# Methods for the validation of model-based flows allocated to the road network: a case study of cycling

## Abstract

## Introduction

Modelling is a vital tool for transport planners as it allows visualisation of current and future patterns of transportation (Schlesinger et al. 1979). These models need to be verified and validated in order to test their reliability and robustness; this is often done by testing the model to a known scenario e.g. a current scenario or a past scenario (Anderson and Woessner, 1992).

This paper will use several datasets from around the UK to validate a cycling infrastructure planning tool, the Propensity to Cycle Tool (PCT). The model predicts the number of cyclists currently communing to work as well as how the number of cyclists might change under certain scenarios. The datasets that will be included consist of screenline counts, camera counts, accident data and GPS data. The main area of study will be Leeds as this where the majority of the data has been collected, however the accident data and GPS data will validate the PCT for London, therefore also testing if the tool is easily applied to other areas.

There are many models using various techniques to study where people choose to cycle to work and for leisure as well as studies which collect data via GPS units and analyse the data to find the most popular routes. (Dill and Carr, 2003; Krizek *et al.*, 2007; Menghini *et al.*, 2010; Broach *et al.*, 2012; Ehrgott *et al.*, 2012; Larsen *et al.*, 2013). However at the time of writing there are not any models which aim to predict the amount of cycling in an area as well as the possible response to cycling becoming more favourable amongst the population. Therefore the PCT is aiming to become a niche tool to help planners.

There are some novel approaches in the literature which study the most where spending will have the most effective spending on the road network (Larsen *et al.*, 2013). Larsen *et al.* (2013) used a Geographical Information System (GIS) approach to assess the cycling network in Montreal, using a form of Multiple Criteria Analysis (MCA) with datasets surrounding Origin-Destination data (OD) for cyclists, car trips, suggested cycling routes from the public, and accident data they evaluated the current system and proposed suitable modifications.

The UK is currently facing a large increase in the number of people choosing to travel by bicycle as there are now 600 million more miles ridden per year in comparison to 1993 (Hollingworth *et al.*, 2015). This rise in cycling has resulted in a rise in incidents, Keep (2013) discovered that there was 32% increase in people being killed or seriously injured while cycling between 2002 levels and 2012 levels. Figure 1 shows the number of people killed or seriously injured over a 5 year period in Leeds, there has been an increasing number of incidents possibly due to the increased levels of cycling (Leeds Data Mill, 2015).

Recent studies into cycling infrastructure prove that spending on infrastructure helps to reduce the amount of people killed or seriously injured while cycling as well as encouraging people to take up cycling (Reynolds *et al.*, 2009; Broach *et al.*, 2012). Unfortunately building cycling infrastructure is not cheap, schemes such as city connected, an infrastructure project linking Bradford and Leeds, is set to cost c£30m while a north-south cycle superhighway through London is costing £160m. Therefore tools such as the PCT can help improve the location of cycling infrastructure projects allowing them to have the most effective cost-benefit scenario.

***Figure 1 the number of people killed or seriously injured while cycling in Leeds (Leeds Data Mill, 2015)***

## Methods

### Screenline

Measuring daily flows of traffic is usually carried out using the screenline method (Nicolaisen and Driscoll, 2014). Screenline counts are usually carried out manually via pen and paper records, therefore opening them up to human error when recording data. Recently there has been an advance in computing that allows the recognition of shapes; this technology is now being used to record the number of cyclists passing a point. The added advantage of this automation is that data can be collected for every hour of everyday, whereas previously manual data collection could only be carried for as long as the user was willing to pay to record data. Therefore collecting data manually would lead to a sub-optimal dataset.

In this paper the screenline data was collected in April and May 2014. To try to make the data as uniform as possible counts were only recorded on days inside school term time and when the weather was not adverse. On the day of collection data was collected over a 12 hour period (7am – 7pm). Figure 1 shows the distribution of the survey points.

*Figure 2 Screen lines for Leeds - each line is placed over a commuter corridor in order to capture the total flow of cyclists moving in or out of the city centre*

### Auto-recognition camera data

Technology can now be used to help provide higher resolution count data because cameras can now detect the shape of a cyclist. Data can be recorded for the whole day over the whole year, whereas manual methods such as the screenline method only offer data for part of the year and day.

The data collected in this study has been collected from the locations seen in figure 3. The cameras detect the number of cyclists on an hourly rate as well as the direction that they are heading. The data is freely available on the Leeds Data Mill website <http://leedsdatamill.org/dataset/leeds-annual-cycle-growth->.

***Figure 3 the location of count cameras around the city of Leeds.***

## Results

## screenline

## Camera

## Refrences

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