Journal of Transport Geography 58 (2017) 186–195

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

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

Miao Fu [a,b,*], J. Andrew Kelly [c], J. Peter Clinch [d]

[a] UCD Planning and Environmental Policy, University College Dublin, Belfield, Dublin 4, Ireland
[b] Collaborative Innovation Center for 21st-Century Maritime Silk Road Studies, Guangdong University of Foreign Studies, Guangzhou, China
[c] EnvEcon, NexusUCD, Block 9, Belfield Office Park, Belfield, Dublin 4, Ireland
[d] UCD Planning and Environmental Policy and UCD Earth Institute, University College Dublin, Belfield, Dublin 4, Ireland

ARTICLE INFO

Article history:
Received 28 October 2015
Received in revised form 25 November 2016
Accepted 4 December 2016
Available online 15 December 2016

Keywords:
Transport
Traffic
Road network
Emissions
Neural network
GIS

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

* Corresponding author at: Office 156, Institute of City Strategy Studies, Faculty Office Building, Guangdong University of Foreign Studies, 178 Waihuandong Road, Higher Education Mega Center, Guangzhou, 510006, China.
E-mail addresses: cnfm@163.com (M. Fu), Andrew.Kelly@EnvEcon.eu (J.A. Kelly), peter.clinch@ucd.ie (J.P. Clinch).

http://dx.doi.org/10.1016/j.jtrangeo.2016.12.002
0966-6923/

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 non-linearities 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.

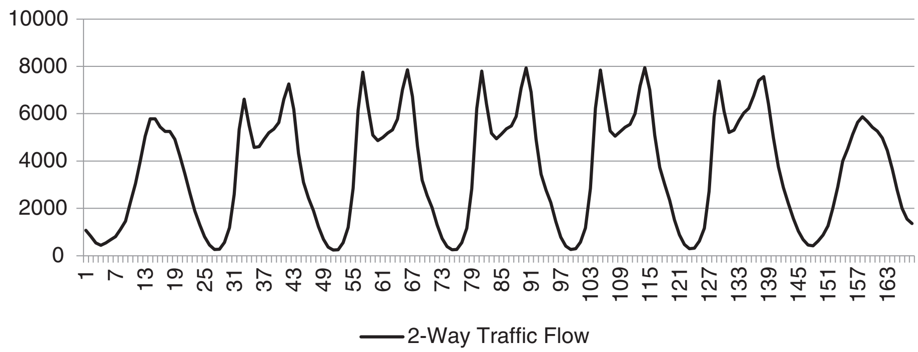


Fig. 3. Hourly and Daily distributions of two-way traffic in urban areas within one week.
Source: The National Roads Authority traffic count data (NRA, 2012).

a junction in Dublin city and found concentrations of pollutants to be related to road traffic on average.

3. Estimation of AADTs for all roads

3.1. Road classification and identification of residential roads

The first step in assigning AADTs to each road in our case study of the Irish network is to sort the roads according to their existing Irish classification and to match them to international classifications that have comparable AADTs. There are motorways (class 1), national ways (class 2), regional ways (class 3), heavy traffic local roads (class 4), light traffic local roads (class 5) and residential roads (class 6) in our model. There are traffic counters on some motorways and national ways in Ireland. Therefore, it is reasonable to use the traffic counter data in those cases, as opposed to estimating them based on a model that uses local features as explanatory variables. In particular, traffic on motorways and national ways are often passing traffic that can have a weaker connection with local characteristics, therefore, the empirical counter data are preferred in those cases.

Below the level of motorways and national routes, there are regional roads and local roads defined for the current Irish road system, most of which do not offer fixed traffic counters. Whilst some survey data are available for these roads, they only cover selected locations (mainly busy roads in urban areas) and reference only specific periods in a given year. To cover those low-class roads and rural areas without traffic counters and without survey data, we use satellite images to calculate the AADTs on those roads, based on the method presented by McCord et al. (2002).

To extend the existing short-period data, either from survey data or from satellite data, to annual average daily traffic data for those relatively low-class roads or rural areas, we require hourly, daily and monthly distributions of road traffic. Given that Ireland shares common road features with the United Kingdom, local roads are divided into (i) local roads with relatively high traffic, (ii) local roads with relatively light traffic and (iii) residential roads, in line with the road classifications of the United Kingdom. These roads are further split into urban and rural areas. However, there are no clear indicators for residential roads in the road network data we have. Thus, GIS methods to identify so-called 'dangling streets' are used to determine residential roads, which signify cul-de-sacs or 'no-through roads' in residential areas. Traffic on local roads (class 4, and 5) in settlement areas and regional roads in all areas are estimated with the model we will present in this paper. However, we treat residential roads (class 6) in all areas, and local roads (class 4 and 5) in rural areas, differently as they present very low AADTs and traffic is closely correlated to the local population in these areas. Prior work by the authors with the POWSCARS (Population of Ireland 2011 Place of Work, School or College Census of Anonymised Records) data from small areas was used to estimate traffic on these roads.

3.2. Calculating AADT from high-resolution satellite images

McCord et al. (2002) present a method to estimate AADT from a single image. Their approach is based on automatic recognition of satellite images and thus can be applied to a large area. However, as noise associated with the images can interfere with this process, a ground-based data source is needed to improve the estimation performance. Other limits in their approach are that on-street parked vehicles are usually mixed with moving vehicles in urban areas, and they extrapolate short period data to AADT by multiplying the length of time. In our model, we manually distinguish moving vehicles from parked vehicles and extrapolate short period data based on the traffic distribution (see Figs. 1 and 2 for relevant samples of satellite imagery).

