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Quantifying uncertainty in travel demand forecasts[1]

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Abstract

Transport planning and investment processes often use transport models to generate travel demand forecasts that extend decades into the future. Currently, most transport models treat the future as being deterministic when it is, in practice, inherently uncertain. In this paper, we outline an approach to quantifying the effects of uncertainty in transport model inputs, such as population and employment growth, on travel demand forecasts. By combining regression models with Monte Carlo methods, the approach helps to quantify the effects of uncertainty in inputs while remaining computationally tractable. To demonstrate the approach, we present illustrative results for a proposed transport project in New Zealand, namely Auckland Light Rail. Although this application is only illustrative and further technical development is needed, we suggest the approach could – even now – help to quantify uncertainty in travel demand forecasts and support better transport planning and investment decisions.

1 Introduction

Transport planning and investment processes often rely on travel demand forecasts that extend decades into the future. These forecasts are commonly derived from travel demand models that make deterministic assumptions about the future, such as population and employment growth. In practice, and as many researchers have noted, the future is inherently uncertain. Willumsen (2014), for example, observes *"uncertainty is unavoidable in any forecast of future conditions*". This begs the question of how uncertainty in travel demand forecasts should be managed within transport planning and investment processes?

In response to this question, current transport planning and investment processes regularly make use of sensitivity testing. These tests proceed by allowing key inputs and assumptions in travel demand models to vary by prescribed amounts. Although these tests do reveal information on the relative sensitivity of outcomes to inputs and assumptions, they are relatively ad-hoc. Sensitivity testing requires practitioners, for example, to identify the relevant inputs that are to be varied as well as the magnitude of the variation to test.

In contrast, this paper presents an approach that has the potential to support more systematic analyses of the effects of uncertainty on travel demand forecasts. By combining regression models with Monte Carlo methods, our proposed approach can provide useful and detailed insights into uncertainty while remaining computationally tractable. Although further development of the approach is needed, for example, careful characterization of

[1] The authors wish to acknowledge this research is published with the kind permission of Auckland Light Rail Limited. We extend our sincere thanks to Tommy Parker, whose support was instrumental in making this work possible; the New Zealand Infrastructure Commission Te Waihanga for their support in reviewing and refining the paper; Luis "Pilo" Willumsen for his inspiration, encouragement, and invaluable insights; Simon Nielsen and Collins Teye of Transport for London for assessing the MSM and for their valuable suggestions to enhance the regression model in the Monte Carlo simulations; and Elliot Clayton from Invise Limited for his insightful recommendations that helped to clarify the implications of this research for decision-makers. All remaining errors are our own.

appropriate probability distributions and parameters to use in the Monte Carlo simulations, we suggest it is sufficiently well developed that it could be used within transport planning and investment processes to improve the quality of public and private sector decision-making.

The following sections of this paper are structured as follows: First, we summarise the transport policy and travel demand modelling process; second, we introduce our proposed approach, which combines regression models with Monte Carlo simulation; and third, we apply the proposed approach to an illustrative case study of a project from Auckland, New Zealand, specifically Auckland Light Rail. Finally, we discuss implications for policy and practice; note some key limitations of the approach; and consider opportunities for further research.

1.1 The planning and policy context

In New Zealand and many other countries, planning and investment in major transport projects and policies usually proceed via structured business cases. Partly because of the long lifetimes and large costs of many transport projects and policies, these business cases tend to rely heavily on transport models that generate travel demand forecasts extending decades into the future. Forecasts from travel demand models are, for example, often used as inputs into economic appraisal processes, such as cost-benefit analysis (CBA), which seek to quantify relative value-for-money over periods of 40 years, if not longer.

To arrive at these forecasts, travel demand models rely on inputs and assumptions – such as, for example, population and employment growth – which are inherently uncertain. As Willumsen & Ortúzar (2016) write, *"the future is not deterministic and no amount of technical skills and models can change that"*. Uncertainty is especially important in major projects which have long planning horizons and where infrastructure lasts for many decades. Changes in demographics, land use, technology, and travel behaviour can all have large effects on travel demands. As summarised below, real-world experience with several major transport projects reveals actual travel demands are subject to material levels of uncertainty.

Docklands Light Railway (DLR) – London, UK. Upon opening in 1987, passenger numbers on the DLR quickly surpassed initial forecasts. The primary cause appears to be the unexpectedly rapid development of the Docklands area into a significant financial and commercial hub (Select Committee on Transport, 2005). The surge in demand subsequently lead to overcrowding and required rapid enhancements, such as platform extensions for longer trains, which incurred additional costs (Transport for London, 2023).

M25 Motorway – London, UK. The M25, encircling London, was initially designed in 1944 for a maximum capacity of 88,000 vehicles per day but, by 1993, accommodated approximately 200,000 vehicles daily. The unanticipated high traffic volumes led to multiple widening projects, expanding sections to four lanes and, in some areas, up to six lanes per direction in attempts to alleviate congestion (Wikipedia, 2024).

Brisbane's Clem Jones Tunnel (CLEM7). The tunnel experienced actual traffic volumes that were less than one-third of forecast, leading to significant revenue shortfalls. Due to lower-than-expected usage, the tunnel's operator (RiverCity Motorways), went into receivership in February 2011, owing $1.3 billion to investors, which included but was not limited to Brisbane City Council (TransApex, 2024).

While differences between modelled and actual travel demands will be caused by many factors that vary between projects, there is little doubt that high levels of uncertainty *per se* present a significant challenge for major transport projects worldwide. Forecasts that are too high, for example, can contribute to higher costs and underutilised infrastructure, whereas forecasts that are too low can delay or prevent much-needed investment and might later require expensive and disruptive expansions to meet unanticipated levels demand.

