Understanding Risks and Uncertainties in Transport Demand Forecasts with Monte Carlo Techniques

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Executive Summary

This paper outlines both the theoretical foundations and practical application of Monte Carlo methods for travel demand forecasting, demonstrating how they can be integrated into business case processes to strengthen infrastructure planning and investment decisions. Although Monte Carlo simulation is commonly used to assess cost uncertainty, its use in transport demand forecasting remains limited. Applied in this context, it offers a powerful way to understand and communicate the range of possible outcomes. By introducing probabilistic insights into demand variability, it complements traditional forecasting and risk assessment methods. This directly addresses government concerns about cost overruns and the need for more robust evidence in infrastructure planning. When embedded within investment appraisal frameworks, it provides more systematic insights into the sensitivity of forecasts from travel demand models to changes in inputs - ultimately supporting more transparent, adaptive, and resilient decision-making.

Key Findings:

1. **Practical Implications for Policymakers and investors:** Monte Carlo simulations provide a probabilistic framework to manage risk and evaluate the robustness of business case forecasts.
2. **Making Monte Carlo a Practical Tool for Major Projects:** For Monte Carlo simulation to be effective in major infrastructure and policy decisions, it must be quick to apply, easy to use, and directly relevant to investment planning. It should help decision-makers understand risks, compare different scenarios, and plan for future uncertainties. This makes Monte Carlo not only faster and more practical to apply but also a more robust tool for real-world infrastructure planning.
3. **Enhanced Predictive Accuracy with the Best-Suited Model:** Selecting a regression model that best fits the available data is crucial and it’s important to test alternative transformations before finalising the simulation approach. In this case, a log-transformed regression model outperformed other models, achieving more precise demand forecasts.
4. **Securing Stakeholder Buy-In:** Recognising that the effectiveness of Monte Carlo analysis depends on stakeholder engagement grounded in sound evidence, a graphical interface was developed to support the collaborative definition of plausible futures. This interactive platform ensures transparency in input selection, while real-time visual feedback enables rapid refinement of assumptions based on simulation results - fostering trust, clarity, and shared understanding throughout the process.
5. **Testing Future Scenarios: Ensuring Adaptability Under Uncertainty**: Monte Carlo simulations are powerful tools for exploring dynamic, plausible futures. A scenario was developed to demonstrate how the model responds to both higher- and lower-than-expected demand drivers over time. The results highlight the risks of overinvestment if demand falls short and the potential for capacity constraints if demand exceeds expectations. This underscores the option value of flexible planning, ensuring that infrastructure investments remain adaptable to a wide range of future demand conditions.
6. **Transferability of Approach:** While developed using results from a rapid transit case study, this Monte Carlo simulation framework is highly versatile. It can be applied to other high-priority transport investments, such as Roads of National Significance, busways and congestion pricing, offering robust decision support for diverse infrastructure projects across New Zealand.

Monte Carlo approaches should be a required component of all major transport investment and policy business cases, providing a systematic framework for assessing uncertainty and improving the credibility of demand forecasts - ensuring uncertainty is a core consideration, not an afterthought.

Contents

1 Introduction

Transport policy and planning largely depend on travel demand models to forecast future transport patterns and guide investment decisions. Yet, like all predictive models, their forecasts are inherently uncertain - raising concerns about overspending, unreliable forecasts, and inadequate evidence in decision-making.

At its core, this paper builds on Willumsen's (2014) assertion that *"uncertainty is unavoidable in any forecast of future conditions*". Recognising that risk is quantified uncertainty, this paper demonstrates how Monte Carlo techniques can systematically capture uncertainty and present it in a way that strengthens decision-making.

This paper first examines transport policy and travel demand modelling before introducing the Monte Carlo approach. It then applies this method to a major Auckland infrastructure project as a case study and concludes with an analysis of its implications for modelling and policy.

Monte Carlo techniques offer a powerful tool for assessing uncertainty in demand forecasts. By simulating a range of possible outcomes under varying assumptions, they provide a probabilistic perspective, enhancing risk management and decision-making. Whether you are a policymaker shaping infrastructure priorities, an investor evaluating returns, a banker assessing repayment risks, a consortium bidding on a major project, or a government agency delivering large-scale infrastructure, this approach offers a data-driven framework to improve how transport projects are planned, funded, and implemented.

2 Background

2.1 Improving Infrastructure Decisions Through Better Risk Assessment

In New Zealand, as in many other countries, transformative projects, from city-shaping infrastructure and region-connecting investments to pricing strategies that manage demand and drive economic growth, are assessed through structured business cases. These cases rely heavily on transport model forecasts to guide investment and policy decisions, underpinning cost-benefit analysis (CBA), funding prioritisation, and risk assessments that shape major infrastructure projects.

However, traditional forecasting approaches tend to present deterministic outputs - single-point estimates that do not fully capture uncertainty. As Willumsen and Ortúzar (2015) note *"the future is not deterministic and no amount of technical skills and models can change that"*. Failing to explore uncertainty in travel demand forecasts can lead to over- or under-estimated project and policy benefits, influencing political and financial commitments to transport investments and policies. Uncertainty is especially important in major projects which have long planning horizons and whose infrastructure lasts for many decades, where unforeseen changes in demographics, land use, technology, and travel behaviour can drastically alter outcomes.

Recent research (Megaprojects and Risk, 2024) (Forecast Bias - How to Reduce Forecast Bias and Increase Accuracy, 2025) and real-world case studies illustrate the risks of neglecting uncertainty. Both overly optimistic and overly pessimistic demand forecasts have led to significant challenges in major transport projects worldwide - excessive projections often result in cost overruns and underutilised infrastructure, while overly cautious estimates can delay or prevent much-needed investments, only to later require expensive and disruptive capacity expansions to meet unforeseen demand. Some examples are:

High Speed Rail 2 (HS2) – United Kingdom

HS2's estimated costs have surged from £37.5 billion in 2009 to nearly £100 billion, leading to the cancellation of both the eastern and western legs under recent governments. Investigations have highlighted mismanagement, inefficient spending, and inadequate governance as contributing factors.

Sir Jon Thompson's resignation as HS2 chair follows reports of a £9 billion increase in project costs, raising the estimated total to between £54 billion and £66 billion in 2019 prices, potentially £80 billion today (Topham, 2024).

An evidence submission to the UK Parliament's Economic Affairs Committee raised concerns that the business and economic cases for HS2 have significantly overstated forecast passenger demand, with estimates potentially exceeding actual demand by 21.4% to over 300% (UK Parliament Economic Affairs Committee, 2025).

Brisbane's Clem Jones Tunnel (CLEM7)

The tunnel experienced actual traffic volumes as low as one-third of forecasted figures, leading to significant revenue shortfalls. Due to lower-than-expected usage, RiverCity Motorways, the tunnel's operator, went into receivership in February 2011, owing $1.3 billion (TransApex, 2024).

Docklands Light Railway (DLR) – London, UK

Upon its inauguration in 1987, the Docklands Light Railway (DLR) in London experienced passenger numbers that quickly surpassed initial forecasts, leading to overcrowding and necessitating rapid capacity enhancements. The original system was designed with a capacity of approximately 9,000 passengers per hour in each direction. However, due to the rapid development of the Docklands area into a significant financial and commercial hub, ridership increased much faster than anticipated. This surge in demand prompted the extension of platforms to accommodate longer trains and the expansion of the network to better serve the growing number of passengers (Select Committee on Transport: Written Evidence, 2005).

These unforeseen high passenger numbers led to the acceleration of capacity improvement projects, resulting in increased costs and logistical challenges to meet the ridership needs. The initial infrastructure had to be upgraded sooner than planned, highlighting the importance of accurate demand forecasting in transport infrastructure projects (Transport for London, 2023).

M25 Motorway – London, UK

The M25, encircling London, was designed for a maximum capacity of 88,000 vehicles per day but, by 1993, was accommodating 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 (M25 motorway, 2024).

A growing body of research highlights the importance of explicitly accounting for uncertainty in infrastructure decision-making (Hall, 2024; Moroni & Chiffi, 2022). One of the most compelling benefits of this is the concept of *option value* - the strategic advantage of designing infrastructure with the flexibility to scale up or down in response to future demand (Option value cost-benefit analysis, 2025; Real options valuation, 2019). Monte Carlo simulation offers a practical means of operationalising option value in transport planning and demand forecasting. By quantifying uncertainty, simulating a wide range of plausible futures, and pinpointing where flexibility in timing, staging, or capacity is most valuable, it helps planners manage the risks of overbuilding or under-provisioning and embed adaptive decision-making directly into project design.

2.2 Why Monte Carlo Matters for Policy-makers and Public Infrastructure Agencies

For the purposes of this paper, policy-makers are considered in two broad groups: **sponsors** and **policy advisors**.

- *Sponsors* are elected officials - such as government ministers, mayors, or chairs of council committees - who are ultimately responsible for major investment decisions.
- *Policy advisors* are public servants who support these decision-makers by providing analysis and recommendations on major transport projects and policy levers, including congestion pricing, fare structures, and tolling strategies.

Alongside them, **public infrastructure agencies -** such as NZTA, TfNSW, and Auckland Transport - play a central role in delivering, operating, and maintaining transport networks. While these agencies are not motivated by direct financial return in the way private investors[1] are, they must still justify public investment, manage demand risk, and ensure the efficiency and sustainability of transport systems. Their role is to implement policies effectively and deliver infrastructure that aligns with strategic objectives, all while remaining accountable to both policy-makers and the public.

[1] While this paper focuses on policy-makers and public infrastructure agencies, Monte Carlo techniques are equally valuable to private investors in transport projects. For investors, understanding the range of possible demand outcomes is critical to assessing risk, informing commercial decisions, and structuring contracts and financing.

In the context of Monte Carlo analysis for travel demand, both groups are particularly focused on two key questions:

- How much confidence can I have in the business case forecasts?
- How do these forecasts compare to a range of plausible futures?

They must evaluate the impact of controllable policy levers (e.g., fares, tolls, or parking prices) alongside less controllable factors (e.g., employment growth), all under real-world uncertainty. Insights from Monte Carlo simulations help guide funding decisions, scenario planning, and strategies to build investor and community confidence.

