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Estimating annual average daily traffic and transport emissions for a national road network: A bottom-up methodology for both nationally-aggregated and spatially-disaggregated results

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ABSTRACT

The regular and robust collection of traffic data for the entire road network in a given country will usually require high-cost investment in traffic surveys and automated traffic counters. This paper provides an alternative and low-cost approach for estimating annual average daily traffic values (AADTs) and the associated transport emissions for all road segments in a country. This is achieved by parsing and processing commonly available information from existing geographical data, census data, traffic data and vehicle fleet data. Ceteris paribus, we find that our annual average daily traffic estimation based on a neural network performs better than traditional regression models, and that the outcomes of our aggregated bottom-up road segment emission estimations are close to the outcomes from top-down models based on total energy consumption in transport. The developed approach can serve as a means of reliably estimating and verifying national road transport emissions, as well as offering a robust means of spatially analysing road transport activity and emissions, so as to support spatial emission inventory compilations, compliance with international environmental agreements, transport simulation modelling and transport planning.

1. Introduction

For road transport planning and air-pollution mapping and modelling, street level annual average daily traffic values (AADTs) are an essential input. Major roads in many developed countries are now equipped with automated traffic counters, tolling systems and other technologies that can deliver regular and reliable data on daily traffic flows. However, this is not the case in all countries, and the availability of such data for secondary and tertiary routes is limited in most countries. National policymakers require affordable and practical methods of estimating daily traffic for a variety of policy challenges, not least, in order to estimate and manage environmental emissions from transport for the purposes of compliance with international environmental agreements regarding air quality and climate. In this paper, we provide a systematic methodology to integrate and utilise commonly available data sources to deliver a low-cost means of estimating AADTs for an entire road network. Specifically, the method draws upon information from the national census, geographical data, vehicle fleet data and traffic data, to estimate AADTs and related pollution for all road segments. Ireland is used as an empirical case study to illustrate the application of the methodology presented. Both aggregated national values and spatially disaggregated values are provided, meeting the requirements for both macro-comparisons with other national models and micro-analysis for estimating localised emissions and impacts associated with road-transport.

The paper is presented in five sections. Section 2 provides a review of literature relating to transport demand modelling and approaches to the estimation of AADTs. Section 3 describes our method for estimating AADTs for all road typologies. There follows a comparison of the performance of our neural network methodology for AADTs with other

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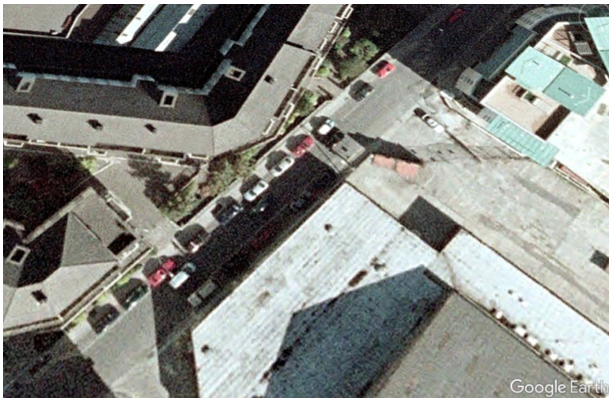

Fig. 1. Parked cars that are mixed with moving vehicles.
Source: Google Earth; Location of the image: Tralee, Ireland.

methods such as regression models. Section 4 calculates street-level air emissions from the generated AADTs and evaluates these estimates against those from other national modelling approaches. Section 5 discusses the relevance of the findings and concludes the paper.

2. Literature

In the literature, there are currently three principal approaches to the estimation of AADTs: econometric regressions, travel-demand modelling and neural network modelling. Each of these are discussed in turn in this literature section, and are later applied to our case study so as to allow for a direct comparison of the performance of some alternative methodologies against the approach developed for this paper.

Explanatory factors are important in the regression model. Neveu (1983) considered population, automobile ownership, number of households, and employment as determinants of road AADTs. Mohamad et al. (1998) emphasised the features of roads as well as population, and Tsapakis et al. (2012) found that road class, population density and locations are key predictors for freight traffic. Thus, population, road types, employment, vehicle fleet and locations (e.g. urban or rural) are oft-cited factors in AADT modelling by this method, with population density being the most significant factor in the estimation.

Travel demand modelling (TDM) usually has a four-step process of trip generation, trip distribution, mode choice and trip assignment, and AADTs can be generated from those simulation processes. Khatib et al. (2001) found that census levels of traffic zones and the types of centroids (geometric, population-weighted, location of central cities) used for the zones, can have a considerable impact on the quality of traffic-demand modelling. Mustafa (2010) emphasises that a model with smaller census units is capable of providing more accurate estimation of AADTs. Although travel demand models are popular in transport simulation and transport planning, Zhong and Hanson (2008) point out that travel demand model availability for low-class roads is limited, given the absence, in most cases, of traffic counting systems for such roads. The prior solutions for low-class roads are therefore more commonly based on regression analysis (i.e. the prediction of transport demand is usually realised through regression analysis in TDM). Zhong and Hanson (2008) developed a method based on geographic information systems (GIS) to estimate the traffic volume for these road types. For the estimation of countrywide AADTs and transport pollution, one should, of course, avoid ignoring lower-classes of roads. Therefore, similar approaches - based on GIS with fine-scale census data and vehicle data - are used in our study.

Neural networks can be used to classify transport sites (Lingras, 1995) and to predict the AADTs (Sharma et al., 2001). Sharma et al. (2001) use short-period traffic counts (mobile traffic recorders or survey data usually based on a short-period) in a neural-network system to estimate AADTs for low-volume roads. They found that a high level of precision is not necessary for those roads, with a 30% error rate deemed acceptable. Karlaftis and Vlahogianni (2011) suggest that the neural-network approach provides another school of thought for the estimation of AADTs and is more flexible in so far as it can deal with nonlinearities and missing data. However, both statistical models and neural-network models may disregard underlying issues such as parameter stability, error distribution and so on.

To transform traffic into pollution estimates, a speed-dependant method is frequently used. A representative model developed by Ntziachristos and Samaras (2000) is used in COPERT, a popular transport emission estimation model in Europe. This model relates emission factors to the speeds of different types of vehicles. In the study of Ntziachristos and Samaras (2000), a pollution minimising speed of between 40 and 80 km/h is found for passenger cars. Based on similar models, Borge et al. (2012) found that the estimation results for urban areas are better than those for rural areas, but estimation quality worsens for situations involving congestion and heavy trucks. Instead of using experimental tests of the relationship between speed and emissions, other researchers focus on real road-side traffic and pollution. For example, Reynolds and Broderick (2000) collected pollution data beside

Fig. 2. Traffic collected from high-resolution satellite images.
Source: Google Earth; Location of the image: Wicklow, Ireland.