Partly for this reason, a growing body of recent research has emphasised the importance of explicitly accounting for uncertainty in infrastructure decision-making (Hall, 2024; Moroni &

Chiffi, 2022). To this end, contemporary business cases will often, for example, present the results of sensitivity testing, which considers the effects on travel demand forecasts from selectively varying individual inputs or assumptions. Despite its usefulness, sensitivity testing is often ad hoc and relies heavily on judgements and assumptions made by practitioners. Taken together, this highlights a need for more robust treatments of uncertainty in transport planning and investment processes, which has provided the motivation for this paper.

1.2 A background to transport modelling

Travel demand forecasts generated by transport models play a key role in transport policy and investment decision-making. These models seek to predict how people will travel in the future, based on, for example, economic, demographic, and network conditions. Over decades of development, transport models have evolved into relatively sophisticated tools.

In many jurisdictions, so-called **four-step models (FSMs)** remain the dominant framework for undertaking travel demand modelling. The “four-steps” in FSMs can be summarised as:

1. *Trip generation*, which predicts how many trips originate in specific zones based on, for example, population, employment, and land use.
2. *Trip distribution*, which determines the destination of trips generated in each zone over potential destination zones in response to, e.g. overall transport costs.
3. *Mode choice*, which allocates trips travelling from one zone to another to the available transport modes (e.g., car, public transit, walking, cycling).
4. *Trip assignment*, which assigns trips from one zone to another by a specific mode to the underlying network, such as road links and public transport stops and services.

While FSMs have proven useful for modelling future transport outcomes, they are relatively resource intensive. Large-scale models require not only significant computational resources but also careful management and oversight. Developing a clear specification, refining inputs, addressing clarifications, running simulations, and validating outputs can take a week or more – particularly when testing multiple scenarios and requiring non-standard outputs to meet business case needs. The considerable time involved in running FSMs makes them somewhat ill-suited to being directly used for uncertainty analysis by, for example, simulating many changes to inputs or assumptions before re-running the FSM.

More recently, a new class of transport models known as activity-based models (“ABMs”) have emerged and are being used in some jurisdictions. Rather than the four steps outlined above (generation, distribution, mode choice and assignment), ABMs seek to predict the travel demands of individuals and households over a typical day. Although their mathematical structure differs from FSMs, ABMs rely on similar inputs and assumptions and are also computationally intensive. Hence, while we frame the approach presented in this paper in the context of conventional FSMs, we suggest the underlying motivation and methods that we use are also relevant and transferable to ABMs.

1.3 Uncertainty in travel demand modelling

Uncertainty in travel demand forecasting arises from multiple sources, which we suggest can be broadly categorised into the following three typologies:

1. *Structural uncertainty*, which arises from limitations in model design (e.g., the omission of certain behavioural responses, such as departure time choice).
2. *Parameter uncertainty*, which arises from uncertainty in the estimated values of the parameters in the behavioural models (e.g., mode specific factors, value of time etc).
3. *Input uncertainty*, which arises from uncertainty in key inputs and assumptions (e.g., demographics, network attributes, policy settings, and technological change).

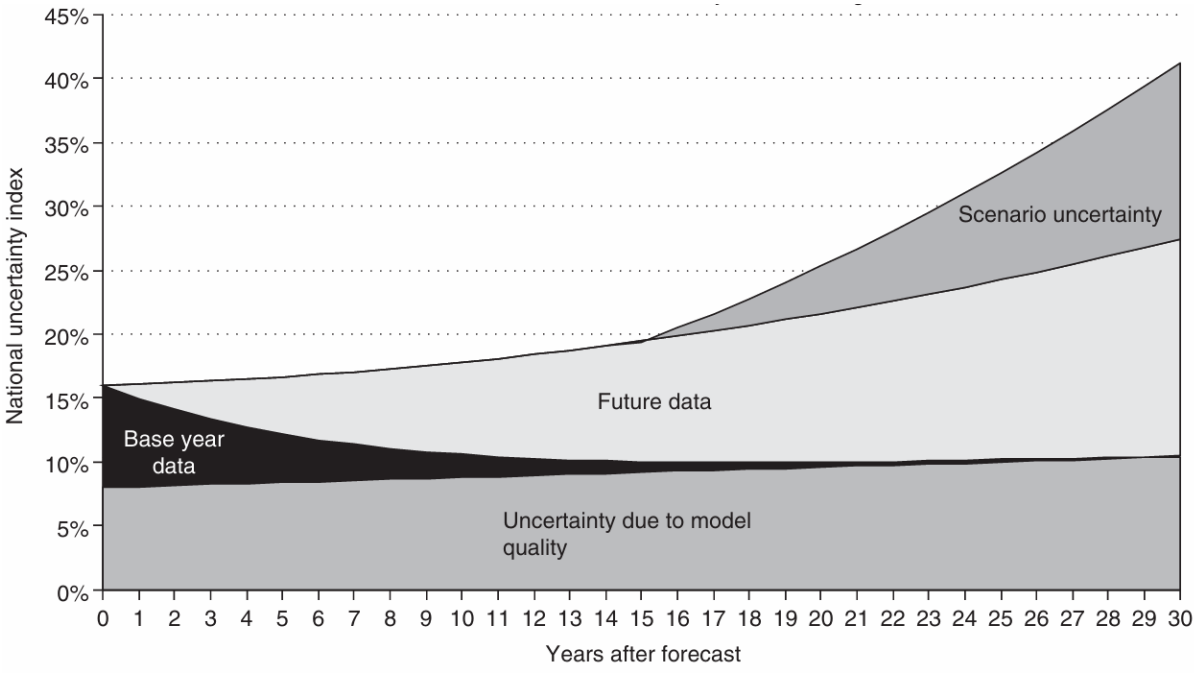
Structural and parameter uncertainty – that is, the first two sources noted above, or what Willumsen & Ortúzar (2016) describes as "model quality" – would seem to be best addressed during the model development and validation phase. That is, structural and parameter uncertainty should typically be addressed *before* the model is used to inform planning and investment processes, for example, in structured business cases.

