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Review of Traffic Forecasting Performance
Toll Roads

Executive Summary

This paper reviews the traffic forecasting performance of toll roads, explores the potential sources of forecasting errors through a literature review and suggest some possible measures that may be used to reduce traffic forecasting errors.

In general, the forecasting performance for toll roads in the world has been found to be poorer than for toll-free roads. There is an asymmetrical pattern of forecasting errors, that is, consistent overestimation. Australia is no exception. Anecdotal evidence suggests that the forecasting performance for Australian toll roads may have been even worse than the world average.

Forecasting errors can be caused by many factors including inadequate models, data limitations, uncertainties in socio-economic and land use forecasts, ramp-up risks, and optimism bias and/or strategic mis-representation.

Forecasting errors can never be eliminated, but they can and should be reduced to a more acceptable level and made more symmetrical. The existing literature has highlighted a number of areas where improvements can be made in traffic forecasting. These, supplemented by some Australian case studies, should form the basis for designing effective measures to mitigate traffic forecasting risks for Australian toll roads.

1 Introduction

Traffic forecasts for Australian toll roads have proven to be highly inaccurate in recent years. Overly optimistic patronage forecasts can

- direct scarce resources to underperforming investments, which reduces productivity
- make it more difficult to attract private-sector funding for future worthwhile infrastructure projects (no PPP in Australia with patronage risk attached has gone ahead since the Global Financial Crisis), and
- hurt investors, possibly reducing confidence in Australia's investment regime.

This discussion paper provides an overview of traffic forecasting performance, investigates the sources of forecast inaccuracy and provides suggestions on how to correct any issues identified.

The methods used to produce urban traffic forecasts are very complex and data intensive. In addition they require a wide range of assumptions about future changes in socio-economic and land use variables. The issue is further complicated by the possible presence of optimism bias and/or strategic misrepresentation in traffic forecasting. Consequently, the potential sources of forecast inaccuracy are many and errors can be compounding. As a first step towards a better understanding of traffic forecasting risks, this paper seeks to provide a desktop-based review of:

- the accuracy of recent traffic forecasts in Australia and also overseas
- the potential sources of forecast inaccuracy, and
- the possible strategies that may be used to reduce forecasting errors.

Ideally, the review would include case studies that would highlight the sources of forecast inaccuracy in the Australian context. Case studies are currently being undertaken by GHD and are expected to be complete by September 2011.

2 Review of accuracies of traffic forecasts

Inaccuracies in traffic forecasts have attracted increased attention from toll road investors, operators, media, financial institutions and governments. Inaccurate traffic forecasts threaten the financial viability of the toll road industry, distort public decisions with respect to risk sharing and resource allocation, and cause costly negotiations (Prozzi et al. 2009).

Bain (2009) provided a review of selected studies that examine the predictive accuracy of traffic forecasting models from different parts of the world, including

- JP Morgan (1997) – USA
- Standard & Poor's (Bain et al. 2002, 2003, 2004 & 2005) – International
- Flyvberg et al. (2005) – International
- US Transport Research Board (Kriger et al. 2006) – USA
- Vassallo (2007) – Spain

- Li and Hensher (2010) – Australia

The international and Australian evidence is briefly reviewed and summarised below.[1]

International evidence

Standard & Poor's (Bain et al. 2002, 2003, 2004 & 2005)

The work undertaken by Bain et al. (2002, 2003, 2004 and 2005) for Standard & Poor's reflects strenuous efforts by a credit rating agency to critically examine toll road traffic forecasting accuracy. Over four years, the rating agency compiled a database containing information on 104 international toll roads, bridges and tunnels. Bain et al. (2002, 2003, 2004 and 2005) used the ratio of actual traffic to forecast traffic to measure inaccuracies in traffic forecasting. Their research focused on the ramp-up period, which is considered to be the most uncertain period of a toll facility.

A number of important conclusions emerge from Bain et al.'s research.

- The mean of the error distribution was found to be 0.77 for the first year of operations (Bain et al. 2005), implying that, on average, actual traffic volumes were 23 per cent below the forecast levels.
- The standard deviation was quite large (0.26), suggesting that there was a wide variation around the mean (Bain et al. 2005).
- There was no evidence of any improvement in predictive performance after year one, with the mean ratio in the range at 0.77–0.80 between year 1 and year 5 (Bain et al. 2005).
- Errors in forecasts of truck usage were even more variable than those made for cars with the standard deviation estimated to be 0.33 (Bain et al. 2005).
- Inaccuracies in traffic forecasts were larger for toll roads (0.76) than for non-toll roads (0.96) (Bain et al. 2004).
- On average, overestimation of traffic was more prevalent in countries with no history of tolling than those with a history of tolling (Bain et al. 2003).

Flyvberg et al. (2005 and 2006)

Flyvbjerg et al. (2005 and 2006) conducted one of the most comprehensive evaluations of the accuracy of traffic forecasts covering 183 road projects (170 highways, ten bridges and three tunnels around the world). The inaccuracy in traffic forecasts is defined as the difference between the actual and forecast traffic divided by the forecast traffic multiplied by 100 (formula 1). The focus of Flyvbjerg et al.'s work was on toll free roads (90 per cent). Key findings included:

- for half of the road projects analysed, the forecasting errors were at least +/- 20 per cent;
- for a quarter of the road projects, the forecasting errors were at least +/- 40 per cent;

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[1] For country-specific reviews, refer to Bain (2009) or cited references.

- there has been no improvement in the accuracy of traffic forecasting over the past 30 years.

Flyvbjerg et al. (2005 and 2006) also found that the main contributors to the forecasting errors were outdated or incomplete traffic data used at the 'trip generation step' and inappropriate assumptions made about land use development on the basis of land use plans.

