Modelling future cycle behaviour changes: Application to transport strategies

Benjamin Loreille and Neil Raha, SYSTRA Limited, Ireland & UK

1 Introduction

Strategic multimodal transport models are calibrated to represent observed mode shares for a given base year. These models are then used in forecast mode to assess schemes, policies or develop transport strategies, just to name a few applications. The forecasted mode shares are highly related to the base year calibration parameters, and these may not capture certain difficult to quantify phenomena such as unrepresented costs or attitudinal variations. This can, in turn, undermine potential future mode shifting and its consequences.

This paper is highlighting a limitation to strategic transport modelling regarding mode choice and behaviour change, focusing on cycling. It also proposes a solution, the Cycle Propensity Tool (CPT), and explain its rationale and principles. We finally conclude with a practical example: the Greater Dublin Area Transport Strategy and demonstrate how the Cycle Propensity Tool was implemented using a practical example.

2 A transport model limitation: Behaviour change

Different modelling techniques are used to achieve an acceptable representation of mode choice, relying on a set of fine-tuned parameters. These parameters are then embedded in the model and used in forecasting mode, assuming that people will behave in the future exactly the same way they behave at the time the model was calibrated.

Any mode shift occurring in forecast mode depends solely on travel costs change, either through cost increase (e.g. traffic congestion increasing car travel time) or cost decrease (e.g. faster Public Transport service reducing journey time). Any change to people’s attitude towards certain modes (in particular cycling) is not captured in strategic transport models.

The market penetration of cargo bikes and e-bikes alleviates some of the barriers to cycling (need to carry loads/children, long distance trips etc…). These types of bike make cycling accessible to a larger population, increasing the number of potentially cyclable trips, and hence lead to actual higher cycle mode share than the one predicted using parameters calibrated on a situation with no or very few cargo bikes and e-bikes.

More generally, there is a need to address such model limitations to behaviour change, for the reasons described precedingly. The Cycle Propensity Tool, presented in the following section, is aiming at representing behaviour change towards cycling.

3 The Cycle Propensity Tool

3.1 Introduction

The Cycle Propensity Tool is an outcome of a larger research project centred on cycle modelling, benchmarking international practice, and testing various options in the National Transport Authority (NTA) Regional Modelling System (RMS). This section gives a general presentation of the tool and its principles, to help the reader understand how it works.

3.2 Data analysis

The approach used analysis of the Irish 2017 National Household Travel Survey (NHTS) data to identify individuals with a higher or a lower propensity to use cycle as a travel mode and relate this behaviour to demographic characteristics of the individuals concerned.

The cycle mode shares of these **High Cycle Propensity (HCP)** and **Low Cycle Propensity (LCP)** individuals for trips by different purposes and travel segments were analysed to demonstrate the significance of the Cycle Propensity classification as an explanatory predictor of cycle use.

Whilst it is not practical (or theoretically desirable) to directly target a specific cycle mode share in the RMS, this analysis can further inform the plausible range of increase in cycle mode share which might be obtained if the propensity to cycle in the LCP population segment could be increased to match that in the HCP population group.

This would be achieved through the application of policies aiming to remove perceived barriers to cycling, with responses primarily focussed on attitudinal changes which enhance the attractiveness of cycling (within the range spanned by current cycle mode shares). Note that still further increases in cycle share could be achieved by changes in perceived cycle costs, due to enhanced provision, or even stronger attitudinal shifts towards acceptance of cycling as a primary mode of choice.

The potential increases in cycle share by population segment were implemented in the RMS through the use of adjustments to Alternative Specific Constants and other measures described below. This Cycle Propensity population adjustment method has been successfully applied in the new Model of Travel in London (MoTiON) recently developed for Transport for London (albeit within a prototypical sample population feeding into a model estimated using the HCP/LCP flag for individuals).[1]

The basis of this population-based propensity to cycle methodology is to analyse household survey data – in this case from NHTS – to identify variables related to individuals such as residential area type, age, gender, and other demographic factors which have a discernible impact on cycle mode shares. Aggregates of the different individual categories are used where cycle shares are similar and to minimise problems with small sample size given the current low incidence of cycle trips (low mode share) observed in the NHTS database. This subset of variables (aggregated over categories where appropriate) is then associated with every trip record and a simple binary flag added to identify whether the trip is made by cycle or not.

A utility-based approach was adopted where a logistic regression was carried out against all the significant variables simultaneously, to produce a **Cycle Propensity Utility (CPU)** measure for each individual, and then a purpose-independent cut-off threshold was defined to distinguish HCP from LCP. This approach proved successful in the London context and was the method applied here for the RMS.