Both policy-makers and agencies must balance economic, social, and environmental considerations. Credible, evidence-based demand forecasts support smarter resource allocation, risk management, and transparency. For sponsors, political credibility matters as much as project performance - missed forecasts can damage reputations and erode public trust.

Key Perspectives

When designing Monte Carlo scenarios and interpreting results, policy-makers and infrastructure agencies are likely to consider the following:

- **Confidence in Forecasts**
  Evaluate demand across the 10th, 50th, and 90th percentiles:
    - Forecasts close to the median (50th percentile) suggest alignment with likely outcomes.
    - Forecasts within the 10^{th} - 90th percentile indicate balanced assumptions and manageable risk.
- **Impact of Policy Variables**
  Understanding the role of key inputs - both individually and in combination - is essential:
    - Controllable variables (e.g., tolls, congestion pricing, fares) can be shaped directly.
    - Limited-influence factors (e.g., employment, population growth) are influenced by broader national or global trends. For example, while immigration policy can affect population growth, it may take years to shift travel demand.
- **Warning Signals**
    - Business case forecasts consistently below the 50th percentile may indicate underdeveloped downside analysis.
    - Right-skewed distributions (positive skewness) suggest reliance on optimistic assumptions.
    - A high coefficient of variation or large changes in standard deviation across years may reflect unstable or uncertain forecasting.
- **Red Flags**
    - Forecasts above the 90th percentile signal a high risk of optimism bias, increasing the chance that actual demand will fall short.
    - Forecasts below the 10th percentile raise capacity concerns, suggesting pessimism bias and a risk of early, costly upgrades - undermining public trust in planning and investment decisions.

For agencies like NZTA and Auckland Transport, option value is critical. Monte Carlo methods support flexible planning, enabling phased infrastructure delivery, modular expansion, and adaptive policy responses - ensuring projects remain financially viable and effective under changing demand conditions.

As noted by Transport for London in its review of Auckland's Light Rail business case:

"While the core forecasting assumptions appear robust, given the experience with COVID and the rapid rate of technological and environmental change, it would be prudent to understand the impacts of the scheme against a broad range of plausible contextual futures" (TfL, 2024).

Monte Carlo techniques are ideally suited to support this kind of analysis, particularly when evaluating flexibility, resilience, and option value in public transport investment.

2.3 Travel Demand Modelling: Structure, Inputs, and Computational Complexity

Travel demand modelling plays a critical role in transport policy and investment decision-making by generating forecasts that inform business cases. These models provide a structured approach to predicting how people will travel in the future, based on economic, demographic, and network conditions. Over decades of international development, they have evolved into sophisticated tools with significant refinements and improvements, in most cases making them the only available method for producing the forecasts necessary for transport business cases.

The four-step model (FSM**)** remains the dominant framework for urban transport planning, including in Auckland's Macro Strategic Model (MSM)**:**

1. Trip Generation – Predicts how many trips originate from and arrive at specific zones based on population, employment, and land use.
2. Trip Distribution – Determines where trips go, estimating interactions between different zones.
3. Mode Choice – Allocates trips to available transport modes (e.g., car, public transit, walking, cycling).
4. Trip Assignment – Assigns trips to the transport network, reflecting congestion effects and route choices.

Moreover, these models rely on key input variables, including:

- Demographic trends (population, employment, household structures).
- Transport network attributes (road capacity, transit availability, fares, road tolls).
- Policy levers (congestion pricing, parking regulations, work-from-home trends).

A good example of refinements to traditional 4 stage models is London's Model of Travel in London (MoTiON). While it follows the conventional stages of trip generation, trip distribution, mode choice, and network assignment, it enhances these steps by adopting a tour-based approach, focusing on home-based tours to better represent actual travel behaviour (Transport for London, 2023).

While FSM models provide structured, interpretable outputs, their use in business cases is constrained not just by computational demands but also by the time-intensive process of model execution. Large-scale models like Auckland's MSM require not only significant processing power but also careful coordination between the business case and modelling teams. Developing a clear model 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. As a result, exhaustive uncertainty analysis is often impractical, leading to simplified assumptions about future demand conditions.

Traditional demand models are therefore not only inherently deterministic but also limited by the time-intensive process of defining, executing, and validating model runs, which constrains their ability to be used to directly assess uncertainty.

2.4 Uncertainty in Travel Demand Modelling: Why Focus on Input Uncertainty?

Uncertainty in travel demand forecasting arises from multiple sources, broadly categorised as:

1. Structural Uncertainty – Limitations in model design and underlying assumptions (e.g., appropriateness of the four-step structure and comprehensiveness of the behavioural responses that are included, such as trip-chaining and departure time choice).
2. Parameter Uncertainty – Variability in the estimated coefficients for the behavioural components of the models (e.g., mode specific factors, value of time, elasticity of demand).
3. Forecast Input Uncertainty – Fluctuations in forecasts of key external inputs such as land use, population growth, pricing policies, and network configurations.

The implications of structural and parameter uncertainties - that is, the first two sources noted above - are generally best addressed during the model development phase, before the model is used for appraisal. While these sources of error can be reduced through better base year data and improved models, Willumsen and Ortúzar (2015) note that they can never be eliminated and remain an inherent challenge.

In contrast, input uncertainty arises during model application in business case development and is the primary focus of this paper. It is often a large driver of variability in demand forecasts, as key factors such as future land use patterns, employment concentrations, work-from-home trends, and travel costs are inherently uncertain yet central to shaping model outcomes. For instance, assumptions about work-from-home adoption or road pricing policies can significantly alter travel behaviour, directly affecting the projected viability of transport investments. A useful diagram illustrating these different sources of uncertainty is shown in Figure 1.

Partly due to the time involved in running travel demand models, Willumsen and Ortúzar (2015) conclude that addressing uncertainties in future inputs requires approaches that extend beyond better models and calibration data, such as stochastic risk analysis and scenario planning.

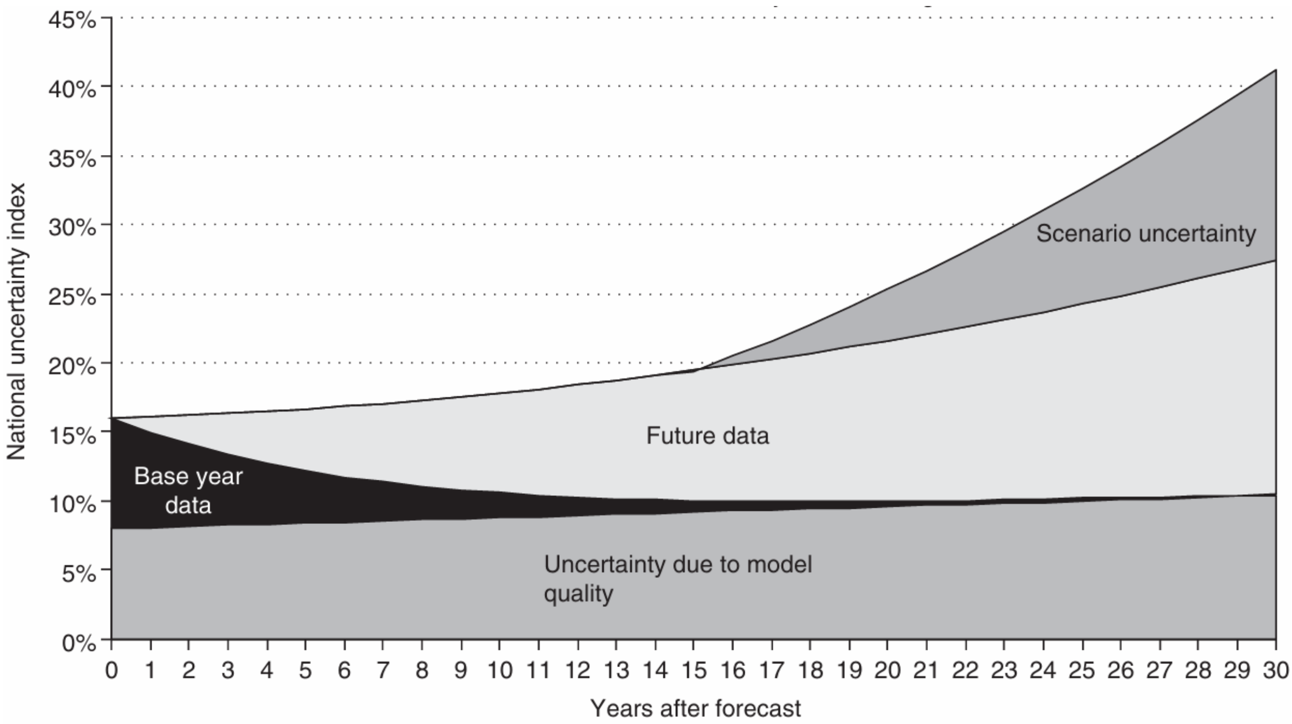

Figure 1: Notional Sources of Uncertainty in Forecasting (Willumsen & Ortúzar, 2015)

3 Case Study: Application to a Transport Project Business Case

3.1 Approach

Establishing a Framework: Monte Carlo Simulation for Travel Demand Forecasting

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), who outlines the following method for simulating transport demand:

- **First**, use a combination of evidence (e.g. ex-post assessments) and stakeholder engagement to identify the input variables most likely to drive uncertainty, and define how model outputs relate to them.
- **Second**, conduct model runs to examine how variation in these inputs affects forecast patronage.
- **Third**, determine appropriate probability distributions for those key inputs, drawing on evidence, expert judgement, and stakeholder input.

- **Finally**, construct a model in which these variables influence patronage outcomes, and repeatedly sample from their distributions using Monte Carlo simulation.

Selecting a Case Study for Demonstration

The Auckland Light Rail (ALR) programme provides a valuable case study for demonstrating how Monte Carlo simulation techniques can be applied to quantify uncertainty in demand forecasting, while also illustrating the benefits of aligning technical modelling with stakeholder-informed, evidence-based scenarios. Although the Monte Carlo method was not fully implemented in the ALR business case itself, the extensive modelling undertaken provides an ideal foundation for demonstration purposes.