Evidence from Australia

Li and Hensher (2010) compared, where possible, actual and forecast traffic levels for 14 Australian toll roads (nine motor ways, three tunnels and two bridges), the majority of which were public-private partnerships (PPPs) with concessions. For 5 roads (M2, M7, Cross-City Tunnel, Lane Cove Tunnel and EastLink), data on both actual and forecast traffic were available for the first year of operations. On average, actual traffic volumes were found to be 45 per cent below the forecast levels. However, given the small size of the sample, it is not clear whether this result is statistically different from the Bain et al. (2002, 2003, 2004 and 2005) findings (23 per cent).

Li and Hensher (2010) also collected some data beyond the first year of operation allowing them to analyse trends in forecasting errors. Their observation was that forecasting errors had become smaller over time, though in some cases actual traffic volumes were still 19 per cent lower than forecasts after six years of operations.

3   Sources of inaccuracies in traffic forecasts

Inaccuracies in traffic forecasts can be caused by many factors including inadequate model structure, limitations of data, uncertainties in input assumptions, ramp up risks and optimism bias and/or strategic misrepresentation. Each of these factors is discussed in some detail below.

Model adequacy

There is a wide range of models that can be used to model toll road traffic demand, including simple spreadsheet models, traditional four-step traffic models and newly emerging tour- or activity-based micro-simulation models. Currently, the general practice is to build upon the existing four-step traffic models originally intended to serve transport planning in the era of capacity expansion (Pendyala 2005). Although this observation is made with respect to most other countries in the world, it may also be true for Australia. Anecdotal evidence suggests that most tools used to estimate the traffic demand for the past Australian PPP/toll road projects belong to the family of four-step transport models.[2] For example the model used by Maunsell for the CLEM7 traffic forecasts was adapted from the Brisbane Strategic Transport Model (RiverCity Motorway 2006) and the model used by Hyder Consulting for EastLink was adapted from the Melbourne Integrated Transport Model (ConnectEast 2004), both four-step models. This raises the question about the suitability of the four-step models for analysing the impact of tolling/pricing policies.

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[2]   The exception is the Sydney Strategic Travel Model, which is a tour-based (though not an activity-based) model (SKM 2009).

A typical four-step urban transport model is illustrated in Figure 2. An important feature of the traditional four-step model is that it is a recursive system with a unidirectional causal relationship. The sub-models first estimate the total number of trips generated, and then proceed to allocate them to destinations, transport modes and routes in the order shown in Figure 2. Current four-step models, such as the large government-developed strategic models of Australia's largest cities, typically include an iterative feedback loop such that generalised travel costs calculated at the assignment step (which include the effect of congestion) are fed back to the modal split and distribution steps (and much less commonly trip generation). The process is repeated until costs across the steps converge to a consistent value.

Trip generation is the first of four sub-models of travel demand that are used in a conventional transport modelling process. The level of aggregate demand for trips originating in, and attracted to, each study zone is determined by the socio-economic and land-use variables forecast for each zone.

Trip distribution modelling involves allocating the total number of trips originating in each zone to all possible destination zones available. As input, it uses a set of zonal trip productions and attractions, and attempts to estimate the way in which the production and attraction will be linked. The resulting trip distribution matrix can then be disaggregated by trip purpose (work trip, shopping trip, school trip, and so on) and time of day (peak and off-peak hours).

Figure 2   Schematic Diagram of a Conventional Four-step Urban Transport Model
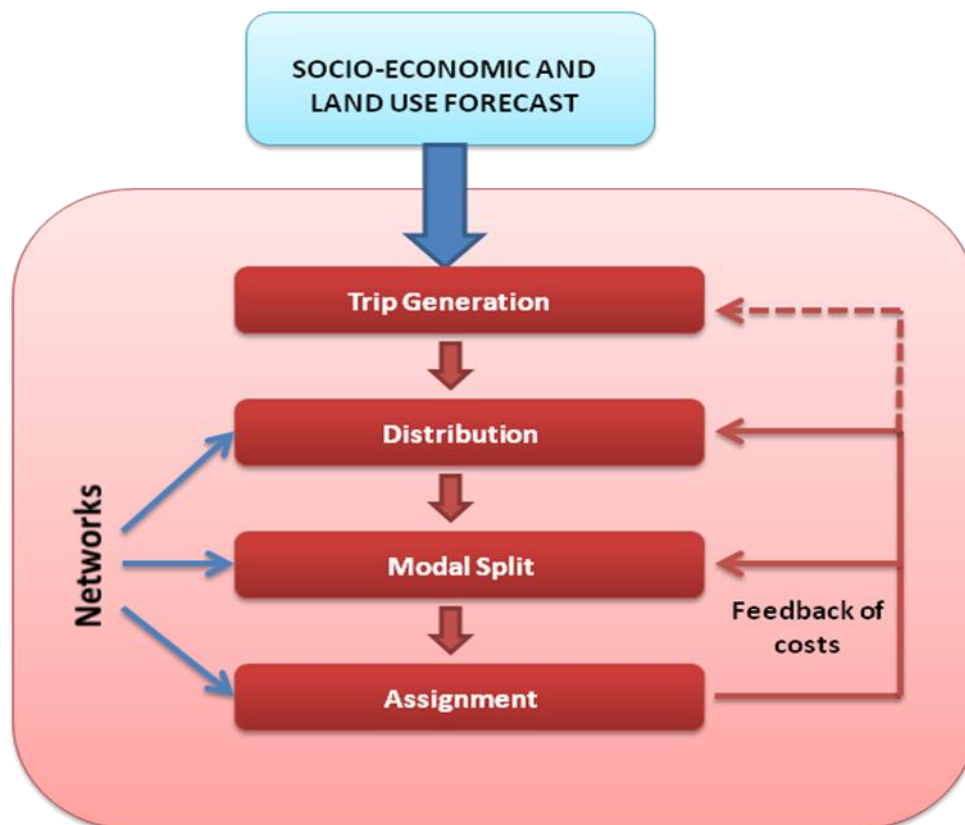
Modelling modal split refers to the allocation or 'distribution' of trips between the various modes available. This step often involves a logit (either binomial or multinomial) analysis based on the economic behavioural theory. The information available for building mode-choice models is the observed modal split, characteristics of the travelling population and the operational characteristics of the competing transport modes.