Vehicle number (N) in a road segment and the length of this segment (L) are collected from satellite images. Average vehicle speed (S) of this segment is obtained from our GIS data. The AADT is calculated with the following equation,

$$\mathrm{AADT}_{i,j} = \frac{N_{i,j}}{L_i/S_i} * \frac{1}{7R_w} * \frac{1}{365R_m} \tag{1}$$

In the equation, i indexes segments of roads and j denotes vehicle types. R_w is a ratio that transforms traffic in an hour to weekly traffic, depending on what hour in a week and the weekly distribution. R_m is a ratio that transforms daily traffic to annual traffic, depending on what day in a year and the monthly distribution. The distributions are given in the next section. Dates of the satellite images can be acquired from

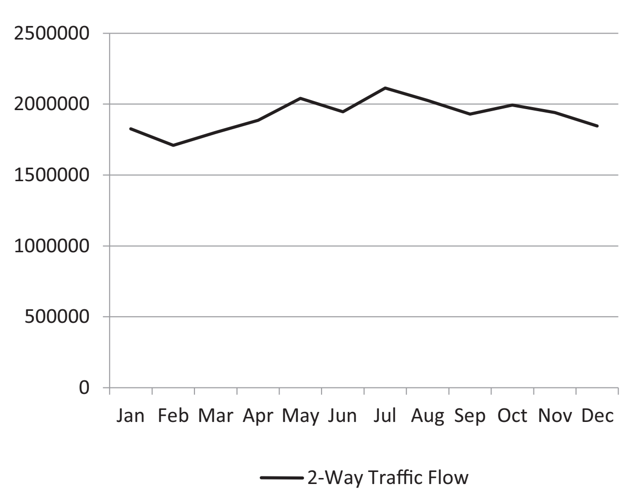
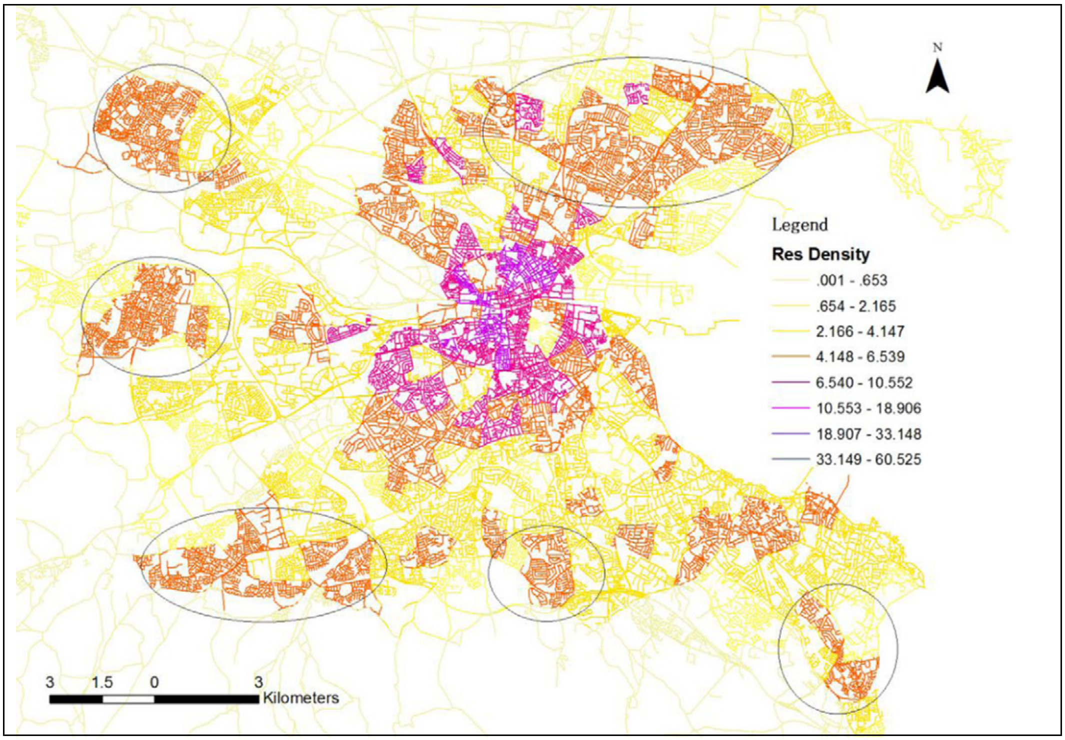
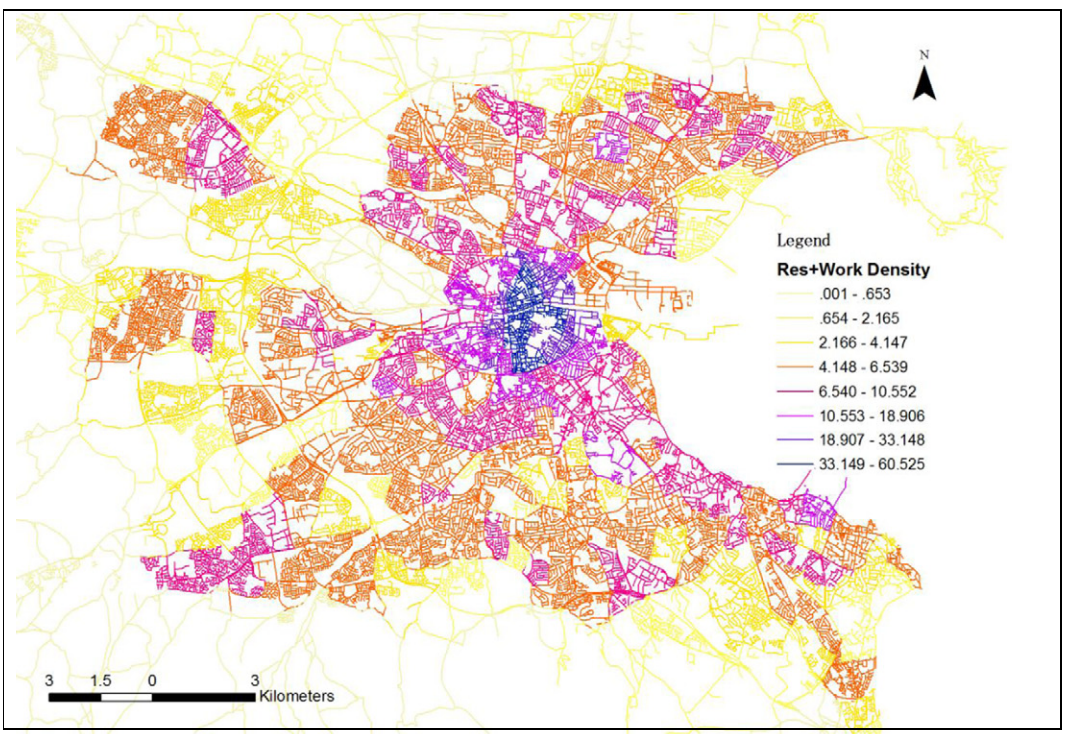


Fig. 4. Monthly distributions of two-way traffic in urban areas within one year.
Source: The National Roads Authority traffic count data (NRA, 2012).



