NACA Conference 2016

COVERING LETTER
CONFERENCE PAPER:
Towards a detailed on-road vehicle emissions inventory: The use of a Travel Demand Model

Reviewer comments addressed as follows:

1) Title of "Dr" removed.
2) Aims included at end of introduction.

Towards a detailed on-road vehicle emissions inventory: The use of a Travel Demand Model

Mogesh Naidoo[1], Mathetha Mokonyama[2] and Muzi Nkosi[2]

[1] CSIR, Natural Resources and the Environment Unit, Climate Studies, Modelling and Environmental Health Research Group, P O Box 395, Pretoria, 0001.
[2] CSIR, Built Environment Unit, Transport Systems and Operations, P O Box 395, Pretoria, 0001.
mnaidoo4@csir.co.za

In terms of air quality management in the urban setting, an on-road vehicle emissions inventory is important, particularly in growing economies as private vehicle ownership increases. The basis of vehicle emissions inventory is an estimate of Vehicle Kilometres Travelled (VKT) for every model grid cell. This has proven difficult in South Africa as well as internationally with methodologies ranging from generalized spatial surrogate application (leading to many assumptions being incorporated) to detailed use of available traffic counts (leading to spatially limited inventories as count information is sparse). A Travel Demand Model (TDM) is used to simulate peak demand through road networks such that for example changes in infrastructure, changes in mode choice and preferential routing may be explored. It is a growing trend to use a TDM for estimating vehicle emissions inventories for air quality modeling. A TDM is used to estimate VKT and speed of different vehicle types. Here the Gauteng Transport Model (based upon an EMME/4 framework), as applied by the CSIR Built Environment's Transport Group, is modified appropriately to estimate VKT on a 1km resolution grid within the City of Johannesburg such that realistic emission estimates are possible for use in an air quality model..

Keywords: traffic emissions, vehicles, travel demand model, emissions modeling, City of Johannesburg

1. Introduction

Air quality is driven by air pollutant concentrations resulting from the release, transport and transformation of pollutants into the atmosphere. Depending on location certain emission sources dominate the contribution to local air quality. In the urban environment emissions from vehicles can make up the bulk of the contribution due to the widespread adoption of private transport and general economic development that depends on the transport system. The proliferation of vehicle use also leads to congestion, thus exacerbating travel time and fuel burnt. The modern combustion engine is capable of emitting various pollutants into the atmosphere, including oxides of nitrogen (NOx), sulphur dioxide (SO_2), carbon monoxide (CO), particulate matter (PM) and volatile organic compounds (VOC). The ambient (outdoor) concentrations of all of these pollutants are regulated in South Africa. Air pollution from traffic is known to have negative health impacts due to factors such as its emission at ground-level (e.g., levels where people can be directly exposed) and its composition. Diesel exhaust was classified as a confirmed human carcinogen in June 2012 (WHO, 2012). For these reasons an emissions inventory for the road transport sector is important for management and air quality modeling considerations.

The basis of a vehicle emissions inventory is an estimate of Vehicle Kilometres Travelled (VKT) for every model grid cell at a temporal granularity that captures vehicle activity appropriately. This has proven difficult in South Africa as well as internationally with methodologies ranging from top-down approaches with generalized spatial surrogate application (leading to many assumptions being incorporated) to detailed use of available traffic counts (leading to spatially limited inventories as count information is sparse). Fuel allocation to the considered vehicle classes and the spatial extent of the fuel use brings much uncertainty into the top-down approach; but even if these are well characterized, finer spatial allocation of activity down to the road link level requires much information such as traffic counts, which are currently sparsely located. This paper describes the application of an alternative approach, i.e. the use of a Transport Demand Model, to estimating

VKT; thus providing a means to develop a bottom-up emissions inventory. Such an approach draws on expertise from both the fields of air quality (emissions inventory development) and traffic modeling.

2. Traffic modeling for emissions

The estimation of VKT may be strengthened by collaboration with transport professionals as there are benefits gained from insights into the transport system, from knowledge of the data available, proprietary data access and simulation of networks. Traffic modeling through Travel Demand Models (TDM) are a valuable tool for assessment of the current network and future scenarios. These are run in order to gain an understanding of traffic flow such that any network changes may be assessed for efficiency. These models can provide an estimate of VKT and network speed and, depending on the input data used, can disaggregate this information to the level required of an emissions inventory, i.e. for the different vehicle classes for which emission factors are available and at the temporal resolution needed. Another benefit is that the TDM simulates traffic flow on the road network that is represented as vector data, typically sourced from an official road network shapefile. This provides great flexibility in terms of re-gridding to any resolution.