In contrast, we describe the third typology above as *input uncertainty*, which arises primarily during the application of travel demand models – for example, to specific projects – and is the focus of this paper. Input uncertainty affects both FSMs and ABMs and includes:

- *Demographic outcomes*, such as population, employment, household structures;
- *Transport network attributes,* such as capacity and availability of infrastructure;
- *Transport policy settings*, such as tolls, fares, and parking policies; and
- *Technological changes,* such as work-from-home technologies.

In **Figure 1**, we replicate a useful diagram from Willumsen & Ortúzar (2016), which illustrates different sources of uncertainty and how their magnitude might be expected to evolve over time. Whereas uncertainty associated with model quality – or, what we have called *structural and parameter uncertainty* – increases only slowly over time, Willumsen & Ortúzar (2016) posit that uncertainty associated with future data and scenarios – or, what we have defined above as *input uncertainty* – increases more rapidly and, over time, becomes dominant.

Figure 1: Notional Sources of Uncertainty in Forecasting



Willumsen & Ortúzar (2016) conclude quantifying *input uncertainty* requires probabilistic approaches. In theory, one could potentially tackle this problem directly by sampling inputs from assumed distributions and re-running transport models, whether they be FSMs or ABMs. As noted above, such a direct approach to quantifying input uncertainty, however, are likely to be computationally impractical due to the time and resources involved in runing travel demand models as well as the myriad of potential input assumptions that could be tested.

In the next section, we instead propose an approach to quantifying uncertainty in travel demand modelling that is less direct and less comprehensive but nonetheless has the key feature of being computationally tractable.

2 Methodology

In this section, we present our methodology for quantifying the effects of uncertainty in inputs on travel demand forecasts and describe the illustrative case study to which it is applied.

2.1 Approach

Our overall approach hews relatively closely to that outlined by Willumsen (2014), which combines regression models with Monte Carlo simulation in two main steps:

- **Step 1 – Estimate regression model.** First, we identify the input variables most relevant to uncertainty, for example, based on historical evidence (e.g. ex-post assessments), expert judgement, and stakeholder engagement. Second, we vary the set of identified input assumptions across multiple transport model runs to quantify how changes in inputs affect travel demands. Third, we use a regression model to estimate the effects of changes in input assumptions on travel demand forecasts.
- **Step 2 – Monte Carlo simulation.** First, we impose probability distributions for key inputs, e.g. based on historical evidence, expert judgement, and/or stakeholder input. Second, we undertake a so-called "Monte Carlo simulation" that involves repeatedly sampling sub-sets of model inputs from these distributions. Each individual sub-set of model inputs is then combined with the estimated regression parameters from step 1 to generate a distribution of estimated travel demand forecasts.

While Monte Carlo analysis is well established in fields such as finance e.g. Glasserman (2004), it is less commonly applied in travel demand forecasting. However, approaches to adapting Monte Carlo techniques to the transport sector are emerging – most notably through the framework proposed by Willumsen (2014).

2.2 Illustrative case study: Auckland Light Rail

We use Auckland Light Rail (ALR) as an illustrative case study to demonstrate our proposed approach. In doing so, we make several assumptions that later sections will return to.

By way of background, ALR is a proposed rapid transit project connecting Auckland's city centre to the Airport located to the south (Auckland Light Rail, 2024). Business cases for ALR relied on the Macro Strategic Model (MSM), which is a FSM operated by the Auckland Forecasting Centre (AFC) that is used to forecast travel demand for major projects in Auckland.[2] During the development of the ALR business case, MSM was used to model 147 scenarios over two years – providing a rich source of data to illustrate our approach.

We apply our approach to two illustrative scenarios for ALR:

- First, the "*Baseline scenario*" focuses on quantifying uncertainty. To do so, we align assumptions with the original ALR business case and demonstrate how the proposed approach can be used to quantify uncertainty around the deterministic ("central") forecasts that are generated by the transport model.
- Second, we consider an "*Alternative scenario*" where input assumptions differ from the original ALR business case. Specifically, we assume demand starts low and rises over time. The aim of this scenario is to show how the proposed approach can be used in a "sketch model" mode to quickly quantify the effects of changes in inputs.

Importantly, we emphasis here that we use forecasts from MSM to explore and illustrate the merits of our proposed approach to quantify uncertainty, rather than to evaluate ALR itself. Neither of these scenarios represent a formal review or critique of the original ALR business case, nor the assumptions, inputs, or views of any sponsoring agency.

[2] Mandated by Auckland Council, Auckland Transport, and NZTA to develop and operate Auckland's regional travel demand and traffic models, ensuring consistent decision support for major transport projects and policies. As part of the ALR project, the MSM was peer reviewed by Transport for London (2023).

3 Results

3.1 Step 1 – Regression model

3.1.1 Identifying relevant variables

While multiple measures of passenger demand could be used as a dependent variable, the results presented here use passengers carried per hour per direction (p/h/d) at the peak load point (PLP) in the AM peak. For ALR, this measure was an important input into several transport planning and investment decisions, such as vehicle capacities, fleet requirements, and service frequency. In other applications, alternative demand measures could be used.

During the ALR business case project, the following explanatory variables were identified by stakeholders as both being most likely to influence passenger demand *and* being associated with relatively high levels of future uncertainty:

- *Population in the corridor*, which is influenced by a combination of market forces and central and local government housing policies, including but not limited to significant tracts of government-owned land along the corridor.
- *Employment in the city centre*, which is largely determined by local, national, and international economic market forces and planning regulations.
- *Work from Home (WfH) uptake*, which depends on both technology and industry and service sector employment policies.
- *Congestion pricing schemes*, which depends on future national and local government decisions.
- *City centre parking prices*, which are influenced by both market forces and national and local government policies regarding the supply of parking.

Several other key drivers of demand, such as train frequency, capacity, and travel times, were identified and included in the regression model as they are important to its predictive power. Some of these drivers were not, however, simulated using Monte Carlo methods in Step 2 as they were deemed to lie more within the control of the operator or authority managing ALR, at least in the medium to long-run. As such, the associated risk and uncertainty was assessed to be somewhat lower than the other variables listed above.