Traffic assignment modelling distributes traffic among the routes of an urban transport network. Separate assignments are made for each of the different travel modes. The equilibrium assignment approach, consistent with Wardrop's first principle[3], is commonly adopted in this step. Under this approach, traffic would be spread over all the alternative transport routes between a particular zonal pair in such a way that travel time or costs become equal for using these different routes. The result is an equilibrium that is optimal from the viewpoint of each user. No individual traveller can improve his or her utility by finding a route with less travel time or lower travel costs.

Toll road demand modelling can be incorporated into the four-step modelling framework in a number of ways. The most common approach is to introduce it either in the trip assignment step or in the form of diversion models built as a sub-step in the trip assignment step or a post-processor outside the four-step model (Prozzi et al. 2009).

If the toll roads are analysed in the trip assignment step, they are treated as separate links from non-tolled routes. The toll rate can be converted to represent a time penalty, allowing the model to compare it with congestion conditions on the non-tolled routes. The main advantage of addressing toll roads in trip assignment is the ability to evaluate directly the impact of congestion on demand for the toll roads (Spear 2005).

Diversion models are predominantly used by transport consultants to estimate the market share of travellers who would use the toll road (Spear 2005). They typically take the form of a logit function, using the relative cost or travel time between the toll and non-tolled routes as the key explanatory variable to predict the market share of the toll road (Kriger et al. 2006). Data permitting, the curves can be fitted empirically for different market segments (characterised by trip purpose, income level, automobile occupancy and time period) to derive detailed tolled and non-tolled trip tables. The main advantage of using diversion models is that they can be applied without modifying or calibrating the existing model structure. The downside may be that there is no feedback from the diversion models to the earlier sub-models.

The last decade saw a growing body of literature seeking to understand the limitations associated with toll road demand or road pricing modelling in the traditional four-step

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[3] The Wardrop's first principle assumes that each user non-cooperatively seeks to minimise his/her cost of transportation. A user-optimised equilibrium is reached when no user may lower his transportation cost through unilateral action.

transport modelling framework, and their impact on the accuracy, effectiveness and reliability of traffic forecasts. More recent literature includes:

- *Proceedings of Expert Forum on Road Pricing and Travel Demand Modelling* sponsored by the Office of Transportation Policy of the US Department of Transportation in 2005
- the US National Cooperative Highway Research Program (NCHRP) synthesis on estimating toll road demand and revenue prepared by Kriger et al. (2006)
- a case study review of actual versus forecast toll usage undertaken by Prozzi et al. (2009)
- an evaluation of current practices and future directions of metropolitan travel demand forecasting provided by US Transport Research Board (2007), and
- a critical review of transport modelling tools used in Australia undertaken by Sinclair Knight Merz (2009).

The following discussion of limitations of the traditional four-step transport models in the context of toll traffic modelling is largely (though not exclusively) based on the aforementioned literature.

Trip generation

Trip generation is usually assumed to be determined solely by a host of exogenous factors (socio-economic and land-use variables). Travel costs typically do not feature as an explanatory variable in the trip generation models. Increasing congestion across the whole network and rising fuel prices over time will reduce growth in demand for travel. Not accounting for such negative impacts on demand will lead to upward bias in the total number of forecast trips for four-step models that do not feedback cost changes from later steps to trip generation.

Goldberg (2005 and 2006) noted that for some toll toads (Cross City Tunnel and Lane Cove Tunnel), forecast growth in traffic coincides with increasingly poor levels of service as time progresses. This would not only affect the toll road usage but also the total level of travel demand.

Trips are sometimes combined to form chains or tours. If this happens, the number of trips generated may change even though the same activities are pursued by an individual (Penydala 2005). Unfortunately, the potential effect of road pricing on trip chaining patterns cannot be captured within the usual trip-based four-step transport modelling framework.

Trip distribution

The most common form of trip distribution model is the gravity model, where trips between two zones increase with total trips generated or attracted but decrease with cost of travel between the pair. It has begun to be replaced by destination choice models thanks to the developments in behavioural travel demand modelling over the past two decades. Both types of models are sensitive to changes in transport costs between zonal pairs where there is a feedback mechanism from the traffic assignment to the trip distribution step. Trip distribution

tables are usually prepared according to the trip purposes, so the differential impacts of pricing policies on trips for different purposes can normally be captured.

Trip distribution models generally fail to incorporate the temporal dimension of trip distribution, that is time-of-day disaggregation. In the absence of this capability, the model cannot be used to evaluate accurately the impact of any variable road pricing scheme on travel demand (Penydala 2005).

Modal split

Most mode split models are based on behavioural choice modelling, incorporating a host of level of service variables including time and cost as explanatory factors. Mode split models are generally able to reflect changes in mode choice behaviour in response to a road pricing policy.

However, due to the trip-based nature of most examples of the four-step modelling process, mode choice models are not able to capture and reflect the inter-dependency among trips that are linked in chains. Although the mode choice model may suggest a mode shift in response to a road toll, that shift may not be realistic if it is considered in the context of chained trips. The inability to consider constraints associated with trip chaining behaviour is a shortcoming of the traditional trip-based approach to travel forecasting (Penydala 2005).

Traffic assignment

Traditional static equilibrium traffic assignment algorithms are generally able to capture travellers' responses to changes in generalised costs (vehicle operating and time costs) through shifts to lower priced routes given the chosen destination and mode.

A number of risks exist in this step threatening the accuracy of the demand forecasts. (Penydala 2005) identified three factors that may lead to the failure of simulating correctly route choice behaviour in response to a road roll.