For the most recent ALR business cases, 147 transport model scenarios were developed over two years using the Macro Strategic Model (MSM), operated by the Auckland Forecasting Centre (AFC)[2]. MSM is a multimodal demand model used to forecast travel demand for major projects in Auckland. The MSM model was successfully peer reviewed for suitability by Transport for London (2023), and these model runs provide a rich source of data for developing and testing Monte Carlo simulations of transport demand.

While passenger forecasts from MSM are used to demonstrate the method, the aim is not to evaluate the ALR business case itself, but rather to advance forecasting techniques for quantifying uncertainty - techniques that can be applied to future projects.

Applying the Monte Carlo Framework to the Case Study

To show how Monte Carlo techniques can improve understanding of risk and uncertainty in MSM-based transport demand forecasts, the approach outlined by Willumsen (2014) has been adapted as follows:

1. **Leverage MSM Scenarios for Regression Modelling**: The first step uses the 147 MSM runs from the ALR indicative and detailed business cases to estimate a regression model that predicts passenger demand as a function of key input assumptions.
2. **Characterise Input Variability**: Monte Carlo simulation is then used to introduce variability into the model inputs. This involves generating random draws from selected probability distributions, calibrated to reflect real-world uncertainties.
3. **Simulate Passenger Demand**: Finally, the regression model is applied to the randomly sampled inputs to generate a range of demand forecasts that represent different plausible future scenarios, reflecting real-world uncertainty.

This adapted Monte Carlo method was applied to two illustrative scenarios. These demonstrate how the technique can support infrastructure decision-making by quantifying uncertainty and highlighting risk. The first scenario applies the approach to a baseline case aligned with the original business case assumptions. The second introduces a dynamic scenario designed to explore the concept of option value - showing how Monte Carlo simulation can inform staged investment or adaptive planning strategies.

The assumptions used in both scenarios were developed solely to illustrate how Monte Carlo techniques can be applied during the development of a business case. They are not intended to review or critique the original ALR business case, nor do they reflect the formal assumptions, inputs, or views of any sponsoring agency. In a formal business case, assumptions would be developed in consultation with stakeholders and supported by robust evidence - for example, by comparing historical population and employment projections with actual outcomes. The two illustrative scenarios are outlined below.

Baseline Case: Business Case Assumptions

This scenario uses input assumptions that approximate those adopted in the original ALR business case. The purpose is to demonstrate how Monte Carlo simulation can be used to quantify uncertainty around central demand forecasts, even when based on a fixed set of policy and input assumptions.

Dynamic Scenario: Exploring Option Value

The second scenario constructs a time-varying pathway in which key input variables evolve over time - reflecting a plausible future where growth and policy intervention are delayed before accelerating. Variables

[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.

such as employment, population growth, parking pricing, and the likelihood of congestion charging are assumed to be lower than the business case assumptions in the early years and higher in later years. In contrast, working-from-home uptake is assumed to be higher initially, tapering off over time. The aim is to illustrate how Monte Carlo methods can highlight the option value of flexibility: helping decision-makers understand the benefits of designs or investment strategies that can scale or adapt as uncertainty unfolds.

3.2 Developing the Regression Model

Selecting attributes

Most risk and uncertainty are likely to be associated with attributes that influence passenger demand and are beyond the direct control of any future transport authority or operator. These variables are primarily driven by market forces and/or pending government policy decisions. Consequently, the following variables were selected for developing the Monte Carlo methodology:

- Congestion pricing, which depends on future national and local government decisions.
- City Centre parking prices, influenced by both market forces and national and local government policies regarding the supply of parking.
- City Centre employment growth, largely determined by local, national, and international economic market forces and planning regulations.
- Working from Home (WfH), dependent on industry and service sector employment policies, particularly impacting passenger demand in the City Centre given its high proportion of office workers. This factor was also identified as worth further exploration by the TfL review of the MSM model.
- Population growth along the corridor, influenced by market forces and central and local government housing policies for significant areas of government-owned land along the corridor.

Other key drivers of demand, such as train frequency, capacity, and travel times, were not simulated using Monte Carlo methods for this paper, although were included in the regression model to improve its predictive power. For this case study, these factors were deemed more directly controlled by the transport operator or authority managing the train service, and the associated risk and uncertainty are likely lower compared to the exogenous variables.

Estimating the Model

During the development of this paper, multiple regression models were evaluated and eventually landing 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 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]

The 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
- $\log Pop_i$ 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 (7% or 14%)

[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 (%).

- 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 are shown in Table 1.

Table 1: Regression results

Parameter	Variable	Interpretation / Measure	Coefficient	t-statistic
$\boldsymbol{\beta_0}$	-	Intercept	3.806	8.2
$\boldsymbol{\beta_1}$	$\log Pop_i$	Population in corridor (000s)	0.546	4.0
$\boldsymbol{\beta_2}$	$\log Emp_i$	Employment in city centre (000s)	0.895	4.4
$\boldsymbol{\beta_3}$	$\log IVT_i$	In-vehicle travel time (mins)	-0.847	-16.0
$\boldsymbol{\beta_4}$	$\log Cap_i$	Capacity at PLP (p/h/d, 000s)	0.135	9.3
$\boldsymbol{\beta_5}$	$\log F_i$	Frequency (trains per hour)	0.157	3.8
$\boldsymbol{\beta_6}$	WfH_i	WfH (7%, 14%)	-0.029	-6.5
$\boldsymbol{\beta_7}$	D_i^C	Congestion charge (0=No, 1=Yes)	0.015	0.6
$\boldsymbol{\beta_8}$	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] it was found:

- **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-values of the parameters for continuous variables indicate they are statistically significant and estimated relatively precisely.

For non-transformed variables, the parameters can 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%.

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

The estimated parameter for congestion pricing is small and imprecise, likely due to limited variation across the 147 scenarios, where its implementation was assumed early in the process - an outcome that, while counterintuitive, reflects the constraints of the Business Case approach and resulting forecasts available to estimate regression models.

With an R^2 of 0.92, the model explains 92% of the variance in peak load demand, indicating a strong fit to observed data. We also tested a regression model that included dummy variables for the year associated with the transport model run, although these were not found to improve model performance.

3.3 Results: Baseline Case

Having defined the probability distributions and parameters[5] to broadly reflect business case assumptions, the regression model was applied to randomly sampled inputs to produce a range of plausible demand forecasts. The full set of input parameters and corresponding results are presented in Appendix A.

Recognising that effective Monte Carlo analysis depends on stakeholder engagement and a solid evidence base in defining plausible futures, a Python-based interface (Python, 2025) was developed to support an interactive and transparent process (Appendix B). Designed for use in collaborative workshops - both in person and online - the platform allows stakeholders to adjust key parameters in real time, using evidence-based inputs to inform those changes and receive immediate visual feedback. This approach fosters shared understanding, builds trust in the process, and enables rapid, transparent refinement of scenarios based on simulation outcomes.

Figure 2 shows the simulation's median, 10th, and 90th percentiles, together with the business case forecasts and the probabilities they will be exceeded for each forecast year. This provides a range for decision-making and emphasises the reliability of the model's assumptions.

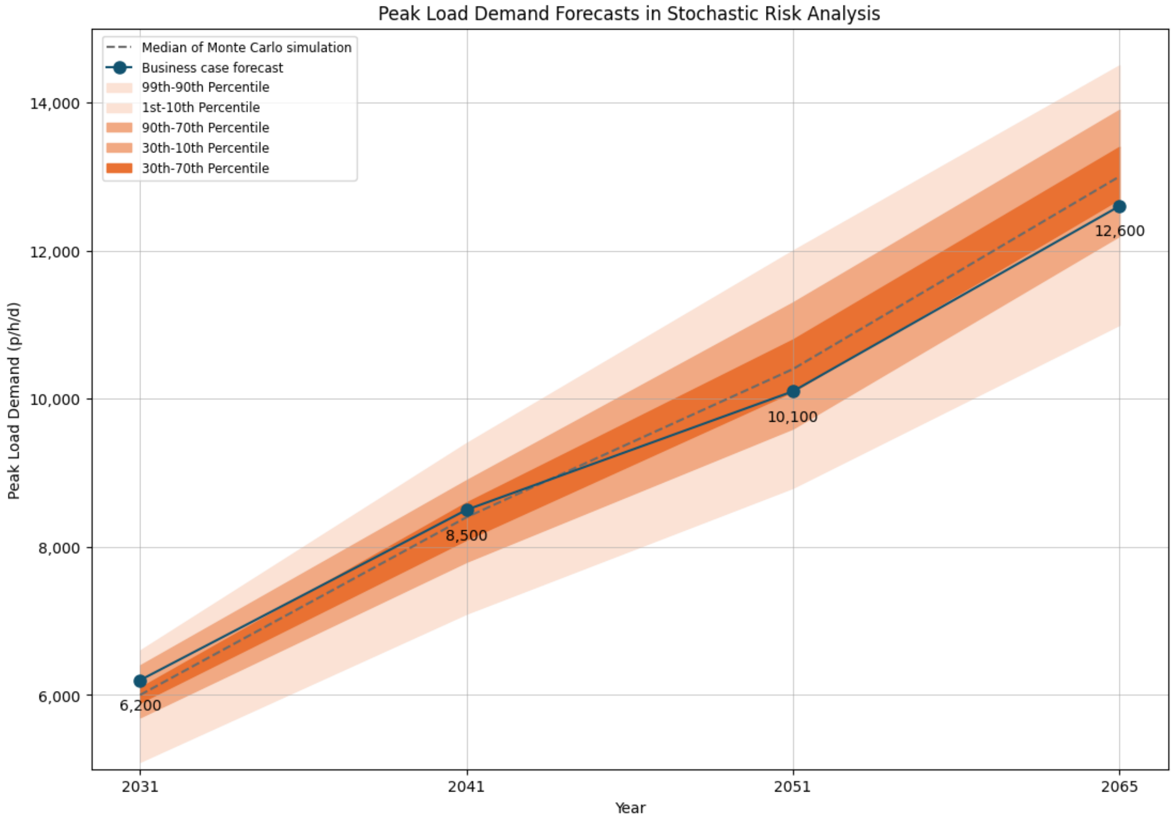

Figure 2: Baseline Case Monte Carlo Simulation

[5] The probability distributions and input parameters used for the Baseline Case in this paper were selected solely to demonstrate the application of Monte Carlo techniques. They do not represent the assumptions or inputs that would be used in a formal business case process for ALR, nor should they be interpreted as reflecting the views or recommendations of any sponsoring agency.