3.1.2 Estimating the regression model

During the development of this paper, we evaluated multiple regression models and eventually landed on a log-log specification as being most suitable. Not only did the log-log model perform well, but it also allows for some of the resulting parameter estimates to be interpreted as constant elasticities, which in turn allows them to be compared to the wider transport economic literature. In our preferred log-log model, continuous variables were log-transformed, whereas dummy variables and those expressed as percentages were left untransformed.[3] Our preferred specification for the regression model is as follows:

$$\log D_i = \beta_0 + \beta_1 \log Pop_i + \beta_2 \log Emp_i + \beta_3 \log IVT_i + \beta_4 \log Cap_i + \beta_5 \log F_i + \beta_6 WfH_i + \beta_7 D_i^C + \beta_8 D_i^P$$

Where for each model run i:

- $\log D_i$ denotes passengers per hour per direction (p/h/d) at the peak load point (PLP) in the AM peak

[3] Specifically, we applied log transformations applied to Peak load demand (dependent variable), Corridor population, City centre employment, In-vehicle time, Capacity at peak load point, and Frequency. The following variables were not transformed, Congestion pricing (dummy), Parking prices (dummy), and work-from-home rates (%).

- $\log Pop_i$ denotes population in the corridor (000s)
- $\log Emp_i$ denotes employment in the city centre (000s)
- $\log IVT_i$ denotes in-vehicle travel-time between the city centre and the airport (mins)
- $\log Cap_i$ denotes passenger capacity at the peak load point (p/h/d, 000s)
- $\log F_i$ denotes frequency (trains per hour)
- WfH_i denotes work from home uptake (%)
- D_i^C denotes a dummy for congestion charging (0=No, 1=Yes)
- D_i^P denotes a dummy for parking prices (0=No, 1=Yes)
- β denote parameters in the regression model to be estimated.

Regression results for our preferred specification are shown in **Table 1**.

Table 1: Regression results

Parameter	Variable	Interpretation / Measure	Coefficient	t-statistic
β_0	-	Intercept	3.806	8.2
β_1	$\log Pop_i$	Population in corridor (000s)	0.546	4.0
β_2	$\log Emp_i$	Employment in city centre (000s)	0.895	4.4
β_3	$\log IVT_i$	In-vehicle travel time (mins)	-0.847	-16.0
β_4	$\log Cap_i$	Capacity at PLP (p/h/d, 000s)	0.135	9.3
β_5	$\log F_i$	Frequency (trains per hour)	0.157	3.8
β_6	WfH_i	WfH (7%, 14%)	-0.029	-6.5
β_7	D_i^C	Congestion charge (0=No, 1=Yes)	0.015	0.6
β_8	D_i^P	Parking price increase (0=No; 1=Yes)	0.133	5.4
R^2			*0.92*	
Observations (MSM model runs)			*147*	

For the log-transformed variables that can be interpreted as constant elasticities[4] we find:

- **Corridor Population**: The coefficient of 0.546 indicates a 10% increase in corridor population leads approximately to a 5.5% increase in peak load demand.
- **City Centre Employment**: The coefficient of 0.895 indicates a 10% increase in City Centre employment results in an approximately 9% increase in peak load demand.
- **In-Vehicle Travel Time**: The coefficient of -0.847 indicates a 10% increase in in-vehicle travel time reduces peak load demand by approximately 8.5%.
- **Frequency.** The coefficient of 0.157 indicates a 10% increase in frequent increased peak load demand by approximately 15%.

The elasticity for in-vehicle time appears plausible when compared to external evidence. It is, for example, slightly higher than the upper end of observed short-term elasticities and well within long-term elasticities (Wallis, 2004; Balcombe, et al., 2004). Although the estimated elasticity for frequency appears slightly low compared to external evidence, this may reflect the choice of peak load as our demand measure – given that most evidence reports larger elasticities in off-peak periods. The relatively large t-statistics for estimates of continuous parameters indicate they are statistically significant at conventional levels and precisely estimated (NB: To estimate standard errors, one can divide the coefficient by the t-statistic).

[4] The coefficient approximately denotes the percentage change in peak load demand for a 1% change in the corresponding variable.

For non-transformed variables, the parameters can be interpreted as follows:

- **Work from Home:** The coefficient of -0.029 suggests that an increase in the proportion of people working from home from 7% to 14% (from 0 to 1) reduces peak load demand by approximately 2.9%.
- **Increased Parking Prices:** The coefficient of 0.133 suggests that doubling parking prices in the city centre (from 0 to 1) increases peak load demand by approximately 13%.

Unfortunately, the estimated parameter for congestion pricing is small and imprecise, likely due to limited variation across the 147 scenarios. We return to this issue in Section 4.2.

With an R^2 of 0.92, the model explains most of the variance in peak load demand, indicating a strong fit to observed data and reasonable internal validity. We also estimated a regression model that included individual variables for the year associated with the transport model run, although these were not found to improve out-of-sample model performance.

3.2 Step 2 – Monte Carlo simulation

To implement the Monte Carlo simulation, we developed interfaces in both Python (2025) and Excel. As run-times for the Monte Carlo simulation was only approximately 5 minutes, these tools are fast enough to be used in real-time during stakeholder meetings, where participants could adjust key parameters and generate almost immediate results.

In the following sub-sections, we present results for the two scenarios described above: First, a “Baseline Scenario” that adopts assumptions from the original travel demand modelling and, second, an “Alternative Scenario”, where key inputs are initially set at low levels and then rise over time. Results for each scenario are discussed below.

The results of this simulation are presented for illustrative purposes. However, we do report the underlying assumptions in both scenarios – including statistical distributions and values for the minimum, maximum, and most likely parameters – in The Appendix. These distributional assumptions and parameters can be varied using the Python and Excel tools developed in this research, which are readily available on request from the authors.