Logistic regression can also be carried out against each variable individually and this provides an indicative comparison of their relative influence in explaining cycle share (although some variables are likely to be correlated to some extent). Table 1 shows the goodness of fit criteria for each of the individual variable models together with full (9 variable, 23+1 category) model, ordered with the best fitting model at the top. It can be seen that Car Availability and Household Bikes are the best individual explanatory factors, followed by Area of Residence. Employment Status, Age and Gender are the next three most significant single explanatory variables. Income and Social Class/SEG are the least significant.

[1] http://content.tfl.gov.uk/londons-strategic-transport-models.pdf

Table 1 also shows two goodness of fit measures:

- the Log-Likelihood provides an indication of the explanatory power of the model. The larger (less negative) it is, compared to the Null Log-Likelihood of -6,271, the better the model explains the data.
- The Akaike Information Criterion (AIC) is a similar measure but takes account of the number of degrees of freedom used in the model to achieve this fit. A lower value is a better-quality model.

Table 1 Logistic Model Goodness of Fit by Regression Variable Set

Variable(s)	Degrees of Freedom	Akaike Information Criterion (AIC)	Log-Likelihood
All	***23***	***7,913***	***-3,932***
Car Availability	1	9,963	-4,980
Household Bikes	2	11,240	-5,617
Area of Residence	2	11,825	-5,910
Employment Status	7	11,993	-5,989
Age	3	12,254	-6,123
Gender	1	12,309	-6,152
Income Band	4	12,367	-6,178
SEG	2	12,403	-6,199
Blue/White Collar	1	12,473	-6,235
Null			*-6,271*

3.3 Testing and applying a High Cycle Propensity (HCP) threshold

For each NHTS trip record it is possible to associate a "utility" from the coefficients from the full logistic regression model. This is simply the sum of each of the regression coefficients associated with the category variables that apply to that trip, plus the *Intercept* coefficient. This utility will be termed the **Cycle Propensity Utility (CPU)**.

The exponential of this CPU is the model's estimate of the probability that the trip will be made by cycle. Therefore, the CPU is typically negative, and the higher (less negative) the CPU becomes, the greater is the probability that the trip will be made by cycle. Following the approach adopted for the TfL MoTiON model in London, it is useful to divide the trip records into those with a **High Cycle Propensity (HCP)**, which are above a CPU threshold known as the HCP-cutoff, and those with a **Low Cycle Propensity (LCP)**, based solely on the logistic regression model fit to their demographic characteristics.

This sub-section reports our analysis of the trend in cycle share with increasing Cycle Propensity Utility (CPU) to ensure that the model is successful, and the determination of a suitable cut-off threshold (HCP-cutoff) in CPU to allow the binary distinction between the HCP and LCP categories.

Finally, these were applied to the cycle shares in NHTS by purpose as an *independent* check on the validity and transferability of the results (since "purpose" was not used as one of the independent variables in the regression analysis).

The cycle propensity logistic regression analysis yielded results which can be summarised as follows:

- almost every category variable we had selected was statistically significant in the regression;
- the results proved perfectly satisfactory using just the 1,317 cycle records in the 2017 NHTS dataset (without needing to introduce inconsistencies, both in changes in mode share over time and in variable definitions, by using the 2012 NHTS data as well); and