The use of a TDM to drive emissions inventories for vehicles is not new, and some platforms (e.g. the EMME framework by INRO Software: https://www.inrosoftware.com/en/products/emme) have built-in emissions functions. The approach has received attention for more than a decade. Kahn (1999) highlights the considerations required when utilizing such models (specifically on the INRO EMME/2 platform) for the purpose of GHG emissions estimation. Aspects such as vehicle speed and type are vital to ensuring that vehicle activity is adequately described such that the correct emission factors are applied. Since GHG emissions are related to fuel consumption (and not VKT directly) this introduced an additional layer of potential uncertainty since aggregated fuel efficiency statistics were required. In terms of air pollutant emissions only SO_2 emissions are related to fuel consumption. Kahn (1999) also makes the distinction between macroscopic models and micro-simulation models; with each providing a different approach depending on the aim of the transport modeling study. Micro-simulation models are used at small spatial scale and consider fine vehicle movements, thus accurately depicting flow; but only for a very small region (e.g. an intersection). Macroscopic models tend to utilize more aggregated/generalized information on vehicle movements but cover a much large spatial scale (e.g. a city) such that an entire network and the interactions within may be simulated. It is further suggested that the macroscopic models provide a greater coverage and therefor better estimation of emissions; however refinements to vehicle movement (particularly speed) must be made. It is seen that transport models do provide a platform for better estimation of VKT and other vehicle activity but accuracy then depends on the input data used to drive such models.

One of the most important hurdles to the use of a transport model for emissions inventories is the fact expertise to run such models often lays outside the scope of emissions and air quality modelers. Collaboration is thus necessary, however in order to include the additional VKT considerations required for accurate emissions estimation, the transport model or its inputs need to be modified. This collaboration has been illustrated well in Gagnon et al. (2007) where Canadian environmental and transport authorities shared expertise to develop a comprehensive emissions modeling system comprised of a TDM for Montreal based on the EMME/2 platform and an emissions factor model (US-EPA MOBILE6.2) modified for Canada. Key input to the TDM included a road network (only highways and arterials in this case), demand matrices and temporal factors. The temporal aspect is specific (for the most part) to emissions considerations as TDMs are applied primarily to ascertain a single representative time period, e.g. peak morning or a single season. The Gagnon et al. (2007) study also showed improvements to simulated ambient ozone for a smog episode due to the use of the TDM driven emissions model when compared to that of the normal top-down approach to estimating vehicle emissions. Lindhjem et al. (2010) describe in more detail the process of incorporating vehicle count data to refine the temporal disaggregation for different areas and vehicle classes, thus reducing the uncertainty introduced by using regional temporal and vehicle mix profiling.

Here the Gauteng Strategic Travel Demand Model (GSTDM) as developed by the CSIR Built Environment’s Transport Group, and built upon the EMME/4 platform, is investigated as a source to estimate VKT on a 1km resolution grid within the City of Johannesburg such that realistic emission estimates are possible for use in an air quality model.

3. The top-down approach

Lacking any refined bottom-up vehicle activity data emissions inventories for South Africa are often based on top-down approaches that utilize magisterial fuel sales volume data that is uniformly disaggregated down to the road link level. Differences exist at the spatial surrogate level and either census statistics or vehicle counts are used to further augment disaggregation. Figure 1 shows one such estimate for the City of Johannesburg region, where 2013 magisterial district annual fuel sales information (as reported by Department of Energy) is disaggregated by 2013 National Household Travel Survey data on "Travel Analysis Zones" and then allocated to road links uniformly within these. Disaggregated fuel sales are assumed to equal fuel use on roads and are translated into VKT through fuel efficiency ratings reported by Mervyn et al. (2012). Where vehicle counts are available through SANRAL count stations, these are used to estimate VKT for the immediate link at the station.