3.2.1 Baseline scenario

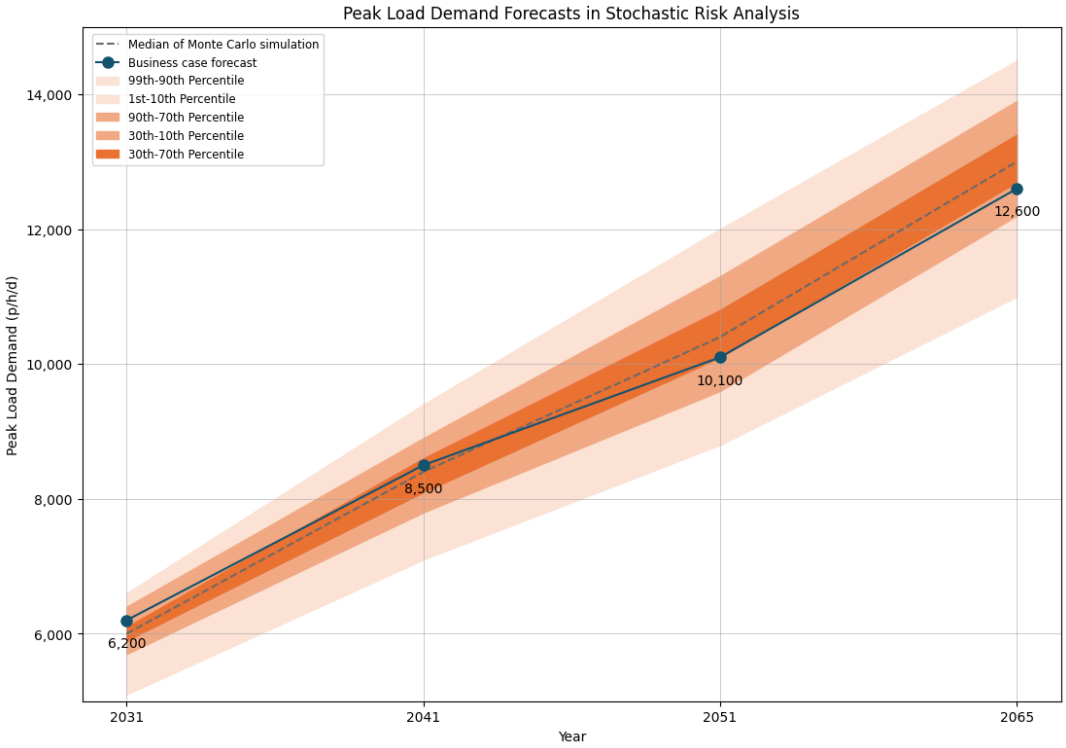
As noted above, the Baseline scenario is designed to broadly reflect the assumptions used in travel demand modelling.

Results from the Monte Carlo simulation are illustrated in **Figure 2**, which shows forecast uncertainty for the 99th–90th percentile, 30th–70th percentile, 10th–30th percentile, and 1st–10th percentile. These bands highlight the distribution of possible demand outcomes across simulations, providing insight into the variability and risk associated with projections.

The deterministic business case forecasts are overlaid for comparison, demonstrating their position within the broader uncertainty range and allowing for an assessment of their alignment with probabilistic demand scenarios. As we might hope, the business case forecasts lie close to the median of the simulations and well within the credibility interval. The uncertainty implied by the simulations extends approximately 5-10% either side of the median estimate and intuitively increases in magnitude over time.

In **Figure 2**, the difference between the simulations and the business case forecasts appears to increase over time. This may reflect assumptions that underpin the regression model, such as linearity in relationships between inputs and outputs. Although the assumption of linear relationships is likely to hold for small changes in inputs, this assumption may be less relevant for larger changes in inputs where non-linear relationships may kick in, for example between travel demands and congestion effects.

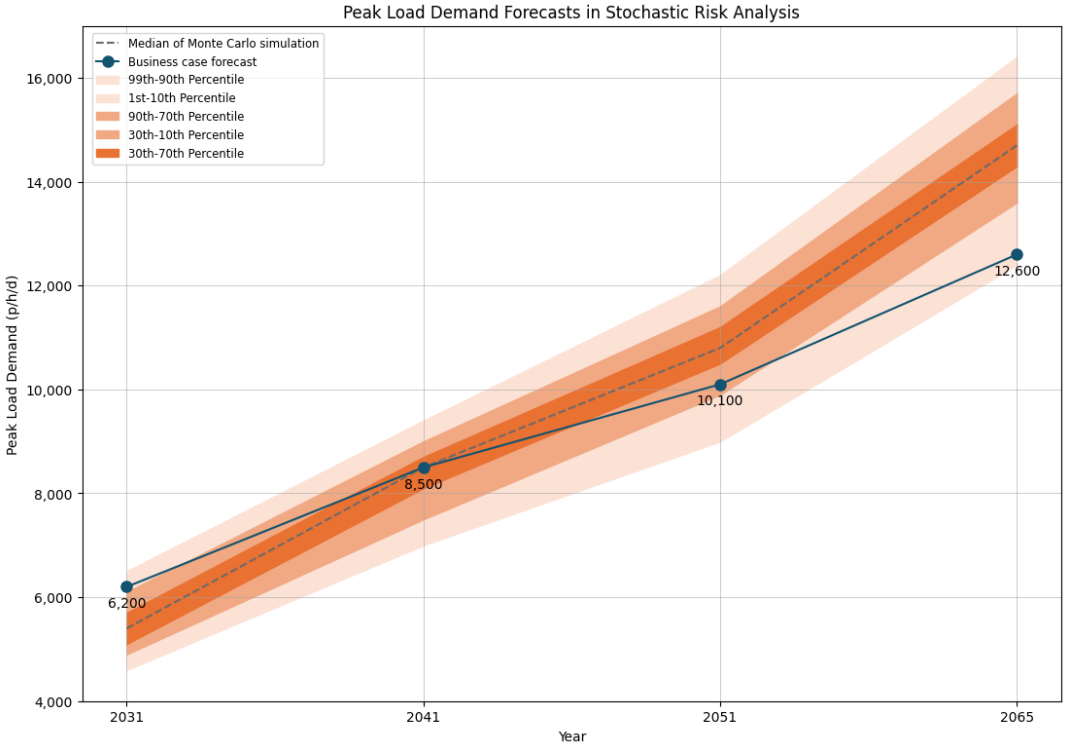
Figure 2: Baseline Case Monte Carlo Simulation



3.2.2 Alternative scenario

In the Alternative scenario, we adopt assumptions with conservative implications for initial demand but that increase over time. The purpose of this scenario is to demonstrate how the approach can be used in “sketch model mode” to quickly understand potential travel demands under different assumptions. Estimated demands are shown in **Figure 3**.