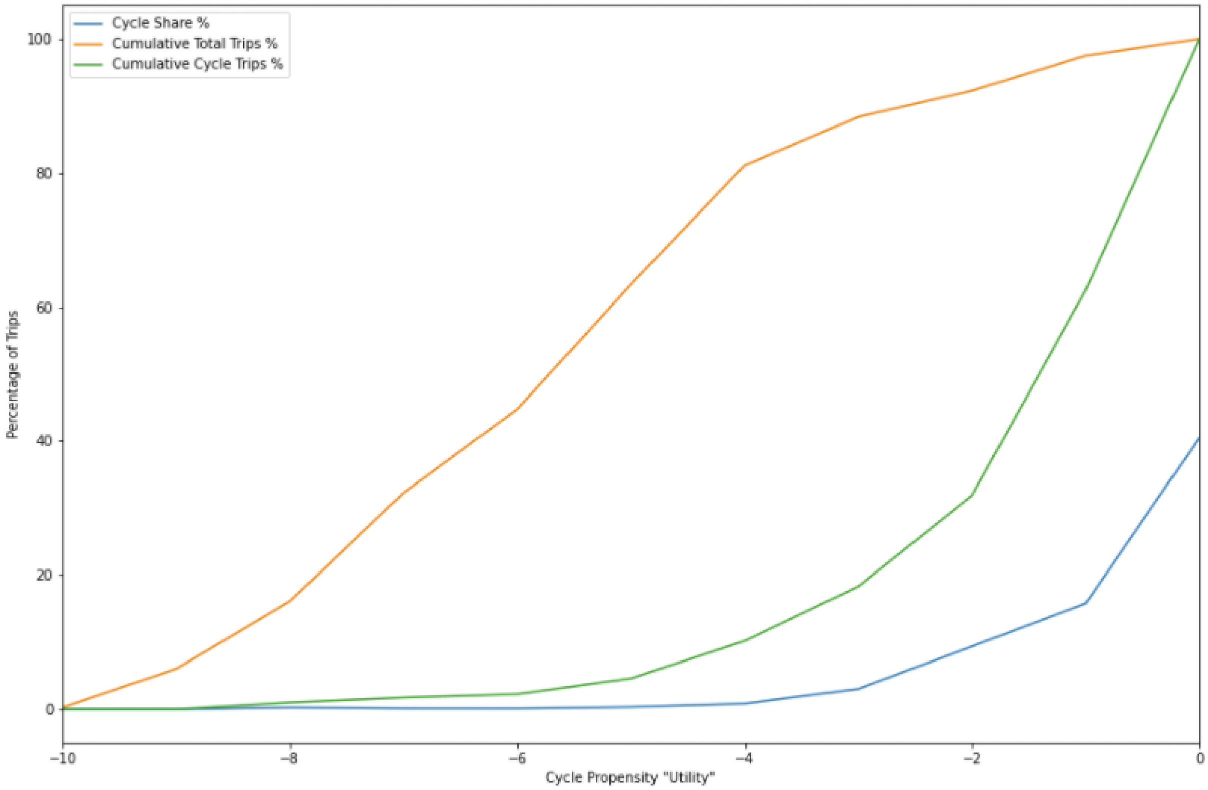
- the variable categories were generally not closely correlated (which is what is needed to avoid an over-specified model).

An initial analysis to determine how well the model performs is to answer the following questions, by binning the records by CPU value and analysing the actual recorded cycle trip flags:

- are the cycle trip records predominantly found in the higher CPU bins?
- does the cycle mode share increase in the higher CPU bins?
- do both of these change in a plausible monotonic way?

Figure 1 below shows that the answer to all three questions is "yes": The x-axis is the measure of "propensity to cycle" in the form of the Cycle Propensity "Utility" (CPU) output from the logistic regression choice model. This increases to the right, so the most "eager" cyclists are at the right-hand side. The y-axis is a percentage up to 100.

Figure 1 – Cumulative Trips and Cycle Mode Share with Cycle Propensity Utility



The upper orange line in Figure 1 is the **cumulative** share of **all** trips (all modes). This increases reasonably quickly over all CPU values because it covers all modes and shouldn't show any significant dependence on Cycle Propensity (which it doesn't). The middle (green) curve is the **cumulative** share of **cycle** trips. This increases slowly over the lower CPU values and then much more rapidly amongst the keener cyclists (as it should if the model is working as intended).

Finally, the lower (blue) line is the **cycle** mode **share** within each CPU band (i.e. an actual mode share, not a cumulative proportion). This is below 1% for CPU up to -4, and nearly matches the actual overall average mode share at ~2.6% at CPU = -3, but then increases rapidly up to a mode share of 41% in the highest ("keenest") CPU bin 0.

