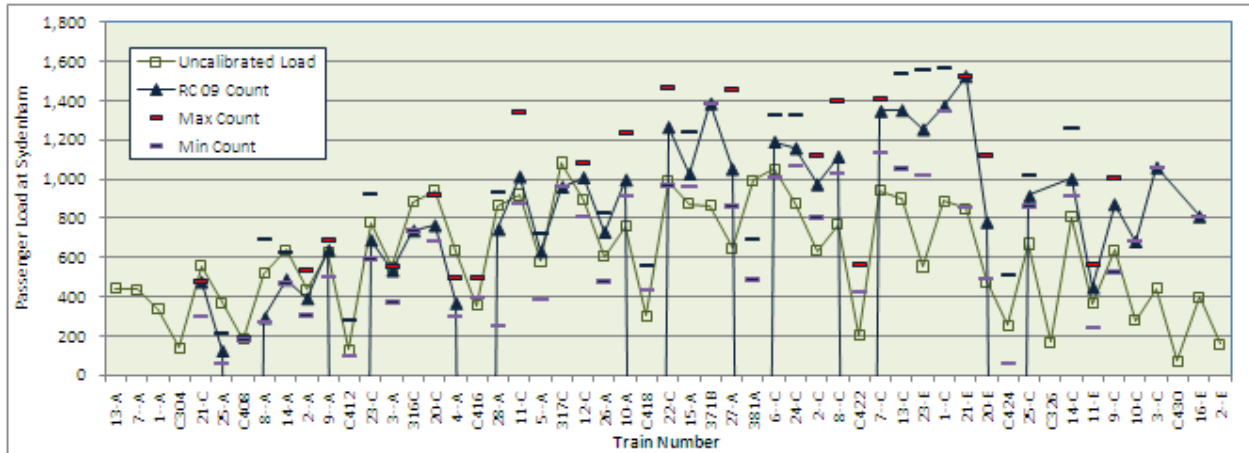
⁴ With a conventional value of waiting time twice onboard train time and assuming passengers who plan their trip arrive 3 minutes before departure (worth 6 minutes of onboard time), the proportion of passengers required to turn up at random is 57% to achieve a service interval valuation of 0.77 with displacement valued at 0.17 of service interval.

⁵ Illawarra train services (excluding intercity services) are surveyed as they depart Sydenham station. South Coast intercity services are surveyed departing Helensburgh.

⁶ It would also be possible to construct a goodness of fit measure akin to the Coefficient of Determination or R^2 in regression analysis. The study by Douglas Economics and Trainbrain for ITSRR calculated such a measure.

The trains are listed in chronological order. The 2009 observed load was only provided for suburban services at the inner cordon station. Intercity loads (usually denoted with a 'C') were not observed at the cordon station which produces the vertical blue lines. As can be seen, the uncalibrated loads tended to be lower than the observed loads for trains in the middle of the peak and also at the end whereas for early peak trains, the predicted loads tended to be higher than the observed loads. In terms of tolerance, 44% of loads were predicted within the range of the observed counts.⁷

Figure 10: Comparison of predicted and observed train loads



Factors were calculated to reduce the difference between the predicted and observed loads for adult trips. Two calibration factors were created: an overall factor to match the observed loading count and a temporal factor which adjusted the desired travel time profile. The two factors were calculated six times. Each successive step used the results of the previous step. Table 4 presents the factors. Also presented is the tolerance statistic which increased from 54% of trains being within the acceptable range to 61%.

Table 4: Calibration statistics

	Overall Load Factor by Factoring Step					
	1	2	3	4	5	6
Model	37,354	39,860	38,495	38,103	37,689	37,492
Count	37,039	37,039	37,039	37,039	37,039	37,039
Error	315	2,821	1,456	1,063	650	453
Model/Count	101%	108%	104%	103%	102%	101%
Trip Factor	99%	93%	96%	97%	98%	99%

	Percentage of Train Loads within Tolerance by Factoring Step					
	1	2	3	4	5	6
Percent Right	54%	54%	59%	61%	61%	61%

Figure 11 shows how calibration reduced the loads for early trains and increased the loads for mid and late peak trains.

The factoring also altered the desired travel time profile as shown in Figure 12 to produce a far more peaked adult profile than the starting distribution which was based on barrier exits.

⁷ The tolerance analysis was based on 41 trains for which the measured could be calculated.