The business case forecast growth in peak load demand from 6,200 p/h/d in 2031 to 12,600 p/h/d in 2065. The Baseline Case Monte Carlo simulations suggests this forecast may be reasonably optimistic for the early years and more conservative for the later years. A summary of the findings from the Baseline simulations is:

- ***2031***: *The business case forecast is 6,200 p/h/d, which is slightly above the median of the Monte Carlo simulations. This indicates a slightly optimistic forecast, with an almost 80% probability that actual demand could be lower. The 90th percentile of the simulations suggests that in more optimistic scenarios, peak load demand could reach approximately 6,350 p/h/d, while the 10th percentile suggests a more conservative estimate of around 5,700 p/h/d.*
- ***2041***: *The forecast of 8,500 p/h/d is also slightly above the median, with about a 60% chance that actual demand could be slightly lower. Optimistic simulations suggest a peak demand of up to 8,950 p/h/d (90th percentile), whereas more conservative simulations project a demand of around 7,850 p/h/d (10th percentile).*
- ***2051***: *The forecast of 10,100 p/h/d is below the median, indicating that it may be somewhat conservative. There is roughly a 70% chance that actual demand could be higher. In optimistic scenarios, demand could reach up to 11,250 p/h/d (90th percentile), while more cautious simulations suggest a demand of around 9,250 p/h/d (10th percentile).*
- ***2065***: *The forecast of 12,600 p/h/d is above the median and is the most optimistic forecast. There is around an 80% chance that actual demand could be higher than this forecast. However, it remains within the expected range, with the 90th percentile indicating a possible peak demand of up to 13,900 p/h/d and the 10th percentile suggesting a more conservative estimate of around 12,200 p/h/d.*

Summary:

Overall, the business case forecasts are generally close to the median projections across all years, suggesting that the forecasts are reasonably robust. The most likely outcomes fall within the 10th to 90th percentile range, which indicates a reasonable level of confidence in the passenger demand forecasts, barring any unforeseen significant events like the recent global COVID epidemic.

3.4 Results: Dynamic Scenario - Exploring Option Value

To demonstrate how Monte Carlo techniques can be used to highlight option value, the regression model was applied to a dynamic scenario in which key inputs evolve over time - starting below and rising above the assumptions used in the business case. This structure reflects the uncertainty and asymmetry often present in long-term infrastructure planning, where short-term conditions may suppress demand, but long-term trends may exceed expectations.

The simulated demand forecasts, shown in Figure 3, illustrate how patronage could respond under these changing conditions. As with the baseline case, the median, 10th, and 90th percentiles are presented alongside the business case forecasts, providing a range of plausible outcomes and demonstrating the importance of flexibility in investment decisions.

This scenario was designed for illustrative purposes only. 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.

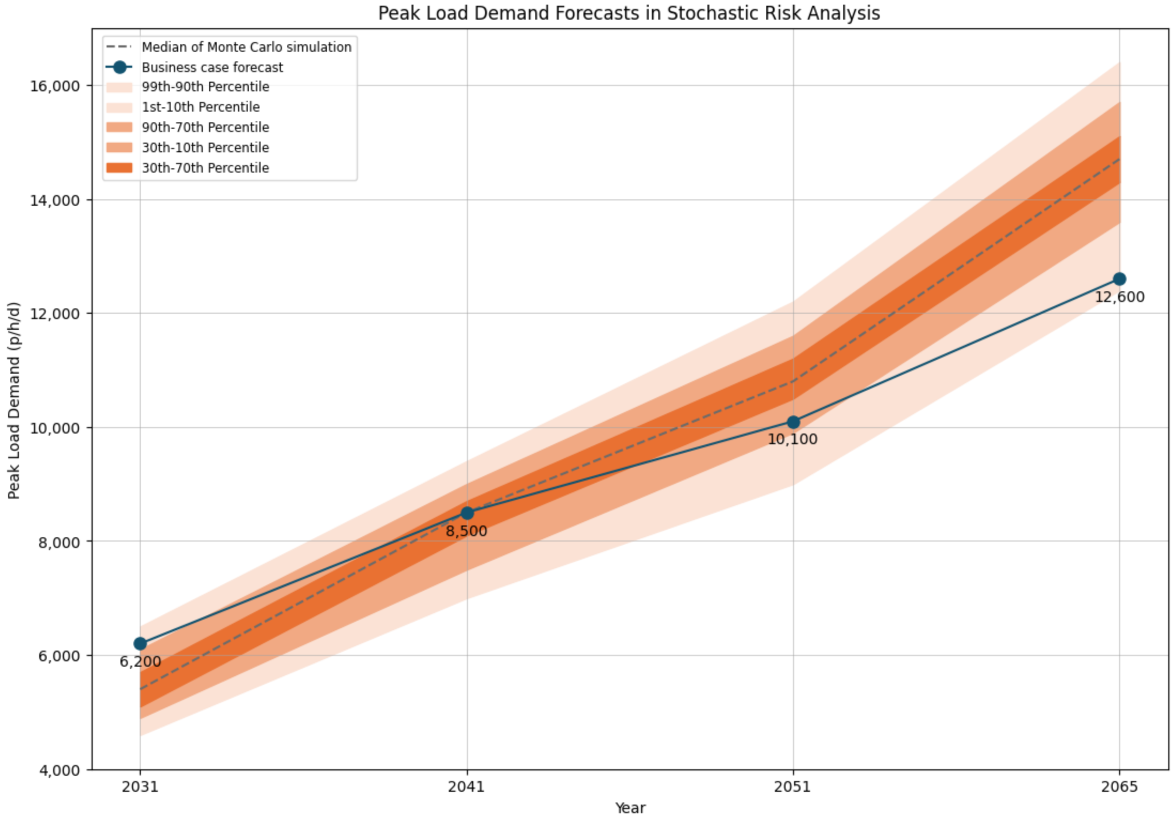

Figure 3: Dynamic Scenario Monte Carlo Simulation

These results illustrate how probabilistic demand forecasts can uncover early signs of over- or under-estimation, highlighting where flexibility in design or timing may be warranted. Table 2 presents these results in RAG form to support clearer interpretation, followed by a summary focused on option value implications of the results. The rationale for RAG colour allocations is detailed in Appendix D.

Table 2: Dynamic Scenario Results

Metric	2031	2041	2051	2065
Business Case demand forecast (p/h/d)	6,200	8,500	10,150	12,600
Probability Business Case demand forecast will be exceeded (%)	6%	48%	85%	98%
90th Percentile demand (p/h/d)	6,100	9,050	11,600	15,700
Median demand (p/h/d)	5,400	8,450	10,850	14,700
10th Percentile demand (p/h/d)	4,900	7,450	9,900	13,550
Demand Standard Deviation (p/h/d)	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
Simulations to reach convergence	10,358	16,722	22,722	35,941

2031: Overestimated Demand – Can Capacity Be Phased?

- The business case forecast (6,200 p/h/d) exceeds even the 90th percentile, with a 94% probability of being of being lower - suggesting over-optimism in early demand projections.
- The median demand (5,400 p/h/d) is 13% lower, increasing the risk of underutilised capacity low return on public investment.
- Positive skewness (0.35) indicates a greater concentration of lower demand outcomes, reinforcing the risk that early demand has been overestimated.

Key Option Value Considerations:

- Can capacity be phased or deferred to reduce upfront capital costs?
- Could smaller initial station sizes, rolling stock, or service frequency optimise resource allocation?
- Can early ridership incentives (fare reductions, targeted promotions) help improve capacity utilisation?

2041: Balanced Projection – Stability for Investment

- The business case forecast (8,500 p/h/d) closely aligns with the median (8,450 p/h/d), with a 48% chance of being exceeded, suggesting a well-balanced forecast.
- Moderate demand variability (CV of 7%) provides stable conditions for investment and expansion planning.

2051: Under-forecasting Risks – Will Capacity Be Enough?

- The business case forecast (10,150 p/h/d) is 7% below the median (10,850 p/h/d), with an 85% chance of being exceeded - raising concerns about capacity constraints.
- Increasing standard deviation (678 p/h/d) requires scalable operational strategies particularly for planning fleet sizes as the standard deviation exceeds the capacity of a train.
- Negative skewness (-0.43) suggests a higher concentration of demand scenarios above the business case forecast, strengthening the case for early capacity expansion planning to avoid costly last-minute upgrades.

2065: Long-term Growth – Is Capacity Scalable?

- The business case forecast (12,600 p/h/d) is well below both the median (14,700 p/h/d) and 10th percentile (13,550 p/h/d), with a 98% probability of being exceeded.
- The risk of severe capacity shortages suggests urgent need for scalable infrastructure planning.

Key Option Value Questions:

- Is the infrastructure scalable? Can it handle 20% more demand than forecasted without costly, disruptive, last-minute expansions?
- Are we planning the right scheme? Would a more flexible design better accommodate long-term growth trends?

4 Discussion and Further Research

4.1 Moving Beyond Point Forecasts: Practicality and Probabilistic Insight

Monte Carlo methods offer a compelling alternative to traditional forecasting approaches, not only in terms of speed and practicality but also in the nature of the insights they provide. The dynamic scenario described in this paper took just over five minutes to run - covering 86,000 simulations. While a collaborative stakeholder process would naturally require more time, the computational demands of the simulation itself are negligible.

By contrast, running 86,000 full model simulations using MSM would be infeasible, highlighting a key reason why traditional transport modelling typically relies on single-point forecasts. These fixed outputs provide limited insight into risk and uncertainty, especially in projects with long planning horizons and high exposure to future variability.

Monte Carlo simulation introduces a probabilistic framework, allowing demand forecasts to be expressed as ranges - through distributions and percentiles - rather than as singular values. This approach not only better reflects the realities of infrastructure planning, but also delivers these insights with remarkable efficiency, generating tens of thousands of simulations almost instantaneously. The ability to rapidly produce probabilistic outcomes enables decision-makers to assess risk, develop adaptable strategies, and engage in evidence-based collaboration with confidence.