- The first factor is related to the ability to code and represent network (node and link) attributes.
- The second factor is concerned with the use of appropriate speed-flow curves that reflect the characteristics of toll and toll-free roads.
- The third factor is that the static traffic assignment algorithm is not applicable to variable tolling where shifts in traffic between periods are expected.

In the event of diversion models being used for modelling the response of traffic to road tolling/pricing, there is a risk of these models being used as a black box. This is because diversion models tend to be proprietary and often little detail is publicly available.

Weekday/weekend, peak/off-peak and time of day modelling

Road pricing affects route choice and time-of-day choice. The latter cannot be accommodated in the conventional 4-step transport model.

Most urban transport models used for capacity planning purposes consider only morning and/or afternoon peak-hour travel on the transportation network. The typical approach for estimating annual demand is to extrapolate forecasts from the peak-hour models using factors for different time periods, such as day, week, month/season and year. However, the use of fixed factors does not account for temporal changes (peak spreading) and/or variations in traffic mixes (Kriger et al. 2006).

Another approach to modelling off-peak traffic in four-step models is to split daily travel demand into different time periods — usually the AM peak, PM peak and off-peak. However, this is usually done only for the final assignment stage and uses fixed factors rather than a time-of-day choice sub-model.

Truck/commercial traffic are not explicitly modelled

Truck and commercial traffic is an important market segment for toll road operators because they are charged more. However, their behaviours are seldom modelled explicitly when developing toll road forecasts. The usual approach is to assume a fixed share for truck/commercial traffic based on the proportion of trucks/commercial vehicles in the observed traffic counts. This practice is not useful as there are various types of light commercial vehicles that are not adequately modelled. Peak hours for trucks in many urban areas do not coincide with peak hours dominated by cars (Kriger et al. 2006).

Due to higher toll prices for truck/commercial traffic than cars, this may have a larger impact on revenue than suggested by traffic volumes alone.

Some advanced four-step models in Australia do include more sophisticated freight vehicle modelling, including explicit treatment of light commercial vehicles. However, the sophistication varies amongst models and the freight modelling is done outside of the main four-step model with commercial vehicles added to the main model at the assignment step.

Trip-based versus tour- or activity-based modelling

A general criticism of the traditional four-step transport models is that they are trip-based models, lacking realism in travel demand decisions. More advanced models[4], such as tour- and activity-based models and dynamic traffic assignment models, provide opportunities for addressing many of the limitations of the four-step models. Tour-based travel models accommodate trip reorganisation within a tour; activity-based models allow traveller adaptations to price structure that vary in time and space; and dynamic traffic assignment models simulate time-varying route choice behaviour (Schofer 2005).

Developments based on the more advanced travel models require very detailed data that historically have not been collected. Also, new models have yet to show they perform better than the traditional four-step models in forecasting toll road traffic (Prozzi, et al. 2006).

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[4] For a review of advanced travel models, refer to Donnelly et al. (2010).

Limitations of data

Data limitations have been identified as another major source of potential forecasting errors (Kriger et al. 2006). Data required for traffic modelling may include, among other things, traffic counts, network characteristics and generalised travel costs. These data are sometime lacking or subject to sampling/processing errors.

Calibration and validation data

Accurate and current data are critical for model calibration and validation. Model calibration seeks to replicate observed base-year data by adjusting model parameters. Model validation involves comparing backcast and/or forecast results obtained from the calibrated models against observed data and making reasonableness and logic checks (Cambridge Systematics 2010). Inaccurate or outdated data can lead to calibration and validation errors.

Network characteristics

Urban road networks are very complex. Representing and characterising the road network in an urban environment poses a particular challenge for modellers. Lack of data or poor quality of data may lead to incorrect characterisation of the road networks including failure to include competing untolled alternative routes and future changes. This in turn will lead to errors in traffic assignment.

Value of time and willingness to pay

Treatment of the ability and willingness to pay was found to be another factor affecting forecasting performance (Kriger et al. 2006). Road users make route choices on the basis of vehicle operating costs, travel time, safety, comfort and reliability considerations. Often, there are no reliable data on the value of time and other attributes.

Time is normally combined with vehicle operating costs and toll to form the generalised travel costs, which are often assumed to be the only variable affecting a driver's decision to use a toll road. Thus, choice of travel time values are critically important for the sensible outcome of the simulated route choice in traffic assignment.

Value of time can vary across the various market segments depending on trip purpose, income, vehicle types and other factors. Kriger et al. (2006) observes that the value of time has been generally assumed to be single value by trip purpose to represent an average characteristic for a given study area. This approach ignores the actual distribution of users by value of time which can lead to crude mistakes in predicting the number of toll road users for a given type of trips (Vovsha et al. 2005). The distribution of users by value of time has been empirically found to be non-symmetric with a long right tail. In such a case, the number of users who are actually willing to pay a toll would be fewer than the case where a normal distribution is assumed.

Value of time can be derived using the willingness to pay approach. Normally, the willingness-to-pay approach values travel time together with other attributes of the toll roads such as safety and reliability. Most willingness-to-pay studies are based on stated preference surveys which are prone to hypothetical bias. Bain (2009) argues that stated preference

surveys are hypothetical in both the payment and the provision of service in question. Existing research suggests that there is a tendency for people to overstate the amount they would pay for a service when they are not faced with a real choice paid for by hard cash.

Uncertainty in input assumptions

Forecasting errors can also arise from incorrect model input assumptions. In making traffic forecasts, a large number of assumptions have to be made in relation to the future changes in socio-economic and land use variables (such as population, employment and economic growth). While these assumptions may be based on forecasts from expert groups and/or government economic and land-use plans, there are inherent uncertainties in them. If the predicted economic performance or land use scenarios do not transpire, road traffic volumes may not grow as anticipated (Bain 2009).

Kriger et al. (2006) showed two main concerns regarding the impact of socio-economic and land use assumptions on forecasting performance. Firstly, many of the planning assumptions may not necessarily reflect the market trend (and therefore may not materialise). Secondly, there is a lack of consideration of short-term economic fluctuations on travel demand (possibly due to the nature of steady-state forecast). Both of these deficiencies can lead to poor forecasting performance.