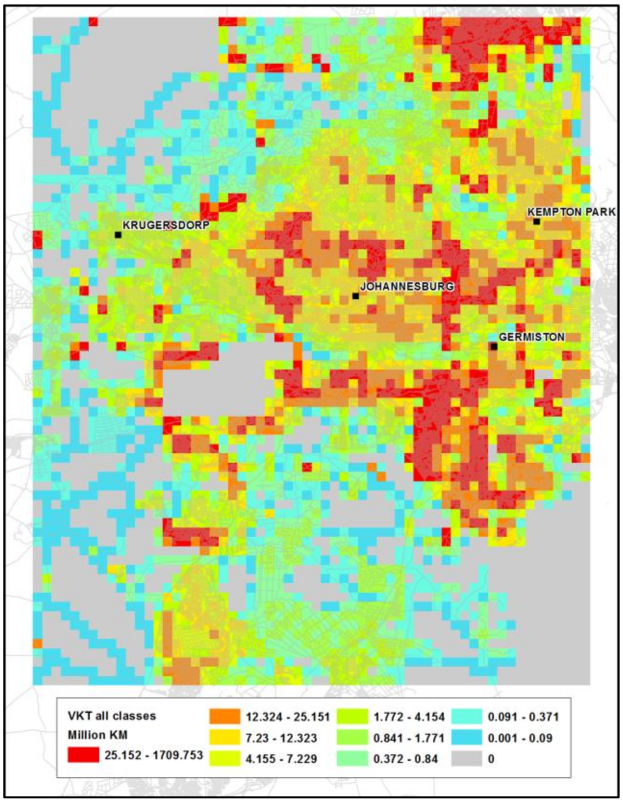

Figure 1: Top-down estimate of VKT for City of Johannesburg

Vehicle class and fuel type split are derived from eNATIS provincial reports. Many assumptions are inherent in such a top-down approach; from the assumptions of fuel sales/use being locally restricted (ignoring inter-district movement) to the uniform distribution of fuel use to roads within "Travel Analysis Zones".

4. The TDM approach

The GSTDM is an AM peak travel demand model used to examine regional transport needs and for understanding aggregated passenger travel choice and travel behaviours under different scenarios in the province. The model estimates AM peak hour travel using 2011 base year demand matrices; the 2011 road network and a set of volume delay functions per network link type to estimate demand for routes, VKTs and other network performance indicators. The assignment procedure in the transport model assumes that every individual traveller perceives travel time (or costs) in the same way, as a result under equilibrium conditions traffic will arrange itself in such a way that no individual traveller may reduce his traveling costs by changing routes, this is also known as Wadrop's principle (Ortúzar & Willumsen, 2005). The modelled road network is from class 1 to class 3. Figure 2 shows an overview of the methodology used to estimate VKT.

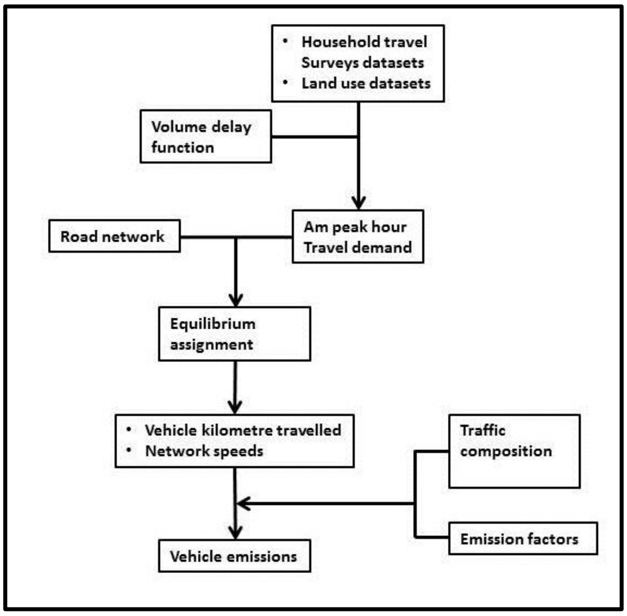

Figure 2: Overview of methodology used to derive GSTDM

The basis for travel demand is derived from household travel surveys from which a demand matrix is then defined; and therefor estimates VKT only for passenger modes of transport.