Figure 11: Percentage difference in calibrated versus uncalibrated load

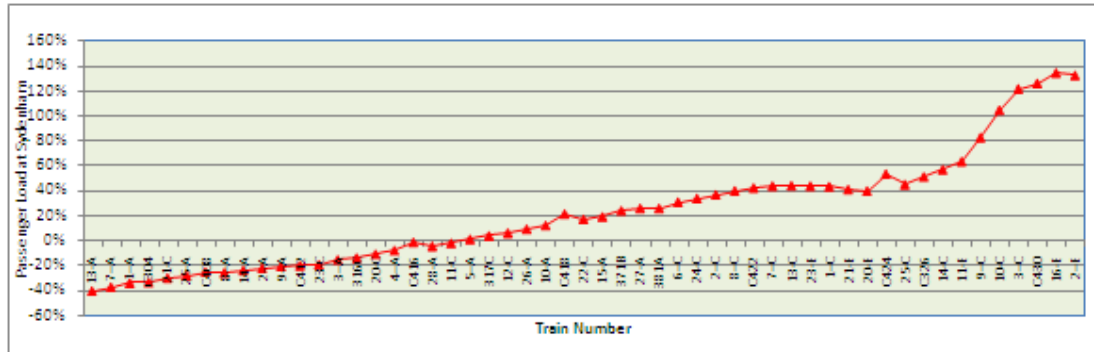
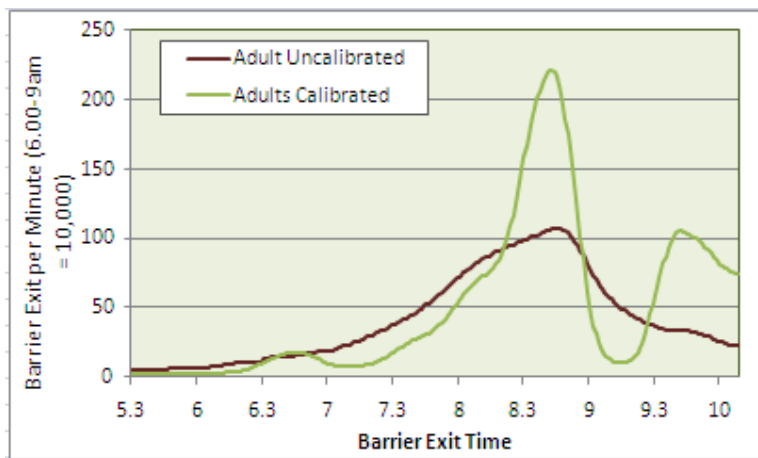


Figure 12: Uncalibrated and calibrated desired travel time profiles



5. Model forecasts

The calibrated rooftops model was used to predict the effectiveness of fare discounts and fare surcharges in spreading passenger loads across the AM peak. Ten fare policies were assessed:

1. 10% Fare discount on trains arriving Central before 0800
2. 10% Fare discount on trains arriving Central after 0900
3. 30% Fare discount on trains arriving Central before 0800
4. 30% Fare discount on trains arriving Central after 0900
5. 10% Fare discount on trains arriving Central before 0800 and after 0900
6. 30% Fare discount on trains arriving Central before 0800 and after 0900
7. 10% fare surcharge on train arriving Central between 0800 and 0900
8. 30% fare surcharge on trains arriving Central between 0800 and 0900
9. 10% fare discount on trains arriving Central before 0800 and after 0900 and a 30% fare surcharge on trains arriving between 0800 and 0900
10. 30% fare discount on trains arriving Central before 0800 and after 0900 and a 30% fare surcharge on trains arriving between 0800 and 0900

The fare discounts and surcharges were applied to all adult passengers travelling on affected trains. School children were assumed to be unaffected. The average adult fare was set at \$3.30 based on survey results. The discounts and surcharges were introduced as flat fare changes affecting all adult trips equally. A 10% discount therefore reduced the adult fare

by 33 cents per trip. With the discount value of time of \$33.80 per hour, the fare discount was equivalent to a reduction in onboard travel time of 0.6 minutes. By comparison, a 10% surcharge had a greater 'time' of 1.46 minutes because of the lower value of time of \$13.56 per hour.