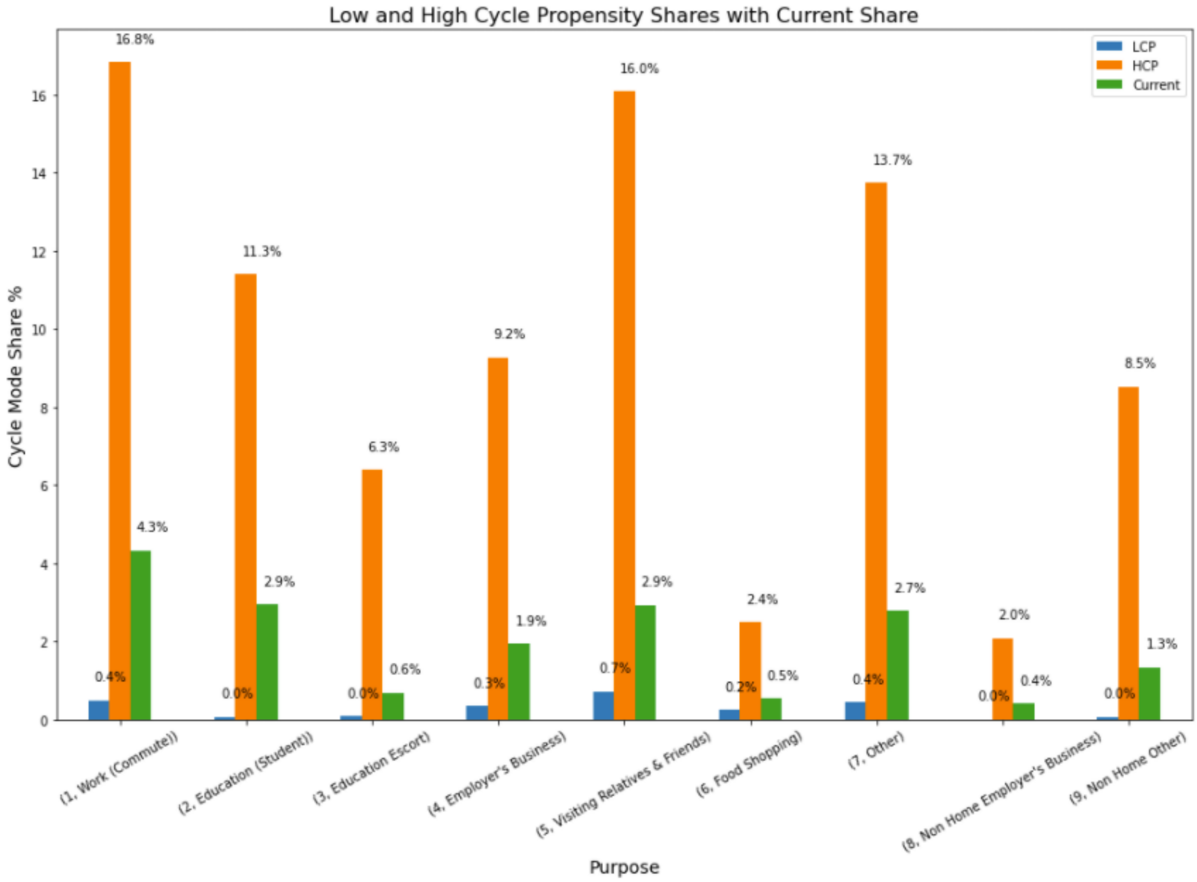
Note that this means that even the keenest cyclists do not cycle everywhere, just 41% of their trips, and this makes sense given the need to make longer distance trips or shopping trips etc.

Following discussion with NTA, we proposed a CPU = -4 cut off (HCP-cut off) which would place ~90% of (weighted) cycle trips in the High Cycle Propensity (HCP) category, but only ~19% of total trips. The total HCP (weighted) cycle share in this caucus is ~13%. The cycle mode share in the remaining Low Cycle Propensity (LCP) block is only 0.3%.

This might imply that we could naively hope to achieve an increase in cycle mode share from the current value of ~2.7% up to 13%, i.e. a factor of ~5 times, if everyone started cycling at the same rate as the "eager" HCP group. However, in practice that would not be achieved because some trips are not at all easy to make by cycle and will largely remain so.

The next step of the Cycle Propensity regression model verification process was to examine the cycle shares using an entirely independent disaggregation (i.e. not one which formed part of the regression). This was carried out by *purpose* as shown in Figure 2 and this demonstrates that LCP cycle shares (blue) are always below the current average shares (green) and HCP (orange) are considerably higher for all purposes. This is exactly what we would hope to see if the demographic factors used to assess Cycle Propensity in the model operated across all purposes and were not dependent on purpose.

Figure 2 – Low and High Cycle Propensity and Current Cycle Mode Shares by Purpose



However, Figure 2 also shows that HCP people are very happy to make over one sixth of commuter trips by bike, but that some purposes are much less amenable to cycling with relatively low HCP shares (especially food shopping, education escort and employer's business). These would, in turn, be less susceptible to significant increase in cycle share even if a significant fraction of the population became more attitudinally favourably disposed towards cycling as a mode (i.e. started to respond as the HCP group).

3.4 Potentially Cyclable Trips

To make an independent determination the proportion of trips that could potentially shift to cycling, the Irish 2017 National Household Travel Survey (NHTS) dataset was interrogated by looking at the available variables and by defining a set of criteria. The criteria applied to the dataset follow the example of the cycling modelling tool Cynemon[2] and are applied to the Irish context by looking at the data available within the NHTS. The selected criteria involved:

- Trip Purpose, by excluding Education Escort and Food Shopping;
- Time of Day, by excluding trips made between 10PM and 6AM;
- Age, by excluding people who are less than 6 and more than 64 years old;
- Distance, by excluding trips of more than 10km; and
- Trip Chaining, by excluding those tours that include even one trip that falls in the aforementioned criteria.