4.2 Barriers to Widespread Adoption and the Path Forward

The case study effectively demonstrates the value of Monte Carlo approaches, but two key limitations must be addressed to make them more practical for real-world application:

- **Extensive model run requirements** – The regression equations were derived from 147 transport model runs conducted over two years, an effort and timeframe that is unrealistic for most major projects.
- **Multicollinearity from business case assumptions** – Model runs were structured to support business case requirements, resulting in limited variation in key policy variables such as congestion pricing, which was assumed early in the process. This lack of variation reduced statistical significance (e.g., a low t-statistic of 0.6 for congestion pricing) and introduced multicollinearity, weakening regression stability.

While the case study highlights Monte Carlo's potential, its practical viability hinges on addressing these challenges. Without solutions to streamline model runs and mitigate multicollinearity, Monte Carlo remains more of a theoretical exercise - few projects can afford to wait two years and generate 150 transport model runs for a regression that fails to effectively isolate all key policy impacts.

To evaluate the extent of multicollinearity, a correlation analysis was conducted (Appendix E), with results illustrated in Figure 4.

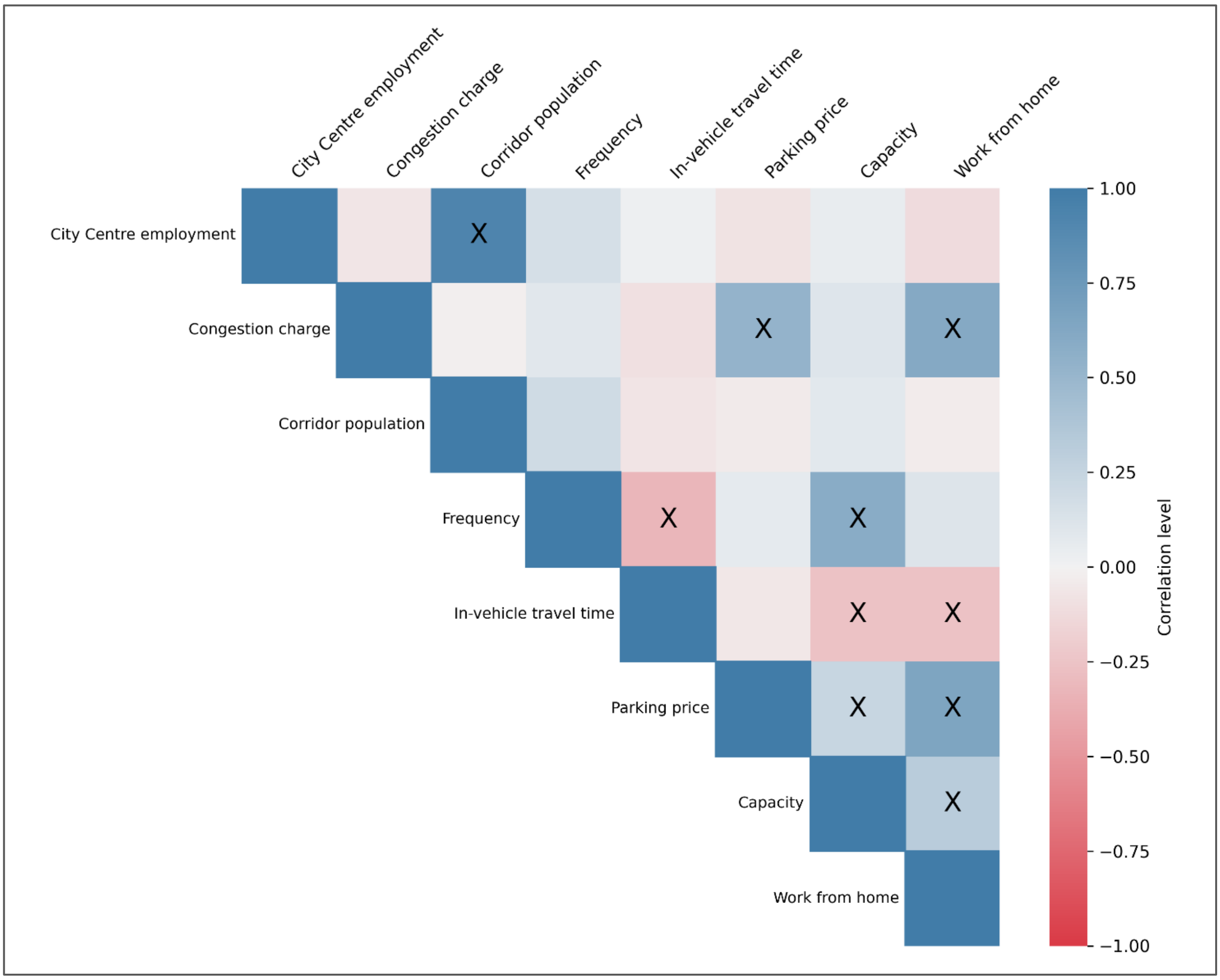

Figure 4: Correlation Plot of Regression Model Attributes

Evidence of multicollinearity is shown by the strong correlations between variables in Figure 4:

- Blue shades indicate positive correlations, while umber shades represent negative relationships.
- Significant correlations ($p \leq 0.01$) are marked with a cross.
- High correlation values (close to ± 1) suggest strong relationships, while values near 0 indicate weak or no association.

Multicollinearity arises because business case-driven model runs were structured to meet policy needs rather than to optimise regression estimation. For example, the 0.52 correlation between parking pricing and congestion charges does not imply causality but reflects how the scenarios were designed. This structure has inflated standard errors and reduced the statistical reliability of key coefficients, making it difficult to isolate individual policy impacts.

A **fractional factorial design** offers a structured and statistically rigorous way to generate new transport model scenarios. By systematically varying key inputs, this approach reduces multicollinearity while dramatically cutting the number of required model runs.

For example, instead of relying on 147 business case scenarios, a fractional factorial design could achieve similar statistical robustness with just 36 strategically selected runs. This ensures each policy and design variable is independently varied, producing more reliable regression outputs.

The benefits include:

- **Fewer model runs** – reducing time and computational demands
- **Improved coefficient reliability** – lower standard errors and stronger t-statistics
- **Clearer insights** – better isolation of individual policy impacts

- **Greater flexibility** – enabling future Monte Carlo applications to incorporate additional variables (e.g. fares) without excessive rework

An example of this approach is shown in Appendix F.

4.3 A More Efficient and Statistically Robust Approach – Bayesian methods

An important enhancement to the fixed-effects (frequentist) regression approach used in this paper is to treat estimated coefficients as random variables, each with its own distribution. **Bayesian methods** (Gelman, et al., 2013) provide a natural framework for capturing this parameter uncertainty, allowing it to be integrated directly into Monte Carlo simulations.

The case study demonstrates how input assumptions affect demand forecasts. A Bayesian approach could further improve model robustness by explicitly accounting for uncertainty in key parameter estimates -reducing the risk of overconfidence in business case forecasts (Gelman, et al., 2013). This represents a valuable direction for future research and real-world application.

A summary of the differences, strengths, and limitations of fixed-effects and Bayesian methods is provided in Appendix G.

4.4 Alternative Approach for Future Transport Modelling Practice

The following is proposed as a practical enhancement to current modelling practice - integrating Monte Carlo techniques into the existing workflow for developing demand forecasts in transport business cases. Rather than replacing conventional methods, this approach builds on them to improve risk assessment and support more robust, evidence-based decision-making.

- **Undertake Business Case development** and associated transport and land use modelling.
- **Complete peer review** of the models to ensure they meet best practice standards.
- **Identify key stochastic drivers of passenger demand**, alongside stakeholders, reviewers, and subject matter experts and drawing on empirical evidence, agree on the most relevant input variables for decision-making.
- **Develop an orthogonal statistical design** for these variables and run transport models accordingly.
- **Estimate a regression model** from the transport model outputs.
- **Agree on appropriate probability distributions** to represent the future variability of key input parameters based on expert insight and empirical evidence.
- **Run Monte Carlo simulations** to assess the probabilistic contribution of each attribute.
- **Estimate travel demand** by applying Monte Carlo-generated values to the regression model.
- **Repeat simulations** until results converge to a stable output.
- **Review results and conduct sensitivity tests** develop and simulate "plausible futures," as suggested by Transport for London.

This is shown in Figure 5.

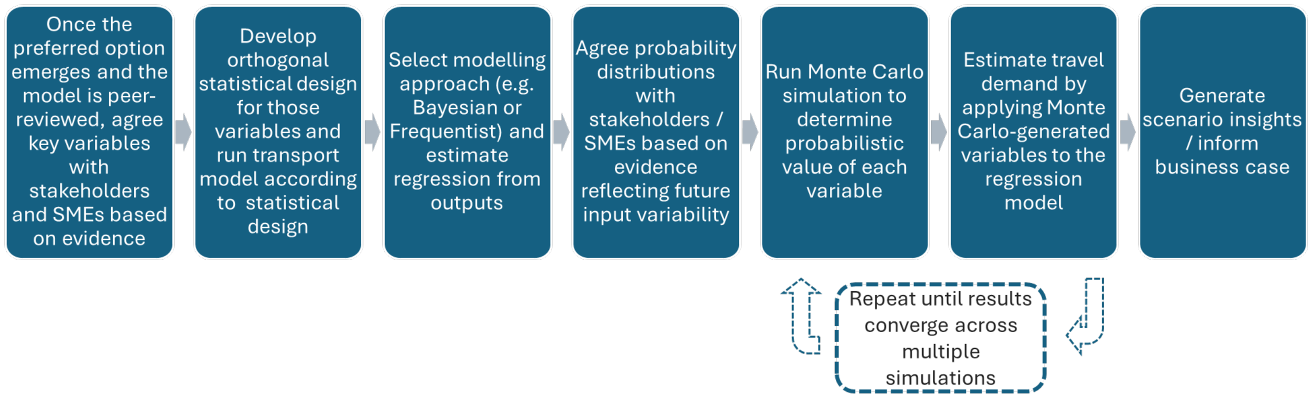

Figure 5: Alternative Approach for Future Transport Modelling Practice

5 Conclusion: Strengthening Transport Decision-Making with Monte Carlo Analysis

Business cases for major transport projects and policies will usually rely on transport model forecasts. 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.