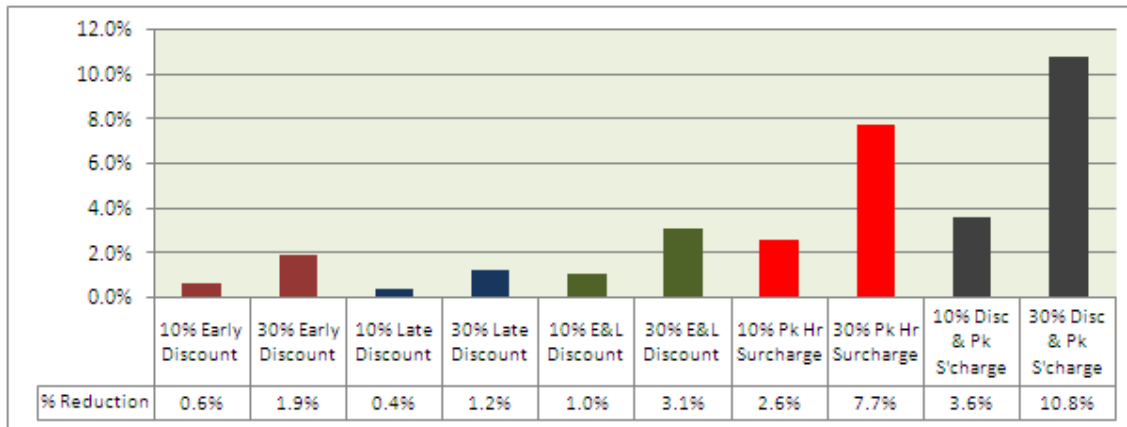
A key limitation of the forecasts is that the forecasts assume that total rail patronage would be unaffected i.e. that the fare discounts and surcharges would not generate or suppress AM peak rail patronage. This assumption could be relaxed in future work by applying elasticities.

The impact of the ten incentives on early peak, peak hour and late peak train loads is presented in Table 5 and Figure 13.

Table 5: Patronage impacts of fare incentives

Test	Incentive	Early Peak Before 0800	Peak Hour 0800-0900	Late Peak 0900-1000
1	10% Early Discount (Before 8am)	1.1%	-0.6%	-0.3%
2	30% Early Discount (Before 8am)	3.2%	-1.9%	-1.0%
3	10% Late Discount (After 9am)	-0.2%	-0.4%	1.2%
4	30% Late Discount (After 9am)	-0.6%	-1.2%	3.7%
5	10% Early & Late Discount	0.9%	-1.0%	0.9%
6	30% Early & Late Discount	2.6%	-3.1%	2.7%
7	10% Peak Hour Surcharge (8-9am)	2.1%	-2.6%	2.2%
8	30% Peak Hour Surcharge (8-9am)	6.4%	-7.7%	6.6%
9	10% Early & Late Discount & 10% Peak Hr Surcharge	3.0%	-3.6%	3.1%
10	30% Early & Late Discount & 30% Peak Hr Surcharge	9.0%	-10.8%	9.2%

Figure 13: Impact of fare incentive on peak hour train load
Train passenger loads measured at Sydenham



The reduction in peak hour loads ranged from 0.4% for a 10% discount on late peak trains to 10.8% for a combined 30% discount on early and late trains and a 30% surcharge on peak hour trains.

Peak hour surcharges had more than double the impact of discounts on early and late peak trains. With a 30% fare change, the peak hour surcharge reduced peak loads by 7.7% compared to 3.1% for a discount on early and late peak trains.

Fare discounts were also predicted to be more effective on early than late peak trains. For a 30% fare reduction, discounting early peak trains reduced peak hour loads by 1.9% compared to 0.6% for late peak trains.

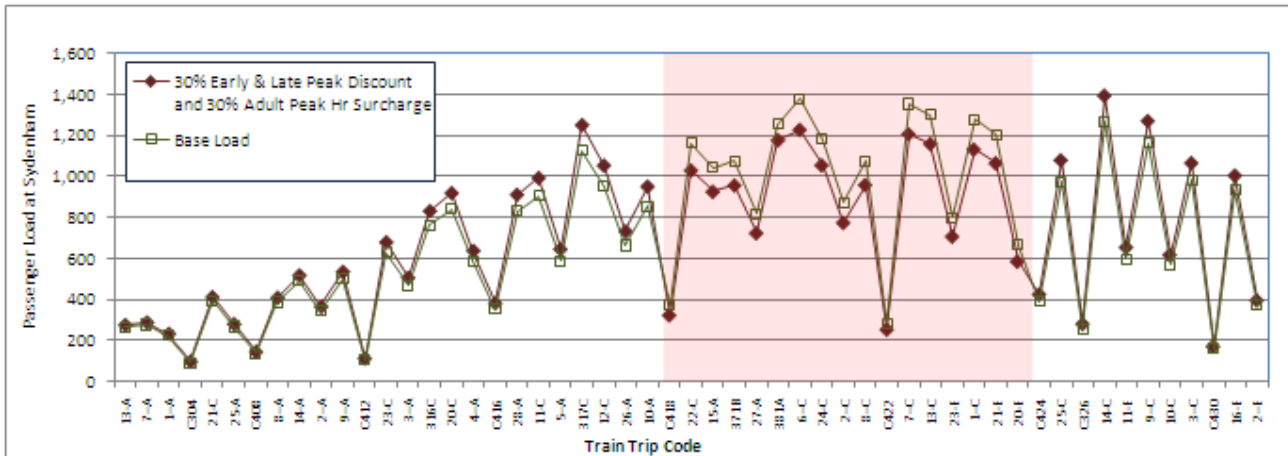
The model also predicted impacts to extend beyond the peak hour. For example, a 30% fare discount on early peak trains reduced late peak loads by 1% as well as reducing peak hour loads by 1.9%. This effect results from using a logistic function with a separation parameter (β) of -0.04 rather than adopting 'all or nothing' assignment that characterises the standard rooftops model. As a result, displacement occurs throughout the peak hour rather than being confined to trains immediately either side when the fare discounts and surcharges come into effect (i.e. 8am and 9am).