Even if the assumptions are correct in aggregate, errors in the details can also have a significant impact. EastLink (previously known as the Mitcham-Frankston Project) is a case in point. More than two years after its opening in 2008, its average daily traffic levels are around 180,000 trips per day, a third below projections. In 2009, ConnectEast (2009) released updated traffic projections which found that, while overall population and employment growth in the EastLink catchment area between 2004 and 2009 were comparable to the 2004 projections (ConnectEast 2004), its distribution was not. ConnectEast believe this contributed -5 to -10% to the differences between the actual and projected traffic levels. Some of this error may be due to the original projections expecting that businesses and households would relocate closer to EastLink (ConnectEast 2004).

Ramp-up risk

'Ramp-up' is the period over which usage of a new transport facility gradually rises to the predicted long-term equilibrium level. Both overseas and Australian experiences point to a problematic ramp-up performance for toll roads (Kriger et al. 2006 and D'Este 2010). The ramp-up period is important for the financial viability of toll roads as it is the time when they are most likely to default (Bain and Wilkins 2002). In Australia, Connector Motorways went into receivership nearly three years after Lane Cove Tunnel opened. The Cross City Tunnel went into receivership one and a half years after opening.

Poor forecasting performance in the ramp-up period can be caused by a number of factors including inappropriate assumptions about the ramp-up profile, bias in the predicted long-term equilibrium demand and neglect of the impact of short-term events on demand such as recessions.

The traditional ramp-up curves are typically of concave shape, rising sharply initially and tapering off toward the end of the assumed ramp-up period (typically 18-24 months). This commonly assumed profile has been increasingly called into question. D'Este (2010) reviewed the recent Australian evidence on changes in the toll road ramp-up profile resulting from an initial toll-free period and examined broader implications for demand forecasting. Based on the experiences of M7 and EastLink, the observed ramp-up is likely to be longer and more gradual than the traditional concave profile and closer to a straight-line.

Factors affecting the ramp-up profile vary with the location and type of projects. Estimating the shape and duration of a ramp-up has been and will remain a challenge for modellers, particularly for greenfield projects.

Optimism bias and strategic misrepresentation

Inappropriate models, poor quality and/or lack of data, and inadequate modelling assumptions are often cited in the literature as the main sources of forecasting errors. Flyvbjerg (2008) argues that these technical factors are not enough to explain the patterns of forecasting errors that have been observed for major road projects. Flyvbjerg's argument goes as follows:

> *First, if technical explanations were valid one would expect the distribution of inaccuracies to be normal or near-normal with an average near zero. Actual distributions of inaccuracies are consistently and significantly non-normal with averages that are significantly different from zero. Thus the problem is bias and not inaccuracy as such. Second, if imperfect data and models were [the] main explanations of inaccuracies, one would expect an improvement in accuracy over time, since in a professional setting errors and their sources would be recognized and addressed, for instance through referee processes with scholarly journals and similar critical expert reviews. Undoubtedly, substantial resources have been spent over several decades on improving data and forecasting models. Nevertheless, this has had no effect on the accuracy of forecasts as demonstrated above. This indicates that something other than poor data and models is at play in generating inaccurate forecasts (Flyvbjerg 2008).*

Flyvbjerg (2008) synthesised two explanations that account for asymmetrical patterns of forecasting errors. The first one is optimism bias which offers an explanation from the psychological perspective and has been developed by Kahneman and Tversky (1979) and Lovallo and Kahneman (2003). The second one is strategic misrepresentation which is based on political-economic standpoint and set forth by Wachs (1989 and 1990) and Flyvbjerg, Holm and Buhl (2002 and 2005).

Optimism bias in the context of transport planning refers to a systematic tendency for people to underestimate the cost and overestimate the benefit (or traffic).

Strategic misrepresentation refers to the planned, systematic distortion or misstatement of fact, with the aim to increase the likelihood of success for an event, say, gaining an approval for funding. Strategic misrepresentation by forecasters and planners can stem from political-economic pressures within organisations. Wachs (1990) investigated the cause of strategic misrepresentation from the ethical dimensions of forecasting and illustrated how forecasters

could be put under political or economic pressure to produce self-serving forecasts while also attempting to maintain objectivity.

Flyvbjerg (2008) further argues:

> *Optimism bias and strategic misrepresentation are both deception, but where the latter is intentional, i.e., lying, the first is not, optimism bias is self-deception. Although the two types of explanation are different, the result is the same: inaccurate forecasts and inflated benefit-cost ratios (Flyvbjerg 2008).*

Flyvbjerg (2008) plotted the explanatory power of the two alternative hypotheses against the degree of political and organisational pressures faced by forecasters and planners. When the political and organisational pressures are high, explanations in terms of strategic misrepresentation may be more powerful than the theory of optimism bias; and, vice versa. In Flyvbjerg's view, the two types of explanation complement each other – both are necessary for understanding the causes of inaccuracies in traffic forecasting.

Flyvbjerg and COWI (2004) identified key actors in the decision-making process in the UK transport planning context and examined the level of their interests in avoiding optimism bias. The results are summarised in Table 1. As seen, there are only a few actors (mostly at the central level) with an active interest in avoiding optimism bias. Local actors are likely to put their local interests first thus having little or no incentive to combat optimism bias. Private consultants are heavily involved in all stages of planning process. It is usually in their economic interest to see projects progressing from inception through to completion because a consultancy company typically follows a project through all the main stages. Individual MPs often get involved in the individual decision-making processes for marginal projects in their constituency.