(a) With residential density



(b) With residential plus work/school density

Fig. 5. Comparison between residential density and residential + work density of roads in Dublin.
Source for original road networks of Ireland: URBIS (http://erg.ucd.ie/ui/urbis.html). Unit: 1000 persons/km^2.

Google Earth directly, and times of images are determined based on the angles of the shadows in the images.

3.3. Extrapolation of data by distributions

AADTs for motorways and national ways are sourced from the National Roads Authority traffic count data (NRA, 2012), and these traffic count data are matched to the URBIS (Urban Information System) road network data by location. Those segments of motorways and national ways without traffic counters use the averages of neighbouring motorways or national ways with traffic counters. Traffic distributions on other roads are not available as their estimation necessitates continuous counting of traffic. For regional roads and busy local roads, survey data from the Road User Monitoring Report of the Dublin

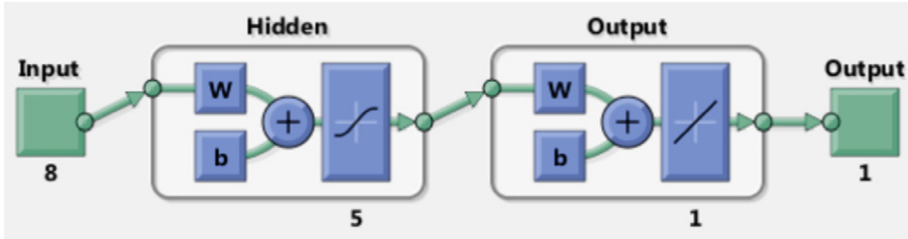


Fig. 6. Structure of the neural network model.

Transportation Office (DTO, 2006) are used. As these survey data were collected in November 2005 at 7 am–10 am,[1] there is a need to extrapolate them to annual averages based on traffic distributions (similar to the satellite data). As an example, hourly, daily, weekly and monthly traffic distributions are calculated from traffic counters on the M50, which is a circular motorway around Dublin showing similar traffic patterns to those on urban roads. The hourly, daily and monthly distributions are shown in Fig. 3 and Fig. 4, respectively. Then, based on the methodology given in the *Traffic Monitoring Guide* (FHA, 2013, p. 3–68, 3–78) and a paper by Sharma et al. (2001), the short duration traffic data from survey data or from satellite data are adjusted to daily average data, weekly average data and annual average data, i.e., AADTs, based on hour-of-week factors and monthly factors calculated from the corresponding distributions mentioned above. Using this methodology provides more robust estimates than extrapolations based solely on the length of time.

By comparing the distributions of motorways and national ways from the Road User Monitoring Report 2006–2009, we found that the distribution patterns from our estimation are close to theirs and these distributions do not vary significantly over time. In addition, the distribution patterns are similar to urban traffic distributions in the U.S. as reported in *Vehicle Volume Distributions by Classification* (Hallenbeck et al., 1997, p. 17, 32). We assume that traffic distributions in urban areas are similar to the distributions above, and extrapolate these data proportionally to rural areas for various vehicles with the urban-rural distribution data for AADTs from the United Kingdom (DFT, 2015). The AADTs are apportioned to different vehicle types - cars, LGVs (Light Goods Vehicles), HGVs (Heavy Goods Vehicles), buses and MCs (Motorcycles) - from the Road User Monitoring Report, with the exception that HGV AADTs on motorways and national ways are taken directly from available ratios provided in the traffic count data of the NRA.

3.4. Estimation of AADTs based on neural network

To estimate AADT for each road segment, POWSCAR (CSO, 2012) data was used as it provides detailed small-area data on place of residence and place of work/school for each person, thereby enabling us to consider population densities of residential areas, work and school areas, as well as car ownership and travel means. We spatially overlap road networks with small area census data to obtain residential and work/school population density attributes for the roads. The explanatory variables used in the neural network are road classes, local residential density, local working density, average road speed, region types (totally urban, urban with minor agricultural areas, settlements with major agricultural areas and totally rural), average car ownership ratio, distance to motorways and national ways and population of local settlement (to represent the size of a city, if no settlement exists in that area the population of that electoral district is used instead). Residential density and working density are used together in the model as combined they offer more accurate estimates. To demonstrate the advantage of using residential plus work/school population density, in Fig. 5, we compare the results from this method (b) with the results using only residential population density (a).

In the residential density map, we can see that in some suburban areas (in black circles) there are very high residential population densities because these are residential towns built in recent years. Although some residential areas have through roads, the traffic in such areas would be quite low. Therefore, assigning AADTs to roads solely based on residential population will relatively underestimate AADTS in central areas of the city and overestimate AADTs for residential areas. In contrast, Fig. 5b is more appropriate as work/school locations are included and represent an important travel destination for people during the day. It also partially represents shopping activities, as places where people go shopping are also places with other people (staff) working there. We find that identified commercial areas and large school campuses have darker colours in Fig. 5b, which is more plausible.