Peak hour surcharges had more than double the impact of early and late peak discounts. With a 30% fare change, the peak hour surcharge reduced peak hour loads by 7.7% compared to 3.1% for a discount on early and late peak trains.

Fare discounts were also predicted to be more effective on early than late peak trains. For a 30% fare reduction, discounting early peak trains reduced peak hour loads by 1.9% compared to a 0.6% on late peak trains.

Figure 14 shows the impact on individual train loads of test 10 which involved a 30% fare surcharge on peak hours trains combined with a 30% discount on early (arriving Central before 0800) and late (arriving after 0900) trains. The loads for peak hour trains (shown in the shaded rectangle) are reduced by the fare incentives and the loads of early and late trains especially those close to 8am and 9am increased. The impact on intercity trains (which have a train trip code starting with C) tended to be less than for suburban trains because they are less frequent which increases the displacement cost.

Figure 14: Impact on train loads of peak period fare incentives
30% discount on early & late peak trains and 30% surcharge on peak hour trains
Passenger loads measured at Sydenham



5. Conclusions

Hotelling's neat approach to modelling spatial location decisions also lends itself to modelling rail passengers' choice of service by creating 'rooftop' catchments for individual trains. By adding in fare, it is possible to assess the ability of 'carrot and stick' fare policies to spread patronage more evenly over the peak period.

The market research undertaken to derive parameters for a 'rooftops' model established that travelling later than desired had a greater displacement cost than travelling earlier. Passengers were also more sensitive to a fare surcharge than to a discount which resulted

in an asymmetry in the value of time. Passengers were less willing to pay more to save time than they were to accept a fare discount for a longer travel time.

The behavioural parameters when included in a model of train choice for an example rail corridor in Sydney forecast that fare discounts on early and late peak trains would be less effective than surcharges imposed on peak hour trains. The spreading of peak loads was maximised when discounts and surcharges were introduced in combination. With a 30% discount offered on early and late peak trains and a 30% surcharge imposed on peak hour trains, peak hour loads were forecast to reduce by just over 10%.

References

- Ashley D. and McPherson C., (2004) *“Estimating Passenger Demand for Fast Rail Services with the Rooftop Model”*, ATRF Adelaide, 2004.
- Douglas Economics & Trainbrain (2009) *“Modelling Passenger Loads and the Impact of Changes to the CityRail Timetable”*, Report to the Independent Transport Safety and Reliability Regulator NSW, April 2009.
- Harrell L., (1987) *“Investigation of the Effects of the Timing and Frequency of Secondary Rail Services on Passenger Demand”*, Cranfield, MSc Dissertation 1987.
- Henn L., Douglas N.J. and Sloan K. (2011) *“The Potential for Displacing Sydney Peak Hour Commuters”*, 34th Australian Transport Research Forum, Adelaide 2011.
- Hotelling H., (1929) *“Stability in Competition”*, The Economic Journal, 39, 1929: 41-57.
- RailCorp (2008) *“A Compendium of CityRail Travel Statistics - Sixth Edition”*, June 2008 RailCorp Sydney.
- RailCorp (2010) *“A Compendium of CityRail Travel Statistics – Seventh Edition”*, July 2010 RailCorp, Sydney.
- Ramjerdi F. and Dillen J. L., (2007) *“Gap between Willingness-to-Pay (WTP) and Willingness-to-Accept (WTA) Measures of Value of Travel Time: Evidence from Norway and Sweden”*, *Transport Reviews*, September, Vol. 27, No. 5, p. 637–651.
- Tyler J. and Hassard R., (1973) *“Gravity/Elasticity Models for the Planning of the Inter-Urban Rail Passenger Business”*, PTRC Annual Meeting University of Sussex.
- UK Passenger Demand Forecasting Council (2002) *“Passenger Demand Forecasting Handbook”*, August 2002.