Table 1   Categorisation of Actors Involved

Actors having no or little direct interest in avoiding cost overruns/optimism bias	Actors having a direct interest in avoiding cost overruns/optimism bias
Local transport authorities	Ministry of Finance
Local politicians	(Department of Transport)
Local economic interests	Partnerships UK[a]
(Local civil servants)	
Consultancy companies	
Individual MPs	

Note: *The brackets indicate the categorisation can be questioned.*
        [a] Partnerships UK assists the UK Government in the development of PPP policy and contract standardisation, helps with project evaluation and implementation, and supports PPPS in difficulty (Flyvbjerg and COWI 2004).
Source: *Flyvbjerg and COWI (2004).*

Flyvbjerg and COWI (2004) noted that a more comprehensive study should also include bidders and constructors in Table 1. This would be particularly useful in informing risk reductions in PPP projects. If the bidder is made both builder and operator of a toll facility, it is likely that there will be increased interest in avoiding optimism bias.

For PPP projects, optimism bias and/or strategic misrepresentation may also stem from the bidding competition which encourages the bidders to take a more optimistic view of traffic forecasts and/or take on more risk simply to win the deal. The incentive to accept a more bullish stance can be greatly heightened when a bidder perceives that the government will not allow the project to fail. Whether the bidding process contributes to optimism bias and/or strategic misrepresentation is an issue worth further investigation in future case studies.

Optimism bias and strategic misrepresentation present key obstacles to reducing forecasting errors. Numbers can be easily tampered with in one way or another in the presence of optimism bias and/or strategic misrepresentation. Bain (2009) listed 21 ways in which toll road traffic and revenue projections can be inflated:

1. Flatter the asset (exaggeration of the attractiveness of the toll asset and/or impairment of the competitiveness of alternative routes).
2. Cherry-pick planning variables (use of the upper ends of the range of forecast socio-economic variables and land use planning variables).
3. Judiciously 'identify' historical trend (selective use of historical data to derive high growth trends).
4. Selectively apply and/or report growth factors (use of area-wide average growth factors to hide high growth rates applied to the area affected by the project).
5. The future will look exactly like the past (continuation of historical trend).
6. The future will look nothing like the past (breakdown of historical trend).
7. Using seasonality to your advantage (use of non-neutral daily or monthly traffic data)
8. Remove inconvenient truth (removal of true observations as outliers).
9. Design & administer surveys to return the required results (particularly true with Stated Preference surveys).
10. The magic of expansion/annualisation factors (use of incorrect conversion factors from weekday peak-hour traffic estimates into annual estimates).
11. Assume that consumers act rationally (underestimation of the consumers' resistance to paying tolls).
12. Assume that consumers make the same choices (failure to recognise selective use of the toll facility by users).
13. Hypothetical bias – a helping hand (a tendency for overestimation of the willingness to pay under the hypothetical scenario).
14. Grow your value of travel time savings (unit value of time increases with income, unit value for small amount of time saved is worth as much that for large amount and unit value of time increases with the level congestion).
15. Overstating the toll road premium (over estimation of non-price attributes of the toll road facility such as ride quality or perceived safety).
16. Overstating the yield (through overestimation of the number of trucks using the toll road).
17. Reliance on speculative development (use of uncommitted land use plans as traffic modelling input).
18. The joy of induced demand (new highway induces new traffic).

19. Introduce your own toll discount (use of perceived electronic toll collection discount to inflate the traffic figures).
20. Assume quick ramp-up (use of instant or short ramp-up assumptions).
21. Ignore physical capacity constraints (forecast future traffic growth without considering capacity constraint).

4 Possible risk mitigation strategies

Forecasting errors can never be eliminated, but they can and should be reduced to a more acceptable level and made more symmetrical.

As discussed in the last section, inaccuracies in traffic forecasts can be caused by technical factors such inadequate models, limitations of data, inappropriate model inputs and poor ramp-up assumptions, and by non-technical factors such as optimism bias and strategic mis-representation. Table 2 summarises some general strategies that have been discussed in the literature and might be used to mitigate traffic forecasting risks. Specific recommendations will have to wait until detailed case studies are undertaken to isolate specific causes of inaccuracies in traffic forecasts for Australian PPP/toll road projects.

As far as the traffic modelling is concerned, there is no consensus among transport researchers and practitioners regarding the best methods for undertaking traffic forecasts for toll roads (Kriger et al. 2006 and Vovsha et al. 2005). However, a number of areas have been identified as requiring improvement to make models better suited to analysing traffic demand for toll roads. These include:

- include travel cost (congestion impacts or increases in fuel prices) as another variable to explain trip generation
- allow for time of day choice or peak spreading
- model freight traffic explicitly, and
- incorporate the feedback from the land use changes to travel demand.

Some of these changes can be implemented within the existing four-step modelling framework while others may have to be considered in more advanced modelling platforms such as tour- or activity-based modelling and dynamic assignment modelling. But in both scenarios, substantial new development efforts are required.

Model validation has been relatively neglected in the past possibly due to lack of data. In future, more effort should be put into validating the predictive power of the model. This could be achieved by undertaking backcast of traffic demand or reasonableness checks. The Travel Model Validation and Reasonableness Checking Manual, prepared by Cambridge Systematics (2010) for the US Federal Highway Administration, provides a useful guide for undertaking such activities. Availability and quality of data are prerequisites for achieving improved results from model validation.

Traffic modelling is a complex process. Peer reviews of modelling practices may help reduce risks of making errors in traffic forecasting. The techniques used in peer reviews may vary. Sometimes, simple back-of-the-envelope calculations or 'sanity checks' can reveal serious

modelling errors. However a peer review process, even by experts, may not provide *certainty* that traffic projections are accurate, given the complexities of the modelling process.