AADTs of regional roads (class 3) in all areas and local roads (class 4 and 5) in settlement areas are estimated with the neural network approach. The structure of our neural network is shown in Fig. 6. Based on a review provided by Sheela et al. (2013), the number of nodes are calculated with the following equation, n is the number of input, in our case, $n = 8$. So we use 5 nodes in the network.

$$N_h = (4n^2 + 3)/(n^2 - 8) \tag{2}$$

A sigmoid function of the Gompertz curve is used to limit the AADTs in the neural network model from 0 to the maximum annual average daily traffic value, excluding radical values (negative or very large values). The neural network model is realised with MATLAB and trained with the Levenberg-Marquardt algorithm. The quality of the fitting, validation and test are shown in Fig. S1. Correlation coefficients for training, validation, test and all are 0.9007, 0.9297, 0.8688 and 0.8288, respectively, and performance of the model, measured with mean squared errors, are given in Fig. 7. The model is accepted in consideration of the complexity of the AADT estimation.

AADTs of motorways and national ways can be obtained from traffic count data. For those segments of motorways or national ways without traffic counters, we get the estimated AADT from the weighted (by distance) average of the close traffic counters. For residential roads (class 6), because there is no through traffic, we assume that the traffic in residential areas is closely related to the number of vehicles owned by the residents and their travel patterns, which can be obtained from the POWSCAR data. For example, if nobody travels with MCs (Motorcycles), we can set the AADTs of MCs on residential road segments in these small areas to zero. Local roads (class 4 and 5) in rural areas without settlements are treated with this approach too, as we found that those low class rural roads are often empty (based on the study of the satellite images). If people drive to rural areas, they will usually drive using national ways or regional ways, unless they want to visit specific locations along the local ways. To check the quality of our estimation, we compare the results from the neural network model with other traditional methods, such as OLS and Log linear. A comparison of MAPEs (Mean Absolute Percentage Errors) for those methods is shown in Table 1.

[1] Although later versions of this report are available (2007–2009), the 2006 report is used as the later versions do not provide AADT tables by vehicle types and monitoring locations.

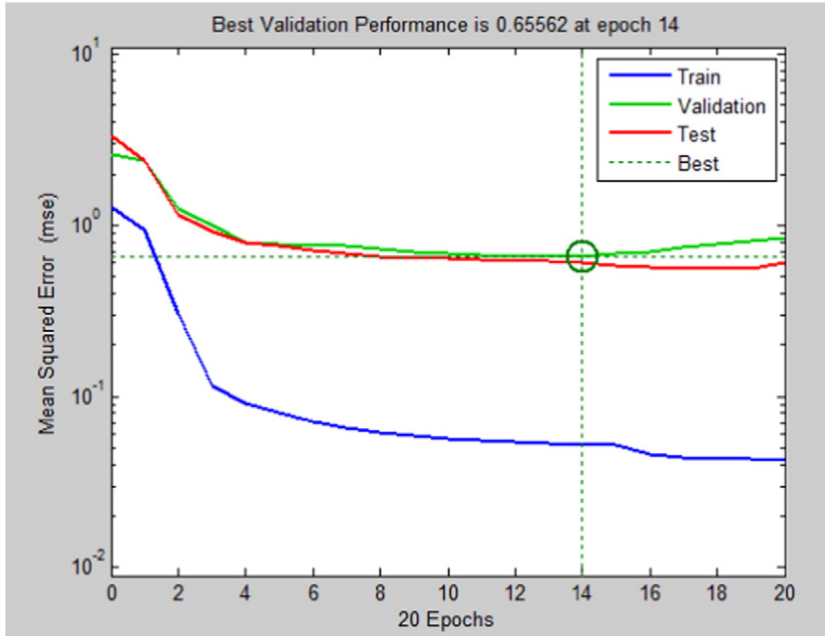


Fig. 7. Neural network model performance measured with mean squared error.

MAPE is a general approach for assessing estimation errors. The calculation of MAPEs for this purpose is shown in the following equation (from Wang et al., 2012; Lowry, 2014). The comparison of results indicates that the neural network method is better than the other two approaches. The total number of data points used in our estimation is 96, including 50 points from survey data and traffic counter data, and 46 points from satellite images. Traffic counter data points on motorways and national ways are excluded from the neural network model and regression models as traffic on national ways and motorways are mostly passing traffic, and are not tightly related to the explanatory variables used in the model. For example, remote motorways in low population areas may still have high traffic regardless of the local features. The MAPE calculated here is in-sample MAPE, as we do not have a particularly large sample. It should be remembered that the objective here is to develop a low-cost method for AADT estimation, and the authors recognise that there are stronger options where significant resources for surveys and automated traffic count data are available.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|EAADT_i - RAADT_i|}{RAADT_i} \tag{3}$$

3.5. Estimated results of AADTs

The final results of the estimated AADTs for the Irish road network are shown in Fig. 8. In this figure, the darker colours signify higher AADT levels. Motorways and national ways with high traffic volumes can be easily identified in the figure. To illustrate the detailed estimated values generated for urban areas, in Fig. 9, we show an enlarged map of AADTs for Dublin city. Red colours indicate high-traffic volumes and green colours indicate roads with less traffic. Whilst the necessary road count data are not available for all of these routes, the results are consistent with regularly observed traffic volumes, in so far as the main high-traffic commuting routes and popular areas present with red colours.

Finally, the distributions of our estimated AADTs by vehicle types, road types and area types are provided in Table 2 for urban areas and in Table 3 for rural areas in Ireland. Most values in the tables seem reasonable, with the exception of zero minimum values for some road types. The reason for this is that we have allowed for minimum values of zero in our neural network model. This can be adjusted if we can identify the true minimum values for these road types into the future. We also find that class 4 and 5 local roads in rural areas do not show large differences. This has been confirmed by the study of satellite images. Therefore, we believe class 4 and 5 can be combined in rural areas.

Table 1
The comparison of MAPEs of methods for estimating AADTs with Irish data.

Method	Neural network	Log linear	OLS
MAPE	28.58%	52.49%	66.6%

Notes: For country scale estimation, the values of MAPEs also depend on the quality of data available. It is true that localised estimation has better quality data. Sharma et al. (2001) suggested that 30% error is acceptable for low-volume roads (without permanent traffic counters). The estimation of Pan (2008), with regression models to assign AADT to all roads in Florida, generates MAPEs ranging from 31.99% to 159.49%.

