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Review of modelling air pollution from traffic at street-level - the state of the science

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Abstract

Traffic emissions are a complex and variable cocktail of toxic chemicals. They are the major source of atmospheric pollution in the parts of cities where people live, commute and work. Reducing exposure requires information about the distribution and nature of emissions. Spatially and temporally detailed data are required, because both the rate of production and the composition of emissions vary significantly with time of day and with local changes in wind, traffic composition and flow. Increasing computer processing power means that models can accept highly detailed inputs of fleet, fuels and road networks. The state of the science models can simulate the behaviour and emissions of all the individual vehicles on a road network, with resolution of a second and tens of metres. The chemistry of the simulated emissions is also highly resolved, due to consideration of multiple engine processes, fuel evaporation and tyre wear. Good results can be achieved with both commercially available and open source models. The extent of a simulation is usually limited by processing capacity; the accuracy by the quality of traffic data. Recent studies have generated real time, detailed emissions data by using inputs from novel traffic sensing technologies and data from intelligent traffic systems (ITS). Increasingly, detailed pollution data is being combined with spatially resolved demographic or epidemiological data for targeted risk analyses.

Capsule for submission:

Technology and software now exist that permit the simulation of traffic emissions at sufficient resolution to estimate the exposure of pedestrians, commuters and vulnerable populations

Keywords:

microsimulation; health; exposure; ITS; agent-based model; open-source

1 Introduction

This review was prompted by the need to better understand people's exposure to traffic pollution on city streets. Broad-scale, background levels of pollution are usually well monitored in major cities, but it remains difficult to determine air quality data at street level in most places. Concentrations can be highly variable over short distances and intervals of time, due to fleet composition, congestion, weather (mainly wind) and the shape of street canyons. For examples of what can be achieved with sufficient resources, readers are referred to the programmes: "Dispersion of Air Pollution and its Penetration into the Local Environment" in Westminster, United Kingdom (DAPPLE 2009), the "New York City Community Air Survey" in New York, USA (NYCCAS 2018) and vehicle-based measurements in Oakland, USA (Apte, Messier et al. 2017). Low cost wireless sensors show promise for the future, but currently there are only very few pollutants that can be measured well without expensive equipment. State of the science traffic emissions modelling provides estimates of a comprehensive suite of pollutants with fine spatial and temporal resolution, saving the considerable expense of monitoring equipment (Gois, Maciel et al. 2007). The data is localised to tens of metres at street level, enabling more accurate estimates of air quality for pedestrians, commuters, children and the aged. Once problems are identified, they can be mitigated with barriers, spatial buffers, improved ventilation in buildings, or alterations to the fleet (Batterman, Ganguly et al. 2015).

The review starts by describing the effects of traffic emissions on air quality and why they are difficult to quantify. Then we examine the risks to health and costs incurred by the suite of gases and aerosols that are produced on urban streets. The majority of the review focusses on the state of the science of modelling traffic emissions. We briefly describe some approaches that can give reasonable estimates of roadside air quality given limited data and resources. There are detailed reviews of each of the 4 main steps of microscopic traffic emissions modelling: trip generation, traffic simulation, emissions modelling and dispersion modelling. The first part contains a summary of the emerging new directions that combine simulation with sensors for real-time emissions mapping. The section ends with a summary table of case studies and recommendations for users.

2 Understanding pedestrian exposure to traffic-related air pollutants

2.1 Traffic pollution in cities

Airborne pollution from traffic is a significant health hazard worldwide for the people who live in cities (UN-Habitat 2013). The amount of freight moved by light commercial vehicles has increased by 300% in recent decades, due to increases in the size of the service sector (Houghton, McRobert et al. 2003). Motor vehicles are responsible for a considerable fraction of many airborne pollutants (Table 1). As the numbers of vehicles using urban roads has increased, so has traffic congestion, exacerbating pollution, greenhouse gas emissions, delays and financial losses from wasted fuel and lost work time (Schrank, Eisele et al. 2015). The financial consequences can be considerable, even neglecting lost productivity. Each emitted tonne of particulate matter smaller than 2.5 microns ($PM_{2.5}$) cost US$208,000 in Sydney, Australia and US$141,000 in Melbourne (Aust, Watkiss et al. 2013). Policy makers require good data to understand the problem and to plan for the future.