Despite advances in computing power, the practical use of transport models remains constrained by the time-intensive process required to define, execute, and validate model runs. Large-scale models like Auckland's MSM 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, uncertainty is frequently oversimplified, limiting the robustness of demand forecasts and the confidence in investment decisions.

Rather than replacing existing forecasting methods, a complementary approach is proposed for Monte Carlo simulation that enriches the understanding of uncertainty and variability. By generating a probabilistic view of future scenarios, it equips decision-makers with powerful insights to manage risks, identify growth opportunities, and develop more resilient investment strategies.

This paper demonstrates the practical application of Monte Carlo analysis through a recent major transport case study. While the case study underscores the value of Monte Carlo techniques, it also highlights key limitations - specifically, the need to streamline model runs and address multicollinearity. Without addressing these challenges, Monte Carlo risks remaining a theoretical exercise, as few projects can justify the time and effort required to generate extensive model runs that fail to effectively isolate all key policy impacts. By adopting orthogonal statistical designs, the number of required model runs can be significantly reduced while improving the statistical robustness of regression estimates.

To ensure more robust and resilient transport decision-making, Monte Carlo approaches should be a required component of all major transport investment and policy business cases. These techniques provide a critical framework for systematically accounting for uncertainty, improving risk assessment, and enhancing the credibility of demand forecasts. To fully integrate Monte Carlo into transport business cases and policy development, a structured process should be adopted, with the approach outlined in Section 4.4 serving as a strong starting point - ensuring that uncertainty is not treated as an afterthought but as a fundamental consideration. This will enable investment and policy decisions to be more resilient to future variability, reduce the risk of costly over - or under-investment, and ensure infrastructure planning remains both adaptable and evidence based.

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Appendix A Baseline Case: Input Assumptions and Results

The input assumptions and results for the Baseline Case are presented below. As noted earlier, these probability distributions and parameters were developed solely to illustrate the application of Monte Carlo techniques. They are not intended to reflect the assumptions of a formal business case for ALR, nor do they represent the views or recommendations of any sponsoring agency.

Metric	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

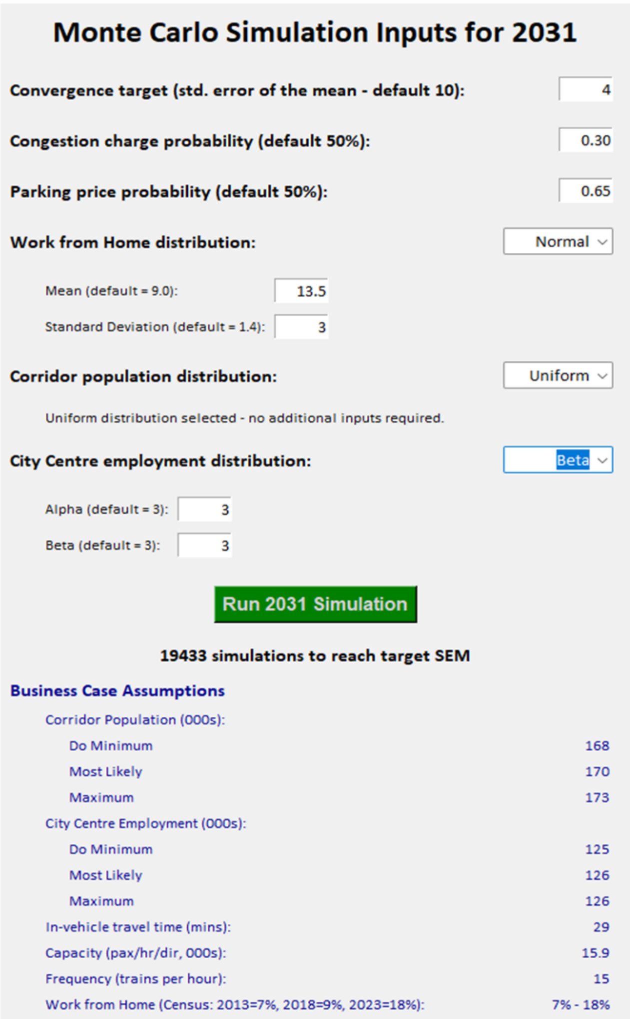
Appendix B Transparent Platform for Evidence-Based, Stakeholder-Driven Monte Carlo Analysis

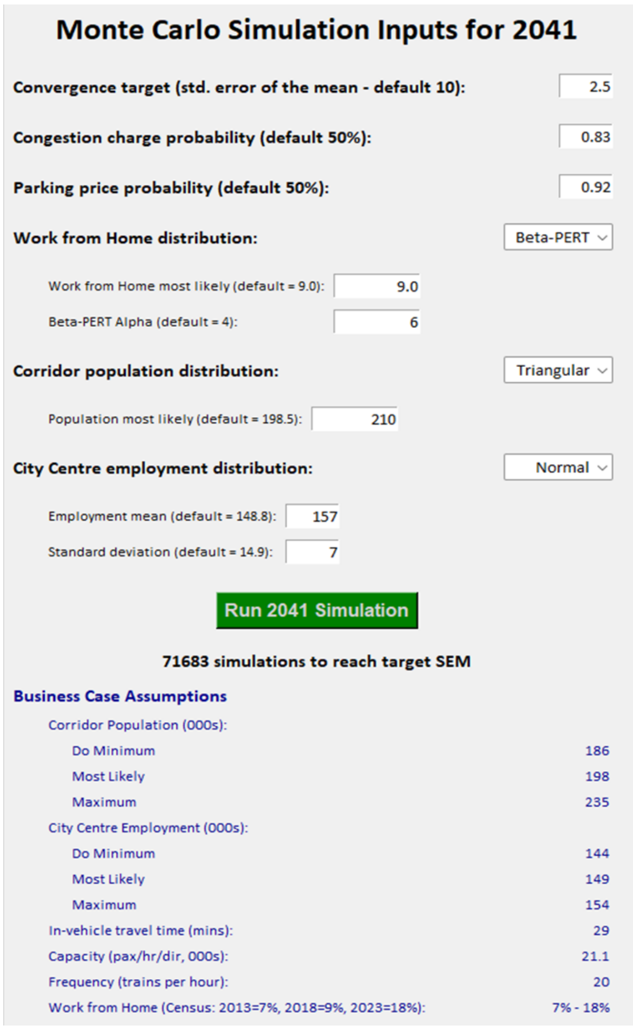
Recognising that the effectiveness of Monte Carlo analysis depends on meaningful stakeholder engagement in defining plausible, evidence-based futures, a Python-based interface (Python, 2025) was developed to support an interactive and transparent process. Designed for use in collaborative workshops - either in person or online - the platform allows stakeholders to adjust key parameters in real time, ensuring that changes are both transparent and evidence-informed, with immediate visual feedback. This fosters shared understanding, strengthens transparency, and enables rapid scenario refinement in response to simulation results.

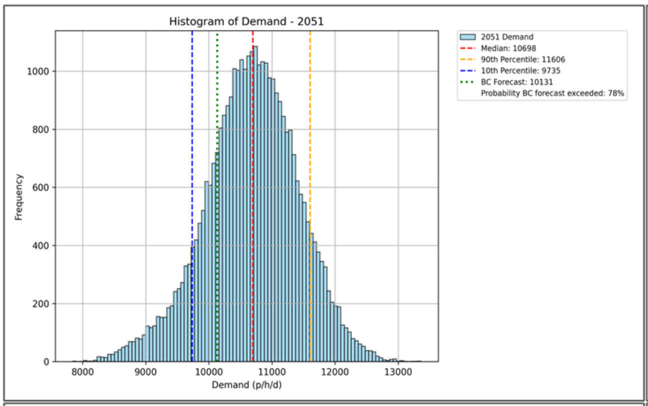
The figures below illustrate key features of the platform:

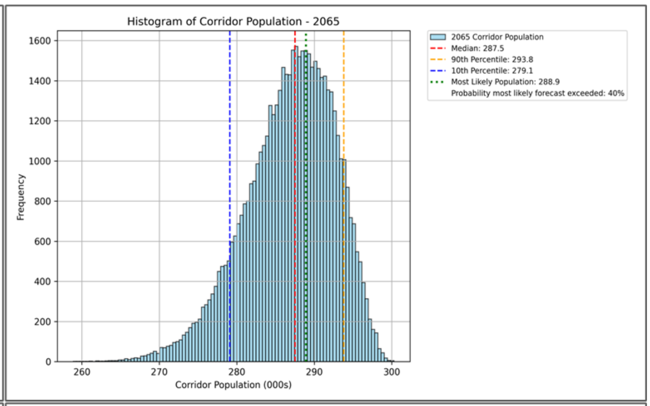
- **Input interfaces for 2031 and 2041**: Users can set convergence targets based on evidence, select probability distributions, and adjust key parameters using dropdown menus. The interface also displays the number of simulations required for convergence, alongside original business case assumptions, to support alignment on critical inputs.
- **Graphical outputs**: Example visualisations generated once simulations are complete, offering a clear summary of results for interpretation and discussion.

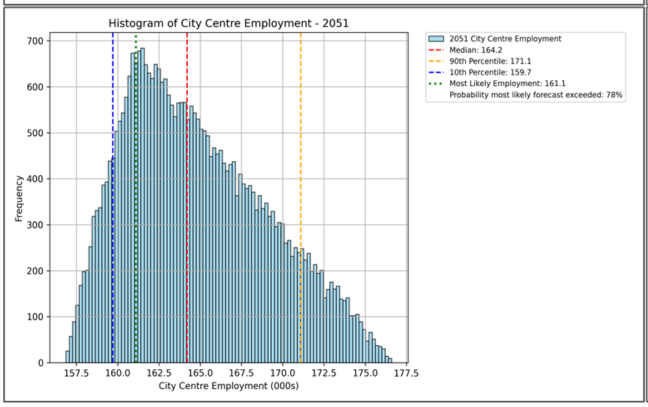
Rather than a one-size-fits-all solution, the platform is designed to be flexible and adaptable to the specific needs of each project. By making assumptions transparent and grounded in evidence, and by fostering collaboration and ownership among sponsors and project teams, it ensures Monte Carlo analysis becomes an integrated, practical decision-support tool rather than a theoretical exercise.