Overall, 33% of the total trips reported in the NHTS are potentially cyclable. When accounting for trip chaining and assuming that people are not willing to change their travel patterns, the cyclable trips are reduced to 28%. The larger share of these trips come from Commute and Education, and a total 32% of car trips see a potential for shift. Looking at car availability, 27% of the observations that reported to have a car available for the trip could potentially become cyclable, while a slightly larger share (34%) see a potential shift from those that reported trips with no car available.

These results from this analysis (in terms of affected Demand Segments and applicable trip distances) were carried forwards into the subsequent application of the Cycle Propensity Tool as discussed below.

3.5 Alternative Specific Constants (ASC)

This sub-section describes the role of mode-specific Alternative Specific Constants (ASC) within the National Transport Authority's Regional Modelling System mode and destination choice model. The mode and destination choice component of the standard 4-stage demand model process determines the number of trips travelling to any given destination for each mode (Road, Public Transport, Park and Ride, Walk and Cycle). The probability of the use of each of the mode choice alternatives is calculated based on the difference in their utilities.

Mode choice utilities are derived from various components, including generalised costs and utility function parameters, such as the ASCs. ASCs represents unquantified costs and are defined for each mode. Mode-specific ASCs are specified for each of the demand segments, split by trip purpose, car availability, employment type and education. Gender differences are not accounted for.

Furthermore, the ASCs in the RMS are represented in matrix form allowing selective application only to specific pairs of zones and thus allowing adjustment of cycle ASCs by e.g. distance band and/or area type.

3.6 Presentation of the tool

The Cycle Propensity Tool modifies the cycle ASCs to represent a reduction in the modelled perceived cost of cycling. The modifications target specific trips and are individually defined by:

- Demand segment (e.g. different reduction for certain purposes);
- Distance (e.g. only trips between 1 and 10km); and
- Geographical area (e.g. only trips within an urban area).

[2] Table 2.4 in: http://content.tfl.gov.uk/analysis-of-cycling-potential-2016.pdf

An initial realism test was undertaken in the East Regional Model (Dublin region) calibrated base year scenario. Decreasing the cycle ASC values increases the attractiveness of this mode within the mode-destination choice model. In the test an adjustment was made to the cycle ASC values in each of the 33 Demand Segments aimed at increasing the cycle mode weight in the mode choice model by a factor of 2. This adjustment resulted in an 80% increase in cycling trips.

Examination of the potential uplift which could feasibly be achieved through such changes suggested that using the ASCs to target a cycle mode weight uplift would be appropriate for policy testing using a “medium cycle growth” factor of 2 and a “high cycle growth” factor of 4. This was based on detailed analysis of the current LCP and HCP mode shares across demand segments. However, the ASC adjustment factors were typically only applied for appropriate distance ranges and purposes determined from the analysis of potentially cyclable trips.

A total of ten realism tests have been undertaken using the Mid-West Regional Model (Limerick area) to determine how much additional mode share can be reasonably expected from the model, based on evidence gained from previous sections, through adjustments to ASC factors alone.

From this work, guidelines were developed to help the modeller define assumptions to use the tool. It is worth noting that the CPT doesn’t provide a single set of parameters but indications on how to include behaviour change in model runs, based on a series of tests run for the calibrated base year. These guidelines were the starting point to implement the CPT in the Greater Dublin Area Transport Strategy, which is the topic of the next section.

4 Application to the Greater Dublin Area Transport Strategy

4.1 The 2042 Greater Dublin Area Transport Strategy

The Transport Strategy for the Greater Dublin Area 2022-2042 updates and supersedes the previous Transport Strategy for the Greater Dublin Area 2016-2035, which was approved by the then Minister for Transport, Tourism and Sport in 2016.

Under the Dublin Transport Authority Act, the National Transport Authority (NTA) must review its transport strategy every six years. Arising from the review of the 2016 plan, an updated strategy has been developed which sets out the framework for investment in transport infrastructure and services over the next two decades to 2042.

This Transport Strategy has been developed to be consistent with the spatial planning policies and objectives set out in the Regional Spatial and Economic Strategy (RSES) as adopted by the Eastern and Midland Regional Assembly. These objectives in turn are consistent with the National Planning Framework and the National Development Plan as set out in Project Ireland 2040.

This Transport Strategy is also based on national policies on sustainability as set out in climate action and low carbon legislation, and in climate action plans. The potential impacts of the on-going Covid-19 pandemic, beyond the short-term, have also been taken into account.

4.2 Application of the Cycle Propensity Tool to the GDA Transport Strategy

NTA policy objectives, including those in support of climate change action, are seeking to encourage rapid growth in cycle use and a step-change increase in cycle mode share through the removal of barriers to cycling.

This is likely to be driven by the availability of cycle facilities (such as cycle hire schemes, cycle parking and shower facilities), infrastructure improvements, and also by changes in the Most of the impacts of these drivers of cycle demand are not easily captured in generalised cost changes currently used as input to the NTA's Regional Model System (RMS) suite of transport modelling and forecasting tools.