4. Estimation of street level air emissions

4.1. Estimation of kilometres of different vehicles (VKMs) in each road segment

AADTs are a useful input into transport emission models. For the estimation of street-level air emissions, additional information is required. The first step is to convert AADTs to VKMs for all vehicle types for each road segment. This can be achieved by multiplying the AADTs for vehicle types by the length of that road segment. The aggregate results of VKMs are shown in Table 4 as proportions. The proportions of different road types and area types (urban and rural) are presented as these are key parameters for major transport emission and policy models, such as COPERT and TREMOVE.

4.2. Street-level air emissions

To estimate air emissions from road transport, we further divide VKM data for different vehicles by fuel types, engine sizes or weights, and control technologies (Pre-Euro, Euro 1, Euro 2, etc.). This process is based on vehicle fleet data from TREMOVE Ireland (Fu and Kelly, 2012). Road speeds are obtained from the URBIS database. The calculation of the emissions is mainly based on COPERT approaches (EMISIA, 2014), and emission factors adjusted by the Transport Research

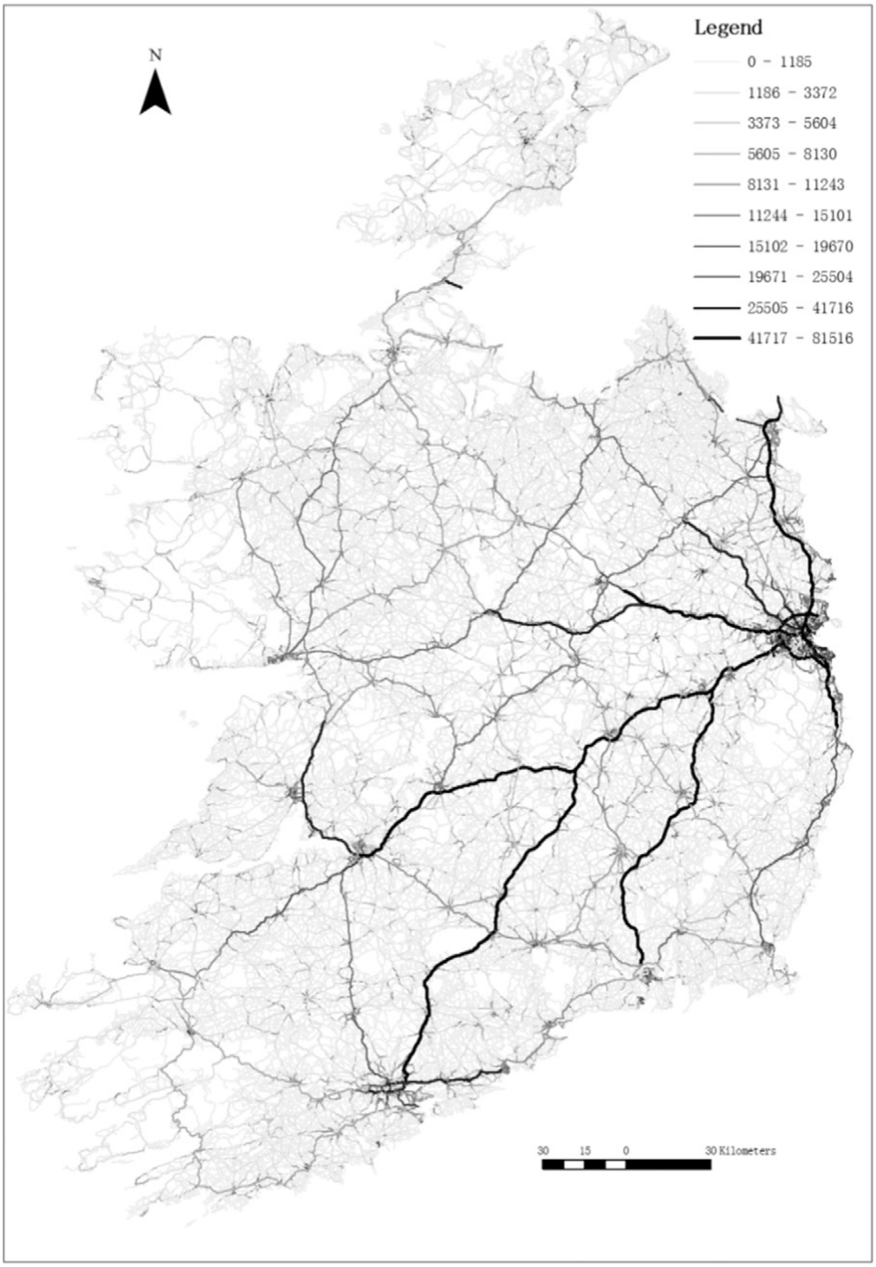


Fig. 8. Estimated AADTs of roads in Ireland.

Laboratory (TRL, 2009). Average daily emissions in 2010 of NO_x, $PM_{2.5}$ and HC are estimated for each road segment in Ireland. As Reynolds and Broderick (2000) point out, a good correlation between road traffic and pollution concentrations can be achieved when these are averaged over periods longer than 1 h. Therefore, it is reasonable to believe that annual average daily traffic data can support the future estimation of concentrations of air pollutants. However, we acknowledge the greater complexity involved with pollution concentration estimation, and retain the focus in this paper exclusively on emissions.

As an illustration, the estimated results of street level NO_x emissions are shown in Fig. 10. Fig. 10a gives the NO_x emission level for each road segment and the values have been divided by segment lengths to calculate the average emissions per kilometre. Area average (road emissions divided by areas, i.e., emissions per km^2) for the Dublin area are shown in Fig. 10b. One can still observe the impacts of heavy traffic roads on the area average map, stretching out from Dublin city in warmer colours.