Table 1. Total annual Australian National Pollutant Inventory (NPI) emissions (kg/yr) for industry and motor vehicles (National Motor Vehicle Emissions Inventory, NMVEI) in 2010 (Smit 2014)

Pollutant	NPI industry	NMVEI	MV Contribution
Acetaldehyde	411,765	886,969	68.29%
Acetone	691,837	301,465	30.35%
Acrolein	11	314,000	100.00%
Ammonia	120,860,415	6,313,888	4.96%
Benzene	1,197,423	4,099,173	77.39%
1,3-Butadiene	14,635	971,856	98.52%
Cadmium	32,053	237	0.73%
Carbon monoxide	1,388,700,000	936,869,323	40.29%
Chromium	590,406	502	0.08%
Copper	677,884	794	0.12%
Cyclohexane	473,055	664,516	58.42%
Dioxins/Furans (i-TEQ)	0.194	0.005	2.75%
Ethylbenzene	138,330	3,116,430	95.75%
Formaldehyde	2,922,758	2,005,013	40.69%
Lead	687,463	17,171	2.44%
Methylethylketone (MEK)	700,618	77,818	10.00%
n-Hexane	1,709,621	1,322,489	43.62%
Nickel	772,525	267	0.03%
Oxides of Nitrogen	1,396,900,000	305,601,721	17.95%
PAHs (BaP-equivalents)	23,709	627	2.58%
Particulate Matter ≤ 10.0 μm	1,238,329,933	14,461,823	1.15%
Particulate Matter ≤ 2.5 μm	56,532,376	11,684,995	17.13%
Selenium	6,348	4	0.06%
Styrene	393,246	470,431	54.47%
Sulfur dioxide	2,509,400,000	1,310,884	0.05%
Toluene	2,525,696	8,243,841	76.55%
Total Volatile Organic Compounds	157,006,103	107,329,985	40.60%
Xylenes	1,882,125	8,085	0.43%
Zinc	1,597,971	47,352	2.88%

The toxic chemicals that comprise traffic emissions are released as gases and primary particles. The two most commonly used fuels generate different mixtures of pollutants in addition to CO_2: petrol vehicles are mainly responsible for emissions of carbon monoxide (CO), volatile organic compounds (VOCs), ammonia (NH_3) and heavy metals. Diesel vehicles produce most of the particles of 2.5 microns and smaller ($PM_{2.5}$) and oxides of nitrogen (NO_x) (Smit 2014). Diesel particulate matter (DPM) is composed of a core of elemental carbon surrounded by organic compounds including polycyclic aromatic hydrocarbons (PAHs), nitro-PAHs, small amounts of sulphate, nitrate, metals and other trace elements. These particles have a large surface area, making them susceptible to adsorption to lung tissue (Wichmann 2007).

The chemistry of emissions is highly variable in time and space (BTRE 2005) and the composition affects toxicity (Rückerl, Schneider et al. 2011). The composition of the mixture of gases and particles changes with time after release from the exhaust pipe. There are a number of possible chemical reactions, coagulation and condensation of gases, aerosols and particles. The transformations can be affected by local conditions such as the concentration of pollutants, temperature, turbulence (particularly wind), sunlight and humidity. For example, the concentrations of particular species, such as NO_x, can determine the production of secondary pollutants such as ozone (Ryu, Baik et al. 2013).

Although numbers of vehicles on roads continue to increase, emissions regulations have mandated increased efficiency of engine technologies to reduce outputs of harmful emissions. Older, carburetted cars released 10 times the HC, 4 times the CO and 3 times the NO_x of newer multi-point ignition engines (Qu, Li et al. 2015). However, while newer cars release less pollution, the expected reduction in emissions from modern vehicles will only be realised if their emissions control equipment is properly maintained (Marquez and Salim 2007).

2.2 Health effects of traffic pollution

Although traffic emissions (Table 1) are not the major fraction of airborne pollution in cities, they are a major source of airborne pollution for people, because traffic occupies space close to walkways, residences, workplaces and schools. The traffic intensity on the nearest road to a person's home address was linked to mortality in a long-term study (Beelen, Hoek et al. 2008). Diesel exhaust poses the greatest risk of cancer of any air pollutant (Wichmann 2007). An extensive sampling program for volatile organic compounds (VOCs) in New York City found that proximity of roads and traffic signals explained 65% of variation in atmospheric concentrations of benzene (Kheirbek, Johnson et al. 2012). Commuters travelling by bicycle, bus, automobile, rail, walking and ferry are exposed to concentrations of ultrafine particles that can elicit acute effects in both healthy and health-compromised individuals (Knibbs, Cole-Hunter et al. 2011). For a typical urban commuting journey in Alameda County, USA, personal exposure to NO_x was found to increase from 29 ppb (parts per billion, 10^{-9}) indoors to 96 ppb outdoors (Su, Jerrett et al. 2015). In a study of different modes of travel to work, the greatest rates of exposure to ultrafine particles were found for those walking or cycling along highly trafficked routes and using buses (Spinazzè, Cattaneo et al. 2015). Some occupations are at significantly elevated risk from traffic emissions. Exposure of traffic policemen in Beijing to polycyclic aromatic hydrocarbons (PAH) was nearly an order of magnitude greater than regulatory limits (Liu, Tao et al. 2007) (Hu, Bai et al. 2007, Liu, Tao et al. 2007). Bus drivers and mail carriers in Copenhagen, Denmark were found to have elevated concentrations of biomarkers for DNA damage (Hansen, Wallin et al. 2004).