Figure 3: Alternative Scenario Monte Carlo Simulation



We emphasise here that input assumptions – such as population and employment growth – were deliberately set to differ from those used to generate the travel demand forecasts in the business case.[5] Outcomes for the Alternative Scenario shown in **Figure 3** thus essentially differ from the travel demand model forecasts *by construction*. As such, our results should not be construed to imply that the latter forecasts are incorrect. Moreover, if the input assumptions in the Alternative scenario were ultimately determined to be more plausible than those in the Baseline scenario, then the logical next step would be to re-run the travel demand model with updated inputs to arrive at updated forecasts.

The purpose of presenting results for this scenario, however, is to illustrate how our proposed approach provides a straightforward method for quickly testing alternative input assumptions without the need to re-estimate transport models. Indeed, implementing and running the Alternative scenario took less than 10 minutes.

4 Discussion, limitations, and further research

4.1 Discussion

The approach outlined in this paper, which combines regression models with Monte Carlo simulation, enables us to quantify uncertainty associated with key inputs into travel demand forecasts and quickly quantify the effects of changes in input assumptions.

From the illustrative case study above, we conclude the computational demands of the simulation itself are essentially negligible and the approach is highly tractable. In contrast, running 86,000 full model simulations of FSMs or ABMs, like we do here for the Monte Carlo simulation, is infeasible. The approach outlined in this paper thus provides a way to quantify uncertainty in key input assumptions in a way that is relatively computationally tractable.

Naturally, if this approach were to be incorporated into a formal business case, then it would require more time, for example, to identify appropriate statistical distributions and their underlying parameters. As this is entirely unfunded research, we do not attempt to answer such questions here but instead leave them as an area for further work.

We also note the full range of uncertainty is likely to be larger than that shown above. Not only does our approach only consider uncertainty affecting a subset of input assumptions, but we also do not consider the effects of what we have called structural and parameter uncertainty. Nonetheless, even allowing for uncertainty in this subset of key inputs reveals considerable levels of uncertainty. We suggest this is an important point in itself.

4.2 Limitations

This paper seeks to demonstrate the potential of an approach that combines regression models with Monte Carlo simulations to quantify uncertainty in travel demand forecasts.

We note three key limitations that will need to be overcome in real-world applications:

- **Extensive model run requirements** – The regression model was estimated on the results of 147 MSM transport model runs that were conducted over two years. This level of effort and timeframe may be unrealistic for many smaller projects.
- **Limited variation in variables** – The model runs undertaken to support the ALR business case resulted in limited variation in some variables, such as congestion pricing, which prevented the effects of these variables from being identified.
- **Detailed empirical analyses to support assumptions –** The Monet Carlo simulation relies on assumptions for statistical distributions and associated parameters that would ideally be grounded in detailed empirical analyses.

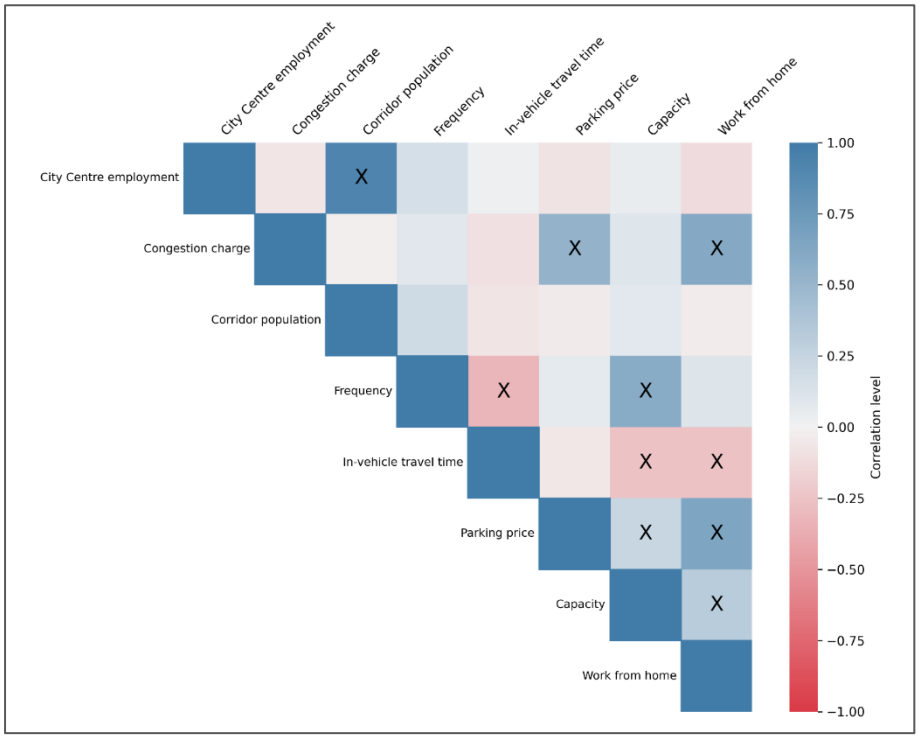
[5] Input assumptions for variables such as population growth, employment, remote working, parking pricing, and the likelihood of congestion charging were deliberately exaggerated to test the resilience of demand forecasts. In a formal business case process, such assumptions would be developed through stakeholder engagement and grounded in evidence.