Table 2   Possible Risk Mitigation Measures

Sources of Errors	Possible measures	References
Technical		
Inadequate models	Include feedback of higher travel costs (caused by rising congestion and fuel prices) to trip generation	SKM (2009)
	Allow for time of day choice (peak spreading)	Kriger et al. (2006); Spear (2005); SKM (2009)
	Improved modelling of freight traffic	Prozzi et al. (2006)
	Inclusion of feedback from land use	Kriger et al. (2006);
	More focus on model validation	Kriger et al. (2006); Cambridge Systematics (2010); Parthasarathi and Levinson (2010)
	Independent peer review of models	Kriger et al. (2006); TRB (2007)
Data limitations	Improved traffic data segmented by travellers' characteristics, type of trips, type of vehicles and time of day	Zmud (2005)
	Improved data on road network and speeds	Zmud (2005)
	Improved willingness-to-pay data such as value of time and reliability.	Zmud (2005)
Unrealistic model input assumptions	Independent expert view on population, employment and land use assumptions	Prozzi et al. (2006)
	Sensitivity analysis of key input variables	Bain (2009); Prozzi (2006)
	Probabilistic modelling (assign probabilities to different scenarios/assumptions: near certain, more than likely, reasonably foreseeable and hypothetical), undertake Monte Carlo simulations	Bain (2009); Prozzi (2006)
Ramp-up risk	Stress test (explore worst case scenarios)	Kriger (2005)
	Probabilistic modelling with Monte Carlo simulations	Kriger (2005)
Non-technical		
Optimism bias	Reference class forecasting (benchmark forecasts against actual observations from a reference class of comparable situations)	Flyvberg et al. (2005 & 2006); Flyvberg (2008)
	Downward adjustments based on past experience	Flyvberg & COWI (2004)
Strategic mis-representation	Reference class forecasting	Flyvberg et al. (2005 & 2006); Flyvberg (2008)
	Institutional change with a focus on transparency and accountability	Flyvberg et al. (2005)

As for data, Zmud (2005) identified the types of data that are required to support road pricing analysis. These include both demand- and supply-side information such as traffic and network data. These data have to be recent and detailed to support better modelling. Modellers need to ensure that they are working with best available data and understand any limitations associated with them.

There is also a need to develop locally accurate estimates of the value of time and reliability, which preferably vary with characteristics of the road users, type of trips, type of vehicles and time of day. Such efforts could initially be directed towards compilation and synthesisation of current and past empirical research on value of time and reliability and then towards identification of priority areas for further research and data collection (Spear 2005).

With respect to model input assumptions, using expert groups could reduce the influence of optimism bias and/or strategic misrepresentation on forecasting results. However there are inherent uncertainties in the socio-economic and land use forecasts. Robust sensitivity analysis and/or probabilistic modelling can be used to address these risks. For example, specification of alternative scenarios for sensitivity analysis may include an upside (equity) case and downside (debt) case[5]. The conventional sensitivity analysis, which produces point estimates, may be supplemented by the probabilistic modelling which provides model outputs in terms of both ranges and likelihoods (Bain 2009).

The NSW Auditor-General in his report (The Audit Office of New South Wales 2006) on the Cross City Tunnel recommended that a risk management approach should be taken for traffic forecasts. This would require forecasters to present their projections as a clearly defined range of likely outcomes and they should consider the outcome of various levels of patronage forecasts on a project's viability.

In so far as the ramp-up profile is concerned, further research is required to identify key drivers influencing ramp-up performance. In an attempt to deal with extreme uncertainties during the ramp-up period, Kriger (2005) suggests use of 'stress tests' to explore the worst case scenarios and employment of Monte Carlo techniques to determine probabilities of simulated outcomes.

As for the non-technical causes, optimum bias and strategic mis-representation, Flyvbjerg (2008) recommends use of reference class forecasting to combat both optimism bias and strategic misrepresentation in planning. The reference class forecasting methodology is aimed at improving accuracy in traffic forecasts by benchmarking them against actual observations from a reference class of comparable situations and thereby guarding against both optimism bias and strategic misrepresentation. One way to implement such an approach would be to provide investors with a summary of other projections done for similar projects in the last few years, including brief explanations of why current projections are different.

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[5] Sometimes labelled as the bank case (Bain 2009).

Flyvbjerg and COWI (2004) recommended use of optimism bias uplifts to address the appraisal bias in construction costs. While the approach was originally designed to address the cost-side bias, it could inform policy formulations in combating optimism bias in demand forecasting. The downpulls, which are explicit adjustments to the estimates of traffic, should be based on data from similar past projects and adjusted for the unique characteristics of the project (Kriger et al. 2006).

Flyvbjerg (2005) suggests that institutional change, with a focus on transparency and accountability, is required as an additional measure to guard against strategic misrepresentation in planning. Flyvbjerg defined two basic types of accountability under liberal democracies, namely, public sector accountability through transparency and public control, and private sector accountability via competition and market control. Measures under both types of accountability (for example, imposition of professional and even criminal penalties for deceptive forecasts, and sharing of financial responsibility by forecasters and their organisations for covering benefit or traffic shortfalls) may be used to curb strategic mis-representation in forecasting and planning.

While this paper presents the full range of factors affecting the accuracy of traffic forecasts, a question remains as to which of them will apply to the Australian context. A few case studies of Australian PPP/toll road projects may provide some answers to that question. They will also help formulate specific measures to deal with traffic forecasting risks in Australia.

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References

Bain, R. 2009, *Toll Road Traffic & Revenue Forecasts – An Interpreter's Guide*, Credit Risk Analysis.

Bain, R. and Wilkins, M. 2002, *The Credit Implications of Traffic Risk in Start-Up Toll facilities*, Standard & Poor's, London.

Bain, R. and Plantagie, J. W. 2003, *Traffic Forecasting Risk Study Update 2003*, Standard & Poor's, London.

Bain, R. and Plantagie, J. W. 2004, *Traffic Forecasting Risk Study Update 2004*, Standard & Poor's, London.

Bain, R. and Polakovic, L. 2005, *Traffic Forecasting Risk Study Update 2005: Through Ramp-Up and Beyond*, Standard & Poor's, London.

Cambridge Systematics 2010, *Travel Model Validation and Reasonableness Checking Manual*, second edition, report prepared for US Highway Administration.