5. TDM modifications

Since the GSTDM is a peak demand model that estimates only passenger transport additional modifications are necessary to derive temporal variation and a VKT for on-road freight transport. It is also necessary to split VKT into vehicle classes according to available emission factors (these include light passenger motor vehicles, minibus taxis, motorcycles, light commercial vehicles, buses and trucks).

The equation below is a synthetic formula used to obtain the daily traffic emissions.

$$d(t) = \sum_{i=1}^{n} \sum_{t=1}^{24} \sum_{j=1}^{u} \sum_{m=1}^{k} F_{jt} V_j^i * \Delta x_j^i \propto_j^i \beta_{jm}^i$$

Where:

i = grid cell reference index (i =1,…., n)
j = Link reference
m = Mode type
t = Time in hours (t =1,….,24)
F_{it} = Link type specific daily kilometre expansion factor in grid cell i and at time t
V_j^i = Link volume as obtained from the transport model
Δx_j^i = Link segment in grid cell i
$\propto_j^i$ = Heavy vehicle factor
β_{jm}^i = Mode specific emission factor

For each link type the F_{it} values for a given time t will be extrapolated to a typical weekday or weekend profile. Traffic counts from SANRAL, GauTRANs and JRA are grouped according to network link type and are used to develop profiles for links with counts. These profiles will be extrapolated to other links in the vicinity according to network link type (e.g. profiles for off-ramps will be allocated to off-ramps only). Similarly vehicle class mix for links will be governed primarily by any count data. A default class split for links without nearby count stations will be based on eNATIS provincial live (as at end of 2014) registration data. It is necessary to use provincial data (as opposed to finer spatial data) since there is much travel between municipalities and using a more aggregated mix aims to reduce the impact of uncertainty.

A grid value map in EMME is a summation of node and/or a link values within the cells of a user-defined grid. The model VKTs will be converted to 1 kilometre by 1 kilometre grid cell values as shown in Figure 3 with Δx_j^i being link length within the 1km x 1 km grid cell and V_j^i the corresponding link volume per peak hour. Freight demand models are fairly undeveloped locally and internationally. As a result, to take heavy vehicle traffic into account, $\propto_j^i$ was introduced as a factor to be drawn from road traffic counts, which is also link specific.

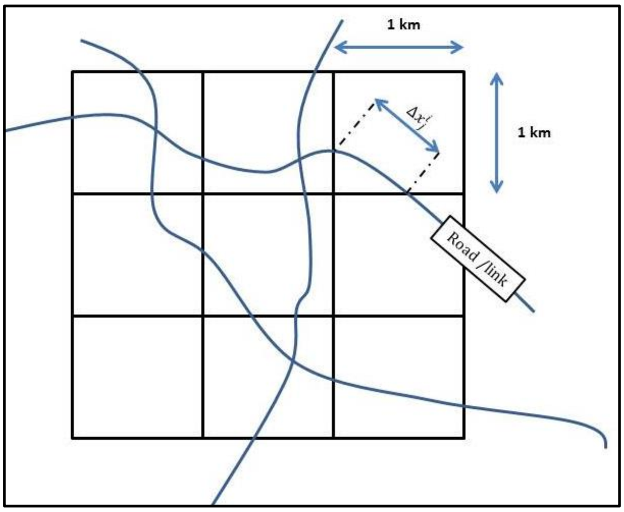

Figure 3: Schematic of gridding procedure

6. Limitations

Macroscopic models (i.e. strategic/regional transport models such as the GSTDM) carry limitations if set up purely for transport analysis. Aspects of transport operations which have been identified in literature as having a significant impact when modelling network vehicle emissions using a macroscopic model include; vehicle idling time, positive acceleration and high speeds (Mamarikas et al., 2015), and in general variations in traffic flow. For example at signalised intersections under different green splits (time given for green light) the regional/macroscopic models were found to be underestimating emissions by up to 6% (Mamarikas et al., 2015). However this depends on the input data used for the macroscopic treatment of vehicle movements. If one artificially introduces lower speeds to account for congestion (e.g. from observations such as vehicle counts) then emissions are increased more appropriately.