The aggregated emissions for all pollutants estimated with our approach are provided in Table 5, and they are compared with those values generated by energy consumption based models, such as the model used by the National Inventory team of the Irish Environmental Protection Agency, and GAINS Ireland. Although we have not used energy consumption in our model, our values are still close to the other two models. Estimation of emissions using methodologically distinct approaches, based on traffic data or energy consumption data provides a valuable contribution to the validation of results, and can also identify areas to target for greater data gathering and research. The findings of our emissions comparison work are reasonably consistent. This suggests that our method provides a reliable alternative approach to generating national emission data from the transport sector, with the added benefit that we can calculate the street level AADTs and spatial distributions of those emissions across the entire road network.

5. Conclusion

The spatial distribution of transport activity, AADT values and estimates of associated emissions are important datasets that can offer

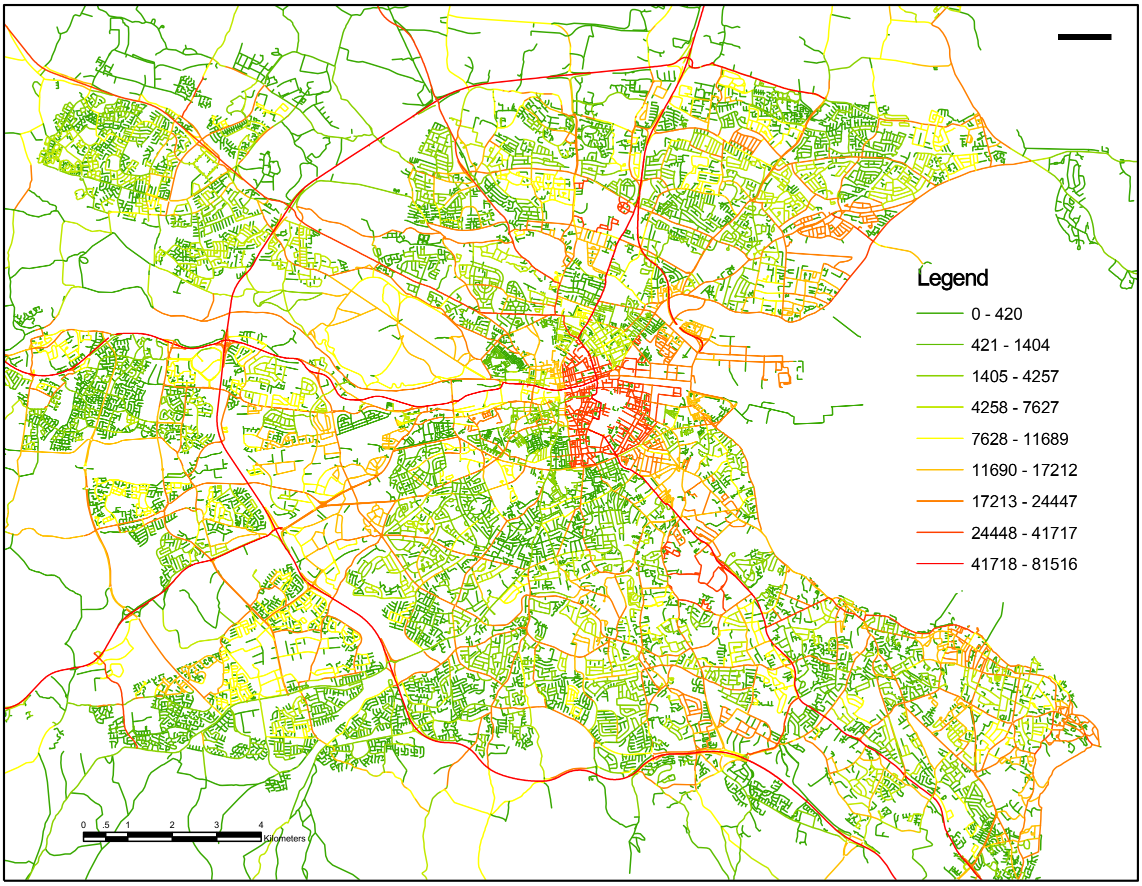


Fig. 9. Estimated AADTs of roads in Dublin.

many potential benefits for research and analysis in an environmental, social, health, planning and commercial context. For major roads equipped with sufficient automated traffic counters or areas of limited scale, it is a straight forward process to collect the requisite traffic data and generate accurate AADT estimates. However, for many countries, data from traffic counters are limited, in particular, for secondary and tertiary routes. In such cases, it is impossible for researchers to survey the entire road network without incurring substantial and, most likely, prohibitive cost.

This paper provides a feasible systematic methodology for generating nationwide AADTs, their distribution, and the associated emissions by integrating existing census data, geographical data, traffic counter data, vehicle fleet data and emission factors. The method avoids high-cost investment in traffic surveys and counters, yet still offers good estimations of AADTs and associated air emission from road transportation. The authors recognise that the approach is more vulnerable to uncertainty; that it is dependent on data quality; that the proportions of components of some pollutants, such as NO and NO_2 in NO_x, may vary according to fuel quality, combustion condition and ambient environment; and that the MAPE is larger than approaches using extensive traffic counter data and survey data. Nonetheless, the method has specifically been developed so as to offer a valuable alternative approach where such investments and infrastructure are unavailable.

Furthermore, in terms of road side pollution concentrations, it is important to note that the approach includes the spatial distribution of emissions, but this is distinct from road side concentrations of pollution. The latter requires consideration of broader factors such as background

Table 2
Average, min and max AADTs by vehicles and types of roads in Ireland (Urban areas).
Sources: Calculated based on the estimated values from our model.