NTA has developed a version of its Regional Modelling System which adjusts behavioural parameters that feed its standard forecasting mechanisms to take account of higher propensity to cycle among the general population: the Cycle Propensity Tool. These adjustments are based on extensive research, that concluded there is significant potential to increase cycle mode shares by:

- Increasing female cycle share to match that of male (through appropriate policies focussing on cycle safety and security, amongst others);
- Attempting to increase cycle share outside Dublin (although analysis of typical trip characteristics show significant limitations in scope to this);
- Increasing urban cycling rates amongst under-20s and over 40s to be closer to those of 20-39 year olds (especially primary students, again through dedicated cycleway provision, safety and security measures as well as attitudinal campaigns);
- Increasing use of cycle by part-time workers;
- Promoting cycle use for trips where a car is available;
- Increasing cycle use in lower income bands (possibly through purchase schemes, increased cycle hire provision and promotional campaigns); and
- Facilitating household cycle availability through purchase schemes, cycle parking and storage provision and promotional campaigns.

A series of model scenarios have therefore been created for this iteration which assume that the above outcomes can be achieved by 2042. These kinds of outcomes would be expected to accrue from the rollout of a comprehensive, Dutch-level of cycle priority on the road network and sustained and successful investment in cycle as a mode.

Two levels of adjustments were applied to cycle costs to reflect what's been described above: High and Low. Decisions to which level applied to each demand segment were discussed with the wider Transport Strategy team and derived from the Cycle Propensity Tool development research. For the GDA Transport Strategy, cycle costs adjustments are:

High reduction:

- Commuter trips between 1 and 10km
- Education trips between 1 and 10km (1 and 6km for Primary)
- Other purposes trips between 1 and 10km

Low reduction:

- Shopping trips between 1 and 10km
- Retired trips between 1 and 6km

4.3 Results and impacts of the Cycle Propensity Tool on the Transport Strategy

The use of the Cycle Propensity Tool to develop the GDA Transport Strategy is just one stage of a complex process that stretched over a long period. For the purpose of this paper, we will solely focus on the impacts the CPT had at a certain stage, by comparing a scenario with the modified cycle costs to a scenario without the modifications.

Figure 3 below shows modelled Mode Shares for different scenarios:

- 2016 Calibrated base year;
- 2042 Do Minimum;
- 2042 GDA Strategy without the Cycle Propensity Tool; and
- 2042 GDA Strategy with the Cycle Propensity Tool.

Reducing cycle costs for targeted trips double the cycle mode share within the GDA, from 6% to 12%. The mode shift is principally coming from Public Transport (-5 %.pts) and Walk (-2%.pts) while Car mode sees a slight increase (+1%.pt).