While our case study serves to highlight the potential of this approach, its usefulness hinges on addressing these limitations. We consider these questions in the next section.

4.3 Further research

We note four main opportunities for further research. First, transport model runs were not undertaken in a strategic or intentional way that sought to minimize multicollinearity. In **Figure 4**, we plot the correlation between attributes in our regression model. Here, blue indicates positive correlations, while amber indicates negative relationships. High correlation values (close to ±1) suggest strong relationships, while values near 0 indicate weak or no association. Statistically significant correlations (1% level) are marked with a cross.

Figure 4: Correlation Plot of Regression Model Attributes

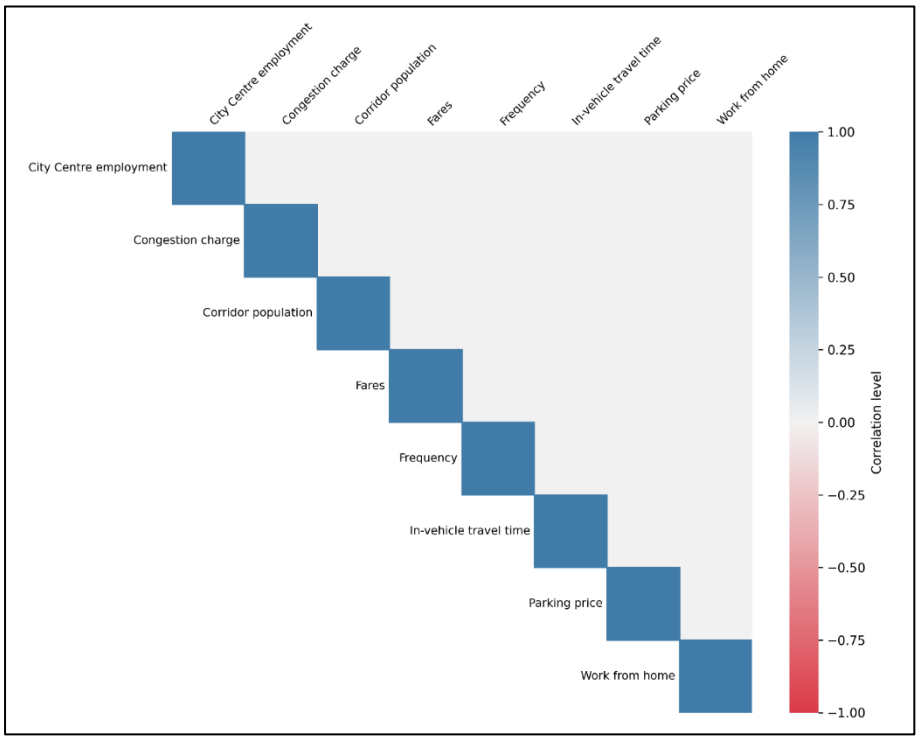


The multicollinearity evident in Figure 4 arises because model runs were structured to meet policy needs from the business case, rather than to optimise the estimation of regression models like we do here. For example, the 0.52 correlation between parking pricing and congestion charges does not imply a causal relationship but instead reflects how the scenarios were designed. These correlations serve to inflate standard errors and reduce the precision of estimated parameters, making it more difficult for us to isolate the individual impacts of some important policy variables, such as congestion pricing.

Transport model runs could, however, be undertaken in a more structured way, for example, using a fractional factorial design. The latter offers a statistically rigorous approach to specifying transport model scenarios, where inputs are systematically varied in a way that increases variance and reduces multicollinearity while using a small number of transport model runs. In our case, and with the benefit of hindsight, a fractional factorial design could have helped to improve the statistical robustness of the case study with far fewer strategically selected runs, rather than the 147 that were undertaken.

An orthogonal design similar to those used for stated choice experiments (Louviere, et al., 2000) for only 36 experiments (Groemping & Morgan-Wall, 2025) – or model runs – could remove this multicollinearity as shown in **Figure 5**.

Figure 5: Correlation Plot of Variables in an Orthogonal Design of 36 variables



Second, our approach does not allow for uncertainty in the parameters estimated from the regression model in Step 1. A simple extension to our simulation could also allow for uncertainty in these parameters. Rather than relying on the asymptotic assumptions that underpin parameter estimates derived using frequentist methods, it may be easier to simply estimate the regression model using Bayesian methods. In this way, the estimated parameters are also treated as random variables, each with their own posterior distributions. These distributions could then be integrated directly into the sampling that is undertaken in the Monte Carlo simulations in Step 2. Not only would this account for uncertainty in parameter estimates but also correlations between the parameter estimates.

Third, the illustrative case presented in this paper required us to make assumptions on the statistical distribution of inputs, such as population and employment, and associated distributional parameters. Although our assumptions were informed by our professional understanding of the nature of the uncertainty that characterizes these outcomes, such assumptions would ideally be grounded in empirical analyses. Using empirical data to characterise uncertainty in inputs would help to strengthen confidence in the results of the Monte Carlo simulations in Step 2, which here rely primarily on experience and engagement and are, by definition, ad-hoc. The latter is something this approach seeks to avoid.

Fourth, and on a related point, we currently model uncertainty in inputs by repeatedly drawing independent samples from the assumed underlying statistical distributions. In practice, we might want to allow for correlations between the underlying inputs, such as population and employment growth, which could then be accounted for directly in the sampling process. Formally allowing for such correlations where they are supported by empirical research would further underscore the added value of our proposed approach compared to more conventional treatments of uncertainty, such as sensitivity testing.

5 Conclusions

Transport planning and investment processes usually rely on travel demand forecasts from transport models. While these models have been continuously refined through decades of research and real-world application, they usually generate deterministic (“point”) estimates

that do not reflect uncertainty in future conditions. As these forecasts often extend decades into the future, uncertainty is an inherent and important aspect of travel demand forecasts.