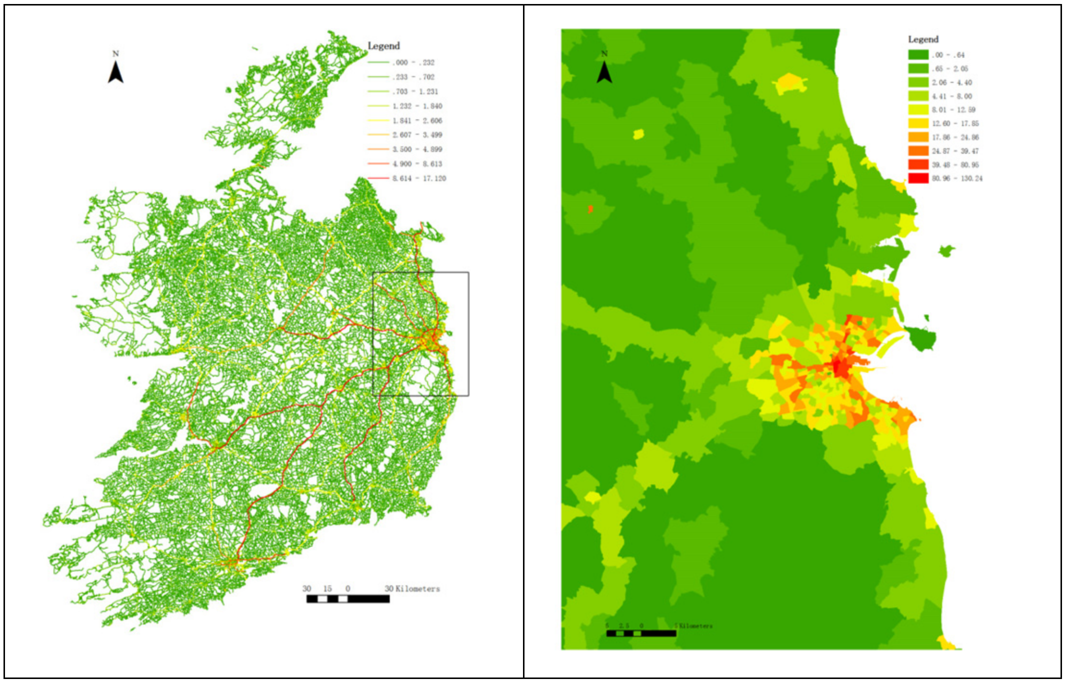
AADTs Urban	Cars	LGVs	HGVs	Buses	MCs	Min	Max
Motorways	46,171	6207	3210	841	721	1758	81,516
National ways	21,299	2890	1330	412	300	38	81,516
Regional ways	13,193	1872	855	358	129	24	29,058
Local roads(heavy)	7779	748	219	55	57	0	28,054
Local roads(light)	5337	593	152	103	27	0	28,050
Residential roads	140	9	1	0	2	0	418

Table 3
Average, min and max AADTs by vehicles and types of roads in Ireland (rural areas).
Sources: See Table 2.

AADTs Rural	Cars	LGVs	HGVs	Buses	MCs	Min	Max
Motorways	31,571	4255	3486	573	493	1459	81,516
National ways	6585	900	602	113	97	96	61,990
Regional ways	4478	660	345	88	36	8	28,561
Local roads(heavy)	388	37	11	3	3	0	16,480
Local roads(light)	444	49	13	9	2	0	12,825
Residential roads	139	14	1	0	1	2	988

Table 4
Aggregate VKM proportions by road types for Cars, HGVs and LGVs.

Aggregate daily VKM	CarVKM %	HGVVKM%	LGVVKM%	BusVKM%	MCVKM%
Motorways	17.57%	24.41%	17.25%	18.33%	26.78%
National ways	20.36%	22.47%	20.15%	20.89%	29.75%
Regional ways	46.52%	47.60%	50.48%	46.87%	34.77%
Local roads	15.02%	5.44%	11.74%	13.90%	8.31%
Residential roads	0.52%	0.08%	0.37%	0.00%	0.39%
Rural	72.14%	82.12%	74.56%	67.87%	75.26%
Urban	27.86%	17.88%	25.44%	32.13%	24.74%



(a) Line emissions (b) Area average emissions

Unit : Tonne/km per annum for line emission, and Tonne/km^2 per annum for areal average

Fig. 10. Street-level NO_x emissions from road transport and its area averages, 2010. Unit: Tonne/km per annum for line emission, and tonne/km^2 per annum for areal average.

pollution, atmospheric transfer, street canyon effects and indeed more detailed temporal disaggregation. These elements are not included in this study and it is important to ensure that the spatially distributed emission estimations are not confused with spatially distributed pollutant concentration values.

The methodology presented can be compared with alternative methods and with those values generated by energy-consumption models. For example, the estimates of emissions aggregated from each road segment generated by the bottom-up model presented in this paper compare favourably with aggregated estimates from a top-down model based on fuel consumption by the road transport sector. This strengthens the case that the methods are reasonably coherent and appropriate.

Overall, transportation and land-use planning, energy policy, and climate and air policy all benefit from the availability of these type of data on annual average daily traffic levels and the associated transport emissions. In this paper, we have presented an approach to deliver this for a national road network in a practical and low-cost manner which compares favourably with the alternatives. In time it is hoped that low cost sensor networks and mobile data will offer increasingly detailed and robust values, however, in the interim this method offers a viable and valuable alternative for researchers and policymakers.

Table 5
Aggregated road transport emissions estimated with AADTs and comparison with energy consumption models, 2010.
Data sources: National Inventory: http://www.epa.ie/climate/emissionsinventoriesandprojections; GAINS Ireland: http://gains.iiasa.ac.at/gains/IE3/index.login.

Pollutants	HC/VOC[a]	NO_x	$PM_{2.5}$
Authors' method	5.79(HC only)	39.12	1.33
National Inventory	8.46(VOC)	36.84	2.09
GAINS Ireland	8.82(VOC)	45.88	1.5

Unit: Kt per annum.
[a] Hydrocarbons (HC), a group of chemical compound composed of carbon and hydrogen, are the main ingredient of Volatile Organic Compounds (VOC).

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jtrangeo.2016.12.002.