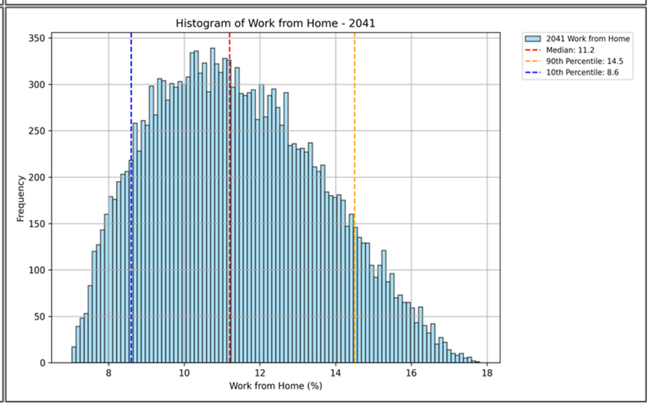


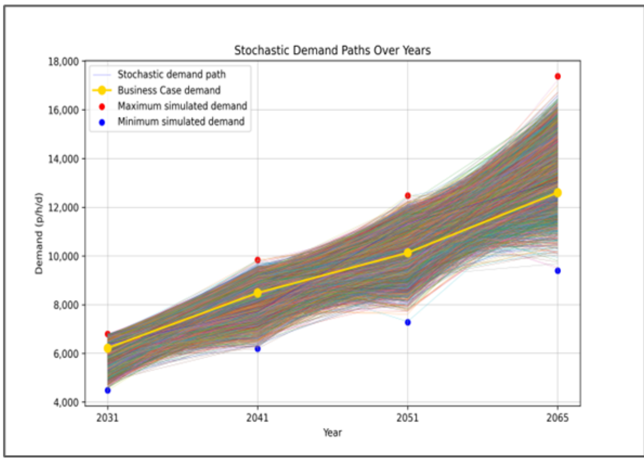


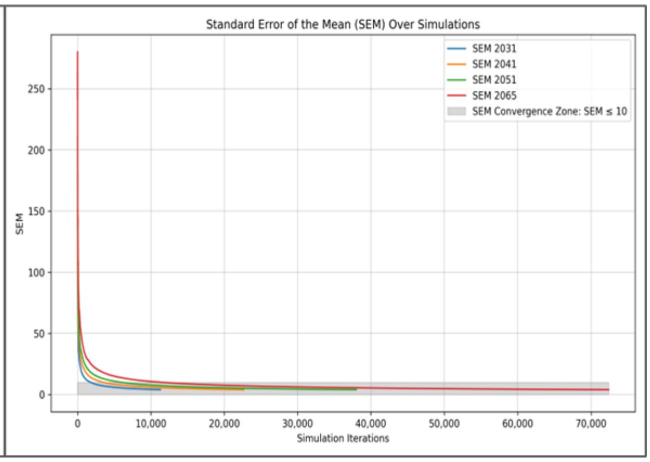

Histogram of Demand - 2051
2051 Demand
Median: 10698
90th Percentile: 11606
10th Percentile: 9735
BC Forecast: 10131
Probability BC forecast exceeded: 78%
Frequency
Demand (p/h/d)


Histogram of Corridor Population - 2065
2065 Corridor Population
Median: 287.5
90th Percentile: 293.8
10th Percentile: 279.1
Most Likely Population: 288.9
Probability most likely forecast exceeded: 40%
Frequency
Corridor Population (000s)


Histogram of City Centre Employment - 2051
2051 City Centre Employment
Median: 164.2
90th Percentile: 171.1
10th Percentile: 159.7
Most Likely Employment: 161.1
Probability most likely forecast exceeded: 78%
Frequency
City Centre Employment (000s)


Histogram of Work from Home - 2041
2041 Work from Home
Median: 11.2
90th Percentile: 14.5
10th Percentile: 8.6
Frequency
Work from Home (%)


Stochastic Demand Paths Over Years
Stochastic demand path
Business Case demand
Maximum simulated demand
Minimum simulated demand
Demand (p/h/d)
Year


Standard Error of the Mean (SEM) Over Simulations
SEM 2031
SEM 2041
SEM 2051
SEM 2065
SEM Convergence Zone: SEM ≤ 10
SEM
Simulation Iterations

Appendix C Dynamic Scenario - Exploring Option Value: Input Assumptions and Results

The input assumptions and results for the Dynamic Scenario are presented below. As previously noted, this scenario is illustrative in nature. Assumptions for key variables - such as population growth, employment, remote working, parking pricing, and the likelihood of congestion charging - were intentionally exaggerated to test the resilience of demand forecasts. In a formal business case context, these assumptions would be developed in consultation with stakeholders and supported by robust evidence.

Metric	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
Simulations to reach convergence	10,358	16,722	22,722	35,941

Appendix D Metrics for Evaluating Demand Scenarios

Metric	Interpretation	Thresholds and Rationale
Business Case Demand	Represents expected demand for planning and investment decisions. Evaluates alignment with plausible demand scenarios, highlighting whether the project is well-scoped, under-scoped, or over-scoped, and guiding decision-makers and investors in assessing risks and potential rewards.	**Green:** 98%-102% of median demand. High confidence in forecasts. **Yellow:** 10th percentile to 98%, or, 102% to 90th percentile. Some risk of being too optimistic/conservative. **Red:** Outside these bounds.
Probability BC Demand will be Exceeded	Shows how often the forecast surpasses the business case, indicating balance between under- and over-estimation.	**Green:** 40%-60%. Indicates well-balanced forecasts. **Yellow:** >10%-<40% or 60%-90%. Slightly optimistic or conservative. **Red:** ≤10% or >90%. High risk of significant misestimation.
90th Percentile Demand (p/h/d)	Represents a high-demand scenario, useful for assessing upside potential and testing whether the business case is conservative.	Benchmarks for evaluating Business Case forecasts
Median Demand (p/h/d)	Represents the central tendency of demand forecasts, showing whether the business case is realistic, optimistic, or under-scoped.	
10th Percentile Demand (p/h/d)	Represents worst-case demand, critical for debt investors assessing repayment risk.	
Demand Standard Deviation	Measures the absolute dispersion of demand forecasts around the mean. higher SD suggests greater variability in demand, indicating higher uncertainty. lower SD implies more stable demand projections, supporting more confident capacity planning and investment decisions.	**Green:** <450 passengers. Low variability. **Yellow:** 450-550 passengers. Monitor for potential capacity strain. **Red:** >550 passengers. Check fleet requirements.
Demand Coefficient of Variation	Quantifies relative variability, indicating confidence in predictability.	**Green:** <5%. High predictability. **Yellow:** 5%-7.5%. Moderate variability. **Red:** >7.5%. Low predictability, requiring further analysis or contingencies.
Demand Skewness	Highlights distribution asymmetry, showing risks of underperformance (right skew) or overperformance (left skew).	**Green:** +0.2 to -0.2. Balanced distribution, forecast demand is symmetric and reliable. **Yellow:** 0.2 to 0.46 Mild right skewed distribution forecast demand may be slightly optimistic -0.2 to -0.46 Mild left skewed distribution, forecast demand may be slightly pessimistic. **Red:** Outside these bounds. Highly skewed distribution, potential over- or under-estimation of demand.

Appendix E Correlation Analysis of Case Study Variables

Row	Column	Cor.	p
Corridor population	City Centre employment	0.93	0.0000
Parking price	WfH	0.65	0.0000
Congestion charge	WfH	0.61	0.0000
Capacity	Frequency	0.57	0.0000
Congestion charge	Parking price	0.52	0.0000
WfH	Capacity	0.43	0.0000
Parking price	Capacity	0.40	0.0000
In-Vehicle time	Frequency	-0.32	0.0001
In-Vehicle time	Capacity	-0.31	0.0002
WfH	In-Vehicle time	-0.29	0.0005
Congestion charge	Capacity	0.22	0.0065
Corridor population	Frequency	0.20	0.0160
City Centre employment	Frequency	0.17	0.0410
Corridor population	Capacity	0.17	0.0370
City Centre employment	WfH	-0.12	0.1300
City Centre employment	Capacity	0.11	0.1800
Congestion charge	In-Vehicle time	-0.11	0.1900
City Centre employment	Parking price	-0.08	0.3400
Congestion charge	Frequency	0.08	0.3200
WfH	Frequency	0.08	0.3600
City Centre employment	Congestion charge	-0.07	0.4200
Parking price	In-Vehicle time	-0.07	0.4300
Corridor population	In-Vehicle time	-0.06	0.4500
Corridor population	Parking price	-0.05	0.5700
Parking price	Frequency	0.05	0.5500
Corridor population	WfH	-0.04	0.6300
City Centre employment	In-Vehicle time	0.03	0.7000
Corridor population	Congestion charge	-0.02	0.8300

To interpret the correlation (Cor.) and p-values (p) in the table, both the strength and direction of the correlation, as well as the significance level indicated by the p-value need to be considered:

Strength of Correlations:

- Strong correlation (cor. > 0.7): Example: Corridor population and City Centre employment.
- Moderate correlation (0.3 ≤ Cor. ≤ 0.7): Several pairs, such as Congestion charge and Work from Home and Parking price increase and Peak load capacity.

Weak correlation (Cor. < 0.3): Most pairs fall into this category, indicating weak relationships.

Positive vs. Negative Correlations:

- Positive correlations (Cor. > 0) indicate that as one variable increases, so does the other. The strongest is between Corridor population and City Centre employment (0.93).

- Negative correlations (cor < 0) suggest an inverse relationship. For example, In-vehicle time and Frequency has a weak to moderate negative correlation (-0.32).

Significant Correlations ($p < 0.05$):

- Pairs where the p-value is less than 0.05, suggesting a statistically significant relationship. Examples include:
  - Corridor population & City Centre employment (very strong positive correlation, 0.93).
  - Parking price increase & Work from Home (strong positive correlation, 0.65).
  - Congestion charge & Work from Home (moderate to strong positive correlation, 0.61).
  - Peak load capacity & Frequency (moderate positive correlation, 0.57).

Non-Significant Correlations ($p \geq 0.05$):

- These pairs have p-values greater than 0.05, indicating no statistically significant relationship, even if the correlation value appears large or small. For instance:
  - Congestion charge and In-vehicle time (weak negative correlation, -0.08).
  - City Centre employment and In-vehicle time (virtually no correlation, -0.02).