Figure 3 – 24h modelled Mode Shares Greater Dublin Area

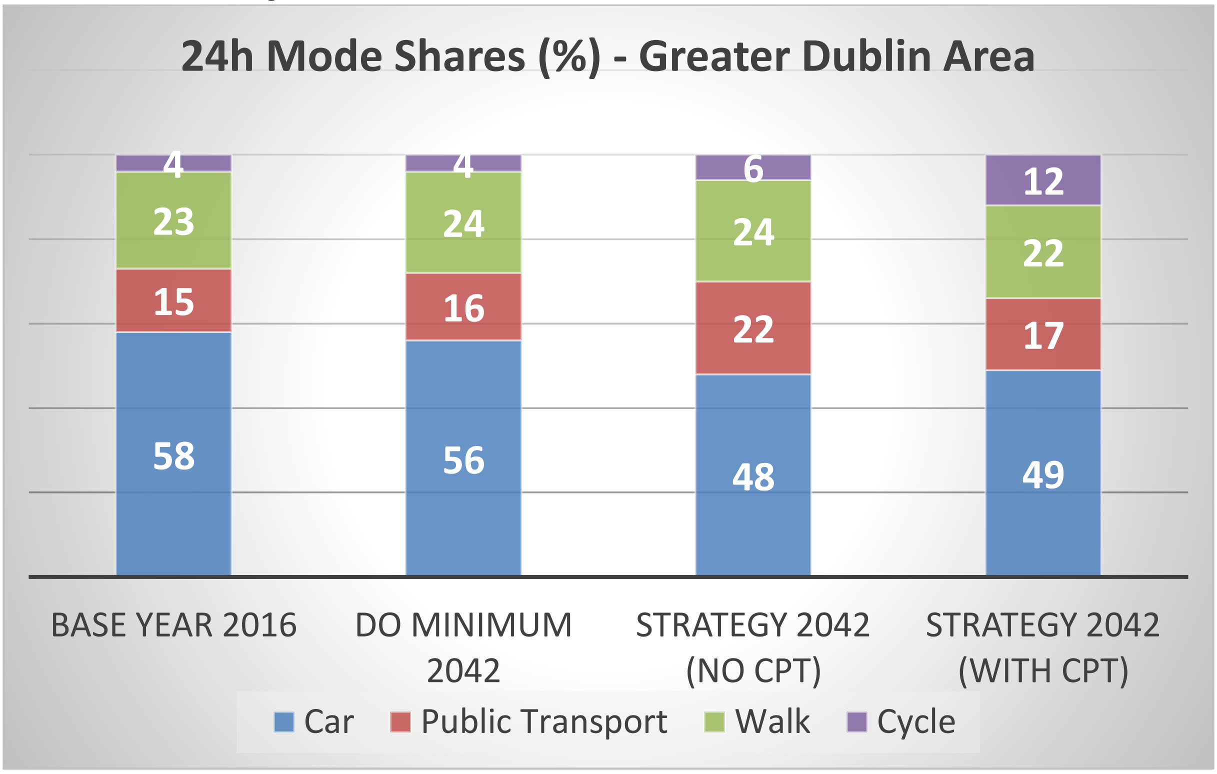


Figure 4 and Figure 5 below represent the AM peak hour Public Transport flows in the 2042 scenarios with the GDA Transport Strategy in place. The Figure 4 scenario doesn't have a Cycle costs reduction while the Figure 5 scenario has. As seen above, applying the CPT reduces Public Transport demand, which can be visualised by comparing modelled PT flows on the maps.

Modelled PT flows with the CPT were considered in the final strategy development, to design PT supply network adapted to the demand, which on certain corridors are significantly lower. The CPT helped identify areas and parts of the network where there is potential for a shift from Public Transport to Cycle. Investment in cycle infrastructure can then be prioritised on the identified corridors to facilitate that shift, while Public Transport investment can focus on the less shiftable trips.