Acknowledgments

The work on this paper has been supported by the Irish Environmental Protection Agency (Grant no. 2013-CCRP-MS14) under the STRIVE programme 2007–2013 and the Foundation for High-level Talents in Higher Education of Guangdong. This work has been completed as part of the Integrated Modelling Project led by EnvEcon Limited. The views expressed are those of the authors. Sincere thanks go to the Central Statistics Office of Ireland for their provision of the Census and other data sets which have been used in this paper.

References

Borge, R., Miguel, I., Paz, D., Lumbreras, J., Pérez, J., Rodríguez, E., 2012. Comparison of road traffic emission models in Madrid (Spain). Atmos. Environ. 62 (Dec), 461–471.
CSO (Central Statistics Office), 2012. Census of Population of Ireland 2011: Place of Work Census of Anonymised Records (POWCAR) User Guide. Central Statistics Office, Dublin (http://www.cso.ie/en/media/csoie/census/documents/powscar2011/Place:of_Work,_School_or_College_-_Census_of_Anonymised_Records__POWSCAR__User_Guide_2011version2.pdf).
DFT (Department for Transport), 2015. GB Road Traffic Counts. London (http://www.dft.gov.uk/traffic-counts/).
DTO (Dublin Transportation Office), 2006. Road User Monitoring Report 2006. Dublin (http://nationaltransport.ie/downloads/archive/road_user_monitoring_2006.pdf).
EMISIA, 2014. Methodology for the Calculation of Exhaust Emissions. Thessaloniki (http://emisia.com/products/copert-4/documentation).
FHA (Federal Highway Administration), 2013. Traffic Monitoring Guide. U.S. Department of Transportation. FHA, Washington DC (http://www.fhwa.dot.gov/policyinformation/tmguide/tmg_fhwa_pl_13_015.pdf, 3-68, 3-78).
Fu, M., Kelly, J.A., 2012. Carbon related taxation policies for road transport: efficacy of ownership and usage taxes, and the role of public transport and motorist cost perception on policy outcomes. Transp. Policy 22 (July), 57–69.
Hallenbeck, M., Rice, M., Smith, B., Cornell-Martinez, C., Wilkinson, J., 1997. Vehicle Volume Distributions by Classification. Washington State Transportation Center.

University of Washington, Seattle (depts.washington.edu/trac/bulkdisk/pdf/VVD_CLASS.pdf).
Karlaftis, M.G., Vlahogianni, E.I., 2011. Statistical methods versus neural networks in transportation research: differences, similarities and some insights. Transp. Res. C 19 (3), 387–399.
Khatib, Z., Chang, K., Ou, Y., 2001. Impacts of analysis zone structures on modeled statewide traffic. J. Transp. Eng. 127 (1), 31–38.
Lingras, P., 1995. Classifying highways: hierarchical grouping versus Kohonen neural networks. J. Transp. Eng. 121 (4), 364–368.
Lowry, M., 2014. Spatial interpolation of traffic counts based on origin–destination centrality. J. Transp. Geogr. 36 (April), 98–105.
McCord, M., Goel, P., Jiang, Z.J., Coifman, B.J., Yang, Y.L., Merry, C., 2002. Improving AADT and VDT Estimation with High-Resolution Satellite Imagery. American Society for Photogrammetry and Remote Sensing, Integrating Remote Sensing at the Global, Regional and Local Scale. Pecora 15/Land Satellite Information IV Conference.
Mohamad, D., Sinha, K.C., Kuczek, T., Scholer, C.F., 1998. Annual average daily traffic prediction model for county roads. Transp. Res. Rec. 1617, 69–77.
Mustafa, R., 2010. Applying High-Fidelity Travel Demand Model for Improved Network-wide Traffic Estimation: New Brunswick Case-Study, Paper Prepared for Presentation at the Best Practices in Urban Transportation Planning Session of the 2010 Annual Conference of the Transportation Association of Canada. Halifax, Nova Scotia.
Neveu, A.J., 1983. Quick response procedures to forecast rural traffic. Transportation Research Record 944. Transportation Research Board, Washington DC, pp. 47–53.
NRA (National Roads Authority), 2012. Automatic Traffic Counter Statistics. https://web.nra.ie/CurrentTrafficCounterData/index.html.
Ntziachristos, L., Samaras, Z., 2000. Speed-dependent representative emission factors for catalyst passenger cars and influencing parameters. Atmos. Environ. 34 (27), 4611–4619.
Pan, T., 2008. Assignment of estimated average annual daily traffic on all roads in Florida. (Graduate Theses and Dissertations). University of South Florida.
Reynolds, A.W., Broderick, B.M., 2000. Development of an emissions inventory model for mobile sources. Transp. Res. Part D: Transp. Environ. 5 (2), 77–101.
Sharma, S., Lingras, P., Xu, F., Kilburn, P., 2001. Application of neural networks to estimate AADT on low-volume roads. J. Transp. Eng. 137 (5), 426–432.
Sheela, K.G., Deepa, S.N., Perc, M., 2013. Review on methods to fix number of hidden neurons in neural networks. Math. Probl. Eng. 2013, 425740. http://dx.doi.org/10.1155/2013/425740.
TRL (Transport Research Laboratory), 2009. Emissions Factors 2009: Report 3 - Exhaust Emission Factors for Road Vehicles in the United Kingdom. TRL Report Number PPR356, Wokingham. http://www.trl.co.uk.
Tsapakis, I., Schneider IV, W.H., Nichols, A.P., 2012. A Bayesian analysis of the effect of estimating annual average daily traffic for heavy-duty trucks using training and validation data-sets. Transp. Plan. Technol. 36 (2), 201–217.
Wang, T., Gan, A.G., Alluri, P., 2012. Estimating Annual Average Daily Traffic (AADT) for Local Roads for Highway Safety Analysis. Transportation Research Board (TRB) 2013 Annual Meeting.
Zhong, M., and Hanson, B.L., 2008. “GIS-based Travel Demand Modeling for Estimating Traffic on Low-Class Roads”. In the 87thTransportation Research Board Annual Meeting, Paper #08-1098, Jan. 12–17, 2008.