Appendix F Orthogonal Fractional Factorial Design Example

In Stated Preference (SP) techniques, orthogonal designs are used to structure surveys in a way that effectively isolates and identifies the main effects of interest, minimising the risk of confounding between variables (Pearmain, Swanson, Kroes, & Bradley, 1991; Hensher, 1993). A fractional factorial design offers similar benefits when designing transport model runs to support regression-based Monte Carlo analysis - reducing multicollinearity, enhancing statistical reliability, and significantly lowering the number of required simulations. For example, rather than relying on 147 business case–driven model runs, a well-structured fractional factorial experiment could reduce this to just 36 strategically selected runs while maintaining statistical rigour. By systematically varying key policy and design variables, this approach yields more robust and interpretable regression estimates.

The Table below outlines the number of model runs required for different orthogonal experimental designs based on 2 variables at 3 levels each and 6 variables at 2 levels each, demonstrating how a carefully structured approach can significantly improve efficiency without compromising analytical robustness.

Full vs. Fractional Factorial Design Examples

Design Type	Total Model Runs Required
Full Factorial (All Scenarios Tested)	576 runs
Fractional Factorial (Strategic Subset of Runs)	96 runs
Orthogonal Fractional Factorial (Optimised for Regression Estimation)	36 runs

To illustrate this, a hypothetical fractional factorial experiment was developed (Groemping & Morgan-Wall, 2025) using:

- 2 variables at 3 levels (Corridor Population, City Centre Employment).
- 6 variables at 2 levels (Congestion Pricing, Parking Pricing, Work-from-Home, Travel Time, Fares, Frequency).

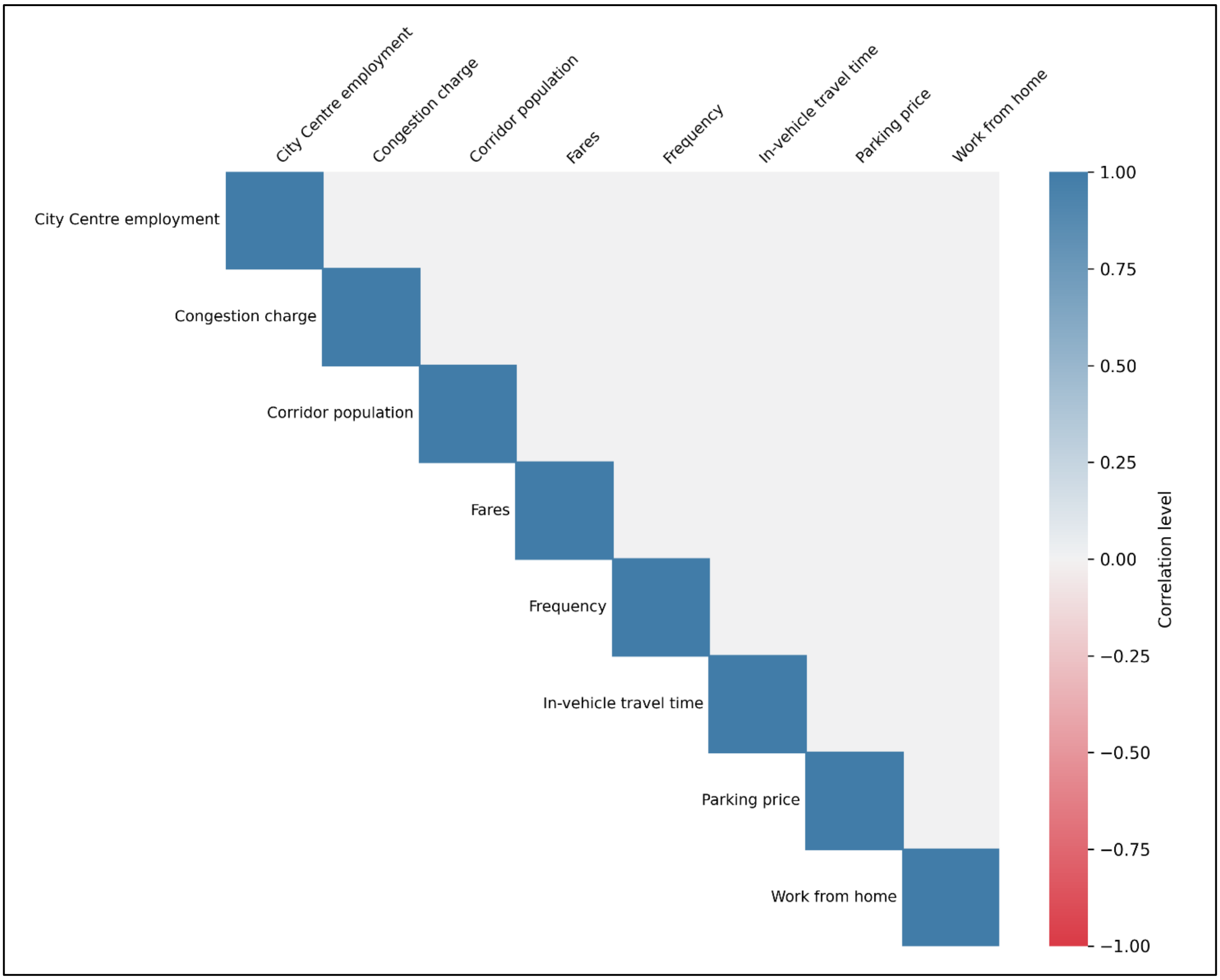
This experimental design structures the model runs to maximise statistical efficiency, ensuring that key variables of interest can be independently assessed while keeping the number of required simulations manageable. The design is shown below:

Experiment #	Corridor population	City Centre employment	Congestion charge	Increase City Centre parking price	Work from Home	Travel time	Fares	Train Frequency
1	2	2	2	1	2	2	1	2
2	3	2	1	1	2	2	2	1
3	3	1	2	2	2	1	2	2
4	2	2	2	1	1	1	2	2
5	1	3	1	2	2	1	2	1
6	1	1	1	2	2	2	1	2
7	3	3	1	2	1	1	1	2
8	2	2	1	1	1	2	2	2
9	2	1	1	1	2	2	2	1
10	1	1	1	1	2	2	2	1
11	3	2	1	2	2	2	1	2
12	2	1	1	2	2	2	1	2
13	1	3	2	2	1	2	2	1
14	3	2	2	2	1	2	2	1
15	3	3	2	1	2	1	1	1
16	1	2	2	2	2	1	2	2
17	1	2	2	2	1	2	1	1
18	2	3	2	2	1	2	2	1
19	2	1	2	2	2	1	2	2
20	1	1	1	1	1	1	1	1
21	3	1	1	1	1	1	1	1

Experiment #	Corridor population	City Centre employment	Congestion charge	Increase City Centre parking price	Work from Home	Travel time	Fares	Train Frequency
22	3	1	2	1	1	1	2	2
23	3	3	2	1	2	2	1	2
24	2	3	2	1	2	1	1	1
25	1	2	2	1	2	1	1	1
26	3	2	1	2	2	1	2	1
27	2	2	1	1	1	1	1	1
28	2	3	1	2	2	1	2	1
29	1	3	2	1	2	2	1	2
30	1	3	1	1	1	2	2	2
31	3	3	1	1	1	2	2	2
32	1	2	1	2	1	1	1	2
33	1	1	2	1	1	1	2	2
34	2	3	1	2	1	1	1	2
35	2	1	2	2	1	2	1	1
36	3	1	2	2	1	2	1	1

(Groemping & Morgan-Wall, 2025)

The correlation analysis of this design is shown in the Figure below.



Correlation Plot of Variables in the Orthogonal Design

This clearly shows all off-diagonal correlations are ±0, ensuring no multicollinearity between explanatory variables.

A regression equation derived from 36 well-structured MSM transport model runs would yield more stable, accurate coefficients, significantly reducing multicollinearity while maintaining key policy insights. Moreover, instead of requiring 147 model runs spread over two years, these targeted runs could be batched and completed within 2–3 weeks or less, as they would not need the full suite of business case outputs (e.g., plots, select link analysis etc.). By focusing solely on the variables required for Monte Carlo simulations, this streamlined approach would improve both efficiency and statistical reliability, making uncertainty analysis more practical for real-world projects.

Appendix G Fixed vs Bayesian Models: Key Differences and Trade-offs

A summary of the differences, strengths and weaknesses of fixed and Bayesian approaches is shown below:

Feature	*Fixed Model (Static Coefficients)*	*Bayesian Model (Drawn Coefficients)*
Terminology	Often called “classical,” “frequentist,” or “fixed-effects” regression.	Bayesian regression using posterior distributions.
Model Coefficients	Uses a single best-fitting coefficient for each variable (point estimate).	Estimates a probability distribution (posterior) for each coefficient.
Treatment of Coefficient Uncertainty	Ignores parameter uncertainty after estimation - coefficients are assumed fixed.	Explicitly models parameter uncertainty via priors and posteriors — each simulation draws new values.
Monte Carlo Implications	All simulations use the same coefficients → only input uncertainty is captured.	Simulations use varying coefficients → captures both input and model (parameter) uncertainty.
Simulation Spread	Reflects only input variability; may understate total forecast uncertainty.	Reflects both input and model uncertainty, typically producing more realistic bounds.
Interpretability	Easier to explain, replicate, and implement. Well-suited to proof-of-concept models.	Richer and more nuanced output; ideal for risk analysis, decision-making under uncertainty, and scenario testing.
Forecast Tendencies	Tends to produce more stable and often higher forecasts due to fixed coefficients.	Can produce more cautious estimates, especially when priors or weak data temper coefficient effects.
Overfitting	Greater risk in small datasets - prone to overfitting noise by locking in point estimates.	Resists overfitting by combining prior beliefs with observed data, shrinking implausible effects. Robust even with smaller samples.
Multicollinearity Handling	Sensitive to multicollinearity - can result in inflated or unstable coefficients.	Mitigates multicollinearity through regularisation (e.g. shrinkage via priors), improving stability.

(Gelman, et al., 2013; Train, 2009; Rossi, Allenby, & McCulloch, 2005)