Figure 4 - 2042 AM peak hour Public Transport flow – WITHOUT CPT

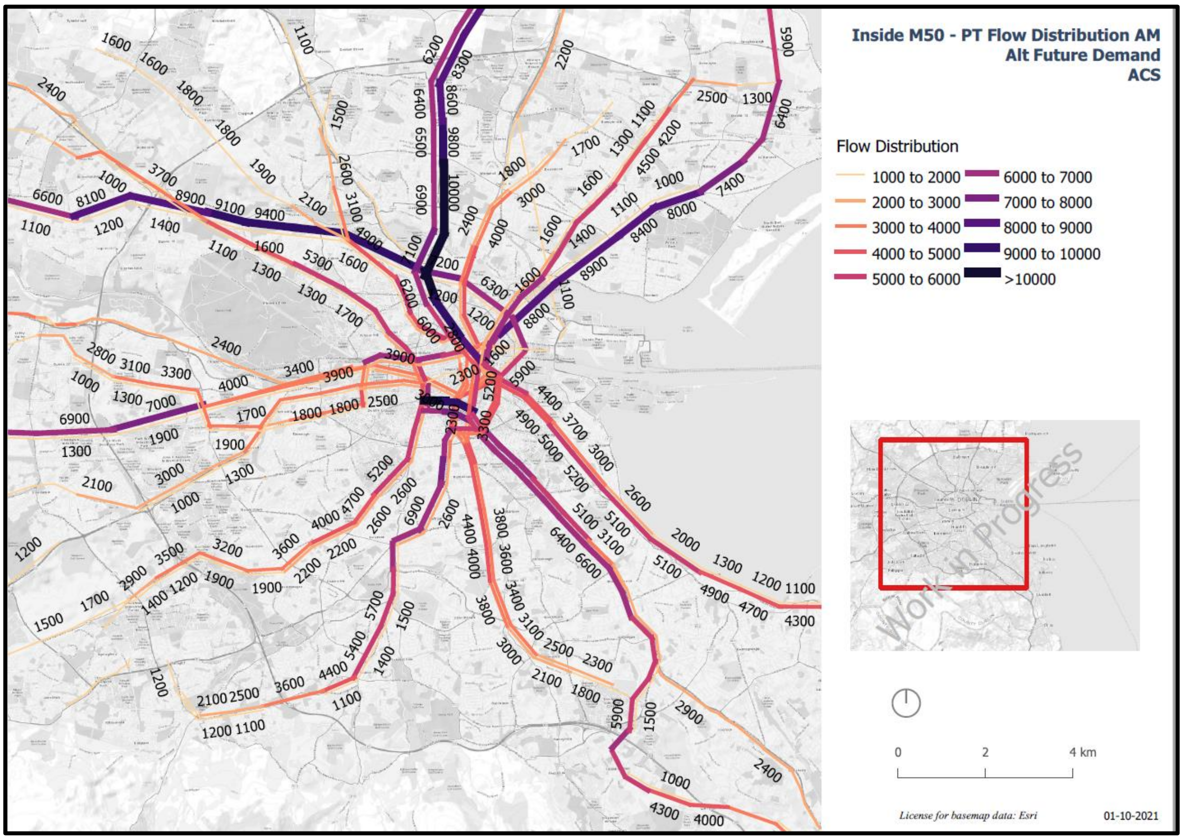
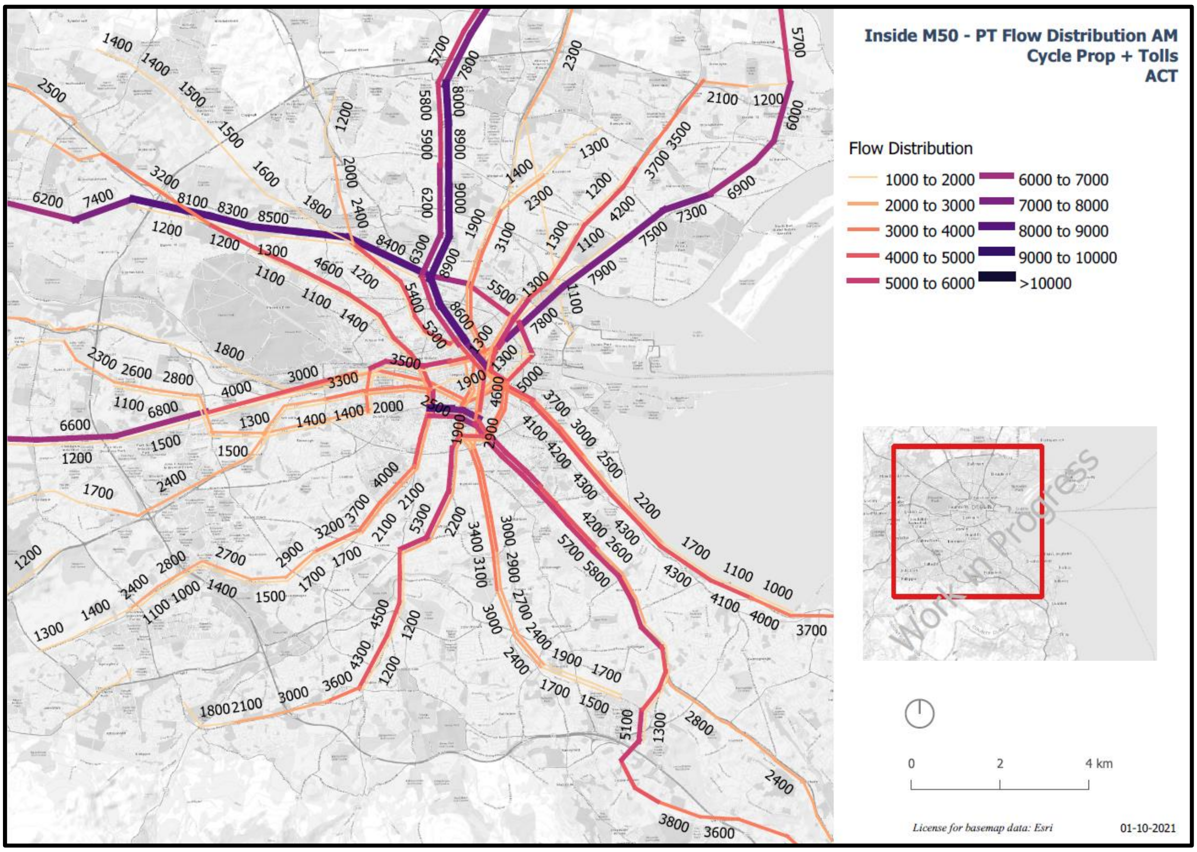


Figure 5 - 2042 AM peak hour Public Transport flow – WITH CPT



5 Conclusion and next steps

This paper started with a strategic transport model limitation that is representing behaviour change. The Cycle Propensity Tool addresses that limitation but requires some assumptions on the level of future behaviour change. It overall provides a way to model alternative versions of the future, to stress test scenarios and it yields valuable insights, as the Greater Dublin Area Transport Strategy case demonstrates.

That approach can be easily transposed to other strategic transport models and can also be developed for other modes than cycling. Alternative versions of the future with different behaviour towards walking, Public Transport or car can be developed on the same principles as the Cycle Propensity Tool.

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