ConnectEast 2004, *Product Disclosure Statement*, 14 October 2004.

ConnectEast 2009, *Asset Impairment Following Independent EastLink Traffic Projections*, 21 August 2009.

D'Este, G. 2010, *What Happens to Toll Road Ramp-up Profile When There Is an Initial Toll-free Period, and the Broader Implications for Demand Forecasting,* Australasian Transport Research Forum 2010 Proceedings, 29 September – 1 October, Canberra, Australia.

Donnelly, R., Erhardt, G. D., Moeckel, R. and Davidson, W. 2010, *Advanced Practices in Travel Forecasting – A Synthesis of Highway Practice*, NCHRP Synthesis 406.

Flyvbjerg, B. 2005, *Measuring Inaccuracy in Travel Demand Forecasting: Methodological Considerations Regarding Ramp Up and Sampling*, Transportation Research, Part A: 39.

Flyvbjerg, B. 2008, *Curbing Optimism Bias and Strategic Misrepresentation in Planning: Reference Class Forecasting in Practice*, European Planning Studies, Vol. 16, No. 1, January.

Flyvbjerg, B., Holm, M. K. S. and Buhl, S. L. 2002, *Underestimating Costs in Public Works Projects: Errors or Lie*, Journal of the American Planning Association, Vol. 68, No. 3, Summer.

Flyvbjerg, B. and COWI 2004, *Procedure for Dealing with Optimism Bias in Transport Planning*, Guidance Document prepared for the British Department for Transport.

Flyvbjerg, B., Holm, M. K. S. and Buhl, S. L. 2005, *How (In)accurate Are Demand Forecasts in Public Works Projects*, Journal of the American Planning Association, Vol. 71, No. 2, Spring.

Flyvbjerg, B., Holm, M. K. S. and Buhl, S. L. 2006, *Inaccuracy in Traffic Forecasts*, Transport Review, Vol. 26, No. 1, January.

Goldberg, J. L. 2005, *Toll Road Operations in Australia: A Critical Examination of the Financial and Economic Realities*, Proceedings of ATRF05, available at www.patrec.org.

Goldberg, J. L. 2006, *The Fatal Flaw in the Financing of Private Road Infrastructure in Australia*, paper presented at the 2006 Australasian Transport Research Forum, Brisbane.

J P Morgan (1997), *Examining Toll Toad Feasibility Studies*, Municipal Finance Journal, Volume 18, No. 1 Spring.

Kahneman, D. and Tversky, A. 1979, *Prospect Theory: An Analysis of Decisions Under Risk*, Econometrica, Vol. 47.

Kriger D. 2005, *Traffic and Revenue Forecasting for Roads and Highways: Concerns, Methods and a Checklist for Practitioners*, paper prepared for Expert Forum on Road Pricing and Travel Demand Modelling, November 14–15, Alexandria, VA.

Kriger, D., Shiu, S. and Naylor, S. 2006, *Estimating Toll Road Demand and Revenue – A Synthesis of Highway Practice*, NCHRP Synthesis 364, Transport Research Board.

Li, Z. and D. A. Hensher 2010, *Toll Roads in Australia: An Overview of Characteristics and Accuracy of Demand Forecasts*, Transport Reviews, 30: 5.

Lovallo, D. and Kahneman, D. 2003, *Delusions of Success: How Optimism Undermines Executives' Decisions*, Harvey Business Review, July.

Parthasarathi, P. and D. Levinson 2010, *Post-construction Evaluation of Traffic Forecast Accuracy*, Transport Policy, doi:10.1016/j.tranpol. 2010.04.010.

Pendyala, R. M. 2005, *Modelling Pricing in the Planning Process*, paper prepared for Expert Forum on Road Pricing and Travel Demand Modelling, November 14–15, Alexandria, VA.

Prozzi, J, K. Flanagan, L. Loftus-Outway, B. Porterfield, K. Persad, J. A. Prozzi and C. M. Walton 2009, *Actual vs. Forecasted Toll Usage: A Case Study Review*, CTR Technical Report, project performed in cooperation with the Texas Department of Transportation and the Federal Highway Administration.

Sinclair Knight Merz (SMK) 2009, *Critical Review of Transport Modelling Tools*, report prepared for the National Transport Modelling Working Group, March.

Schofer, J. 2005, *Summary Statement*, paper prepared for Expert Forum on Road Pricing and Travel Demand Modelling, November 14–15, Alexandria, VA.

Spear, B. D. 2005, *A Summary of the Current State of the Practice in Modelling Road Pricing*, paper prepared for Expert Forum on Road Pricing and Travel Demand Modelling, November 14–15, Alexandria, VA.

The Audit Office of New South Wales 2006, *Auditor-General's Report Performance Audit – The Cross City Tunnel Project*, Sydney, New South Wales Government.

Transport Research Board 2007, *Metropolitan Travel Forecasting – Current Practice and Future Direction*, Special Report 288, Committee for Determination of the State of the Practice in Metropolitan Area Travel Forecasting.

Vassallo, J. M. 2007, *Why Traffic Forecasts in PPP Contracts are Often Overestimated?* EIB University Research Sponsorship Programme, Luxembourg.

Vovsha, P., Davidson, W. and Donnelly, R. 2005, *Making the State of the Art the State of the Practice: Advanced Modelling Techniques for Road Pricing*, paper prepared for Expert Forum on Road Pricing and Travel Demand Modelling, November 14–15, Alexandria, VA.

Wachs, M. 1989, *When Planners Lie with Numbers*, Journal of the American Planning Associations, Vol. 55(4).

Wachs, M. 1990, *Ethics and Advocacy in Forecasting for Public Policy*, Business and Professional Ethics Journal, Vol. 9(1–2).

Zmud J. 2005, *Data Requirements to Support Road Pricing Analysis*, paper prepared for Expert Forum on Road Pricing and Travel Demand Modelling, November 14–15, Alexandria, VA.