Directly using transport models to quantify uncertainty remains challenging due to the computational and human resources involved in, for example, defining, executing, and validating model runs. Large-scale models require careful coordination between business case and modelling teams, with each iteration often taking a week or more depending on the specific outputs required. As a result, using transport models to directly quantify uncertainty in travel demand forecasts currently strikes us as being impractical.

To this end, we propose an approach that is designed to complement existing transport models. This approach combines regression models with Monte Carlo simulation to quantify the uncertainty in travel demand forecasts associated with selected inputs. By generating a probabilistic view of future travel demands, this approach helps to provide decision-makers with new insights that can help to manage risks, identify opportunities, and ultimately make better planning and investment decisions. We illustrate the approach by applying it to a recent major transport case study, where we find uncertainty in key inputs causes estimated demands to vary by approximately 5-15%. This variation is significant and highlights, in our view, the merits of incorporating probabilistic insights into planning work.

That said, we also identify several limitations with our approach and highlight opportunities for further research. These include adopting a structured ("orthogonal") approach to model runs, using Bayesian methods to quantify uncertainty in regression model parameters, supporting assumptions on statistical distributions with empirical analyses, and allowing for correlations between inputs. Despite these opportunities for improvement, we nonetheless consider the approach sufficiently well developed to be applied in practice.

Ultimately, systematically accounting for uncertainty in travel demand forecasts has the potential to contribute to significantly better transport planning and investment decisions. Uncertainty is, in our view, an inherent aspect of the transport planning process and should not be treated as an afterthought to be managed via ad hoc sensitivity testing, but rather as a fundamental design consideration for all major transport interventions.

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Appendix: Assumptions in the Monte Carlo simulations

The assumed statistical distributions and associated distributional parameters for the Baseline and Alternative scenarios discussed above are summarized in the following tables.

Baseline Scenario	**2031**	**2041**	**2051**	**2065**
Congestion pricing distribution	Bernoulli	Bernoulli	Bernoulli	Bernoulli
Congestion price parameter	0.95	0.95	0.95	0.95
Parking price distribution	Bernoulli	Bernoulli	Bernoulli	Bernoulli
Parking price parameter	0.95	0.95	0.95	0.95
WfH distribution	Beta-PERT	Beta-PERT	Beta-PERT	Beta-PERT
pert-alpha parameter	4.0	4.0	4.0	4.0
most likely parameter (%)	11.5	11.5	11.5	11.5
minimum parameter (%)	7	7	7	7
maximum parameter (%)	14	14	14	14
Corridor population distribution	Beta-PERT	Beta-PERT	Beta-PERT	Beta-PERT
pert-alpha parameter	4.0	4.0	4.0	4.0
most likely parameter (000s)	170	198	234	289
minimum parameter (000s)	168	186	204	233
maximum parameter (000s)	173	235	289	301
City Centre employment distribution	Beta-PERT	Beta-PERT	Beta-PERT	Beta-PERT
pert-alpha parameter	4.0	4.0	4.0	4.0
most likely parameter (000s)	126	149	161	175
minimum parameter (000s)	125	144	157	167
maximum parameter (000s)	126	154	177	182
Business Case demand forecast	6,200	8,500	10,150	12,600
Probability Business Case demand forecast will be exceeded	22%	39%	69%	75%
90th Percentile demand	6,350	8,950	11,250	13,900
Median demand	6,000	8,350	10,450	13,050
10th Percentile demand	5,700	7,850	9,650	12,200
40th Percentile demand	5,950	8,250	10,300	12,900
30th Percentile demand	5,900	8,150	10,100	12,700
Demand Standard Deviation	285	452	650	701
Demand Coefficient of Variation	4.7%	5.4%	6.2%	5.4%
Demand Distribution Skewness	-0.647	-0.275	-0.085	-0.398
Simulations to reach convergence	4,009	10,087	20,844	24,255

Alternative scenario	**2031**	**2041**	**2051**	**2065**
Congestion pricing distribution	Bernoulli	Bernoulli	Bernoulli	Bernoulli
Congestion price parameter	0.3	0.6	0.85	0.92
Parking price distribution	Bernoulli	Bernoulli	Bernoulli	Bernoulli
Parking price parameter	0.4	0.75	0.9	0.96
WfH distribution	Beta-PERT	Beta-PERT	Beta-PERT	Beta-PERT
pert-alpha parameter	6	6	6	6
most likely parameter (%)	13.1	11.2	10.5	8.5
minimum parameter (%)	7	7	7	7
maximum parameter (%)	14	14	14	14
Corridor population distribution	Uniform	Beta-PERT	Beta-PERT	Beta-PERT
pert-alpha parameter		6	6	6
most likely parameter (000s)		210	240	293
minimum parameter (000s)	168	186	204	233
maximum parameter (000s)	173	235	289	301
City Centre employment distribution	Normal	Beta-PERT	Beta-PERT	Normal
pert-alpha parameter		6	6	
most likely parameter (000s)		150	165	
minimum parameter (000s)		144	157	
maximum parameter (000s)		154	177	
mean parameter (000s)	129			184
standard deviation parameter	6			8
Business Case demand forecast	6,200	8,500	10,150	12,600
Probability Business Case demand forecast will be exceeded	6%	48%	85%	98%
90th Percentile demand	6,100	9,050	11,600	15,700
Median demand	5,400	8,450	10,850	14,700
10th Percentile demand	4,900	7,450	9,900	13,550
40th Percentile demand	5,250	8,300	10,650	14,450
30th Percentile demand	5,150	8,150	10,500	14,250
Demand Standard Deviation	458	582	678	853
Demand Coefficient of Variation	8.4%	7.0%	6.3%	5.8%
Demand Distribution Skewness	0.350	-0.454	-0.434	-0.338

We emphasise these assumptions have been made based on professional experience and stakeholder feedback and are intended to simply illustrate the potential application of Monte Carlo techniques. These assumptions are not intended to reflect a formal business case for ALR, nor do they represent the views or recommendations of any sponsoring agency. Ideally, the assumptions in the Monte Carlo simulation would be premised in and supported by detailed empirical analyses.