The successful use of a TDM to estimate VKT for use in emissions inventory development hinges on adequate input data. Uncertainty is introduced by not including all roads, generalizing vehicle mix and speed for defaulted areas and extrapolating temporal variation to other roads. It would be Ideal to include more specific data but these often do not exist for all roads within the network. Traffic count data, which retains a level of vehicle class description and speed (such as the SANRAL count data), is the primary limiting data input into the GSTDM. However even though similar data limitations exist to drive top-down approaches, and including increasingly more spatially specific data helps alleviate some of the uncertainty, the TDM provides a more directed framework to eventually arriving at a more accurate representation of the transport system. This is by virtue of the fact that in a TDM roads are treated as a network or system of networks that are dynamic and interact with each other, while for the top-down approach roads are merely spatial surrogates.

While the use of a macroscopic TDM has limitations related to the aggregated treatment of vehicle movements it is still more relevant to emissions estimation for larger road networks, such as those when considering entire urban regions (as opposed to a single intersection). Microscopic modeling and the accuracy it brings will be more useful to the very fine intersection scale emissions and then only to micro-scale dispersion modeling (e.g. the CALINE modeling system developed by US EPA). Additionally the input required to run a microscopic TDM for a large regional coverage (such that macroscopic interactions between different areas like Pretoria and Johannesburg or even the CBD with residential are captured together with each and every intersection and link) is not available currently or in the foreseeable future.

7. Conclusions

Due to the importance of generating accurate emissions inventories for the road transport sector alternative methodologies to the top-down approach of fuel sales/consumption are sought; that capture spatial and temporal variability of VKT realistically. Travel demand models potentially provide a basis for a refined bottom-up approach by treating roads as dynamic networks; that are subject to traffic flows dictated by simulated demand.

However TDMs are often developed for specific transport related scenario analysis and as such do not focus on all requirements of an emissions inventory related VKT. These requirements include VKT for different vehicle classes that vary temporally. Additional modifications must be made for these considerations, by introducing synthetic factors that modulate the peak demand and distribute this among vehicle classes. A primary data source that supports derivation of these factors is vehicle/traffic counts.

The GSTDM provides a platform for estimating VKT in the Gauteng province. The TDM can be modified by including analysis and thus functions that take into account any count data (SANRAL, GauTRANS and JRA in this case). Remaining limitations include appropriateness of extrapolating count temporal variation to surrounding roads and similarly extrapolation of vehicle class mix. This withstanding the TDM platform itself presents a superior framework for continuously improving accuracy of VKT estimates by including more data as they become available.

8. Acknowledgments

This work is supported through Parliamentary Grant funding and is part of the City of Johannesburg Air Quality Management Plan.

9. References

Gagnon, O., Morneau, G., Noriega, Y. and Pentcheva, N. (2007). Improving the Mobile Emissions Inventory for Air Quality Modeling in the Montréal Area, Canada. 16th Annual International Emission Inventory Conference – “Emission Inventories: Integration, Analysis and Communications”. Raleigh, North Carolina, May 2007.

Kahn, A.M. (1999). ISSUES IN THE USE OF EMME/2 AS A PLATFORM FOR THE ESTIMATION OF GREENHOUSE GASES. Journal of University of Shanghai for Science and Technology, 1999-03.

Lindhjem, C.E., DenBleyker, A., Jimenez, M., Haasbeek, J., Pollack, A.K. and Li, Z. (2010). Use of MOVES2010 in Link Level On-Road Vehicle Emissions Modeling Using CONCEPT-MV. 19th Annual International Emission Inventory Conference – “Emissions Inventories – Informing Emerging Issues”. San Antonio, Texas, Sept 2010.

Mamarikas, S., Mintsis, E., Mitsakis, E. & Salanova, J. M. (2015). Comparison of macroscopic and microscopic emission estimation approaches in the evaluation of ITS. Pilea, s.n., pp. 1-14.

Mervyn, B., Stone, A., Hughes, A., & Cohen, B. (2012). Quantifying the energy needs of the transport sector for South Africa: A bottom-up model. Research Report, Energy Research Cente, University of Cape Town, Cape Town: South African National Energy Development Institute (SANEDI).

Ortúzar, J. d. D. & Willumsen, L. G. (2005). Modelling Transport. 4th Edition ed. West Sussex: John Wiley & Sons.

WHO (2012). International Agency for Research on Cancer: Diesel engine exhaust carcinogenic. WHO Press Release number 213, 12 June 2012.