Evidence of harm from traffic pollution is abundant and mounting, it affects multiple systems of the body. For example, there are links to a range of serious damages to the heart, some fatal. Emissions of NO_2 can cause a 5% enlargement of the right ventricle and 3% increase in its volume after emptying (end diastolic volume). These changes are quantitatively similar to those caused by diabetes or smoking (Holguin and McCormack 2014). Traffic emissions have also been associated with increased levels of inflammatory nasal markers, increased urinary concentrations of urea and metabolites of nitric oxide (Steerenberg, Nierkens et al. 2001). Long term exposure to traffic and $PM_{2.5}$ reduced respiratory function in adults (WHO 2013, Badyda, Dabrowiecki et al. 2015, Rice, Ljungman et al. 2015) and the irritant and carcinogenic chemicals cause a range of morbidities including asthma. Children's rapidly growing lungs and immature immune systems make them susceptible to diseases associated with airborne pollution from traffic, such as asthma, allergy, bronchitis and deficits of lung function and growth (Chen, Salam et al. 2015, Gehring, Beelen et al. 2015).

The capacity of particulate pollution to cause harm is related to its size, surface area and composition. Particulate matter (PM) is usually classified into size ranges: PM_{10} is less than or equal to 10 μm (micrometres, 10^{-6} m) in diameter, $PM_{2.5}$ is less than or equal to 2.5 μm and $PM_{0.1}$, or ultrafine particles, are less than or equal to 100 nm (nanometres, 10^{-9} m). The smaller the size of the particle, the deeper it can travel into the lungs. Ultrafine particles can reach the alveoli where 50% are retained in the lung parenchyma (Valavanidis, Fiotakis et al. 2008). Linear dose-response associations have been found between particulate matter (PM) pollution and mortality in the United States (Daniels, Dominici et al. 2000), Canada (Requia, Higgins et al. 2018) and in Europe (Samoli, Analitis et al. 2005). Most of the urban $PM_{2.5}$ emissions are due to traffic, particularly diesel-fuelled trucks and buses (Chan, Simpson et al. 1999, Salameh, Detournay et al. 2015). A review of adverse health effects of short-term exposure to $PM_{2.5}$ in China showed a 0.40% increase in non-accident mortality with every 10 ng m^{-3} increase in concentration (Lu, Xu et al. 2015). Recent work has connected urban exposure to $PM_{2.5}$ with an increased risk of low birth weight (Coker, Ghosh et al. 2015). Commonly, reports of particulate pollution have $PM_{2.5}$ as the smallest class, but this may not be adequate. Not only do ultrafine particles have the capacity to penetrate deep into the airways, but their greater surface area and porosity give an increased capacity to adsorb and retain toxic substances (Valavanidis, Fiotakis et al. 2008). Some authors suggest that it is important to extend consideration to particles of 1 nm size, due to the potential for coagulation and condensation processes at the street level. New particles can form through chemical transformation processes (secondary production) over time in locations like road tunnels, with prolonged residence times and increased concentrations. For example, the mass of secondary nitrate was four times that of primary nitrate in fine aerosols at a site in

Brisbane, Australia (Chan, Simpson et al. 1999). Transformation processes include aggregation, homogeneous nucleation and changes from gas to particle. Because of the complexity of the chemistry and of the modelling, it is particularly important to validate model results with in-situ sensor measurements (Kumar, Ketzel et al. 2011).

It is common practice to reduce PM pollution by diesel fuelled vehicles with the use of particle traps. These devices can be very effective if used and maintained properly, but an undesirable by-product is a substantial increase in the production of primary NO_2 (Feng, Ge et al. 2014, Tang, Zhang et al. 2014, He, Li et al. 2015). The resulting effect of NO_2 on premature mortality is greater than ten times that of $PM_{2.5}$ in pre particle-trap concentrations (Harrison and Beddows 2017).

Modelling of transport in Adelaide, Australia showed the benefits in reduction of pollution and other health benefits of switching commuter travel from private vehicles to public transport. If 40% of vehicle kilometres travelled were changed to alternative transport by 2030 (projected population 1.4 M), $PM_{2.5}$ would decline by about 0.4 μg m^{-3}. This was estimated to reduce adverse health effects by 13 deaths/year, and 118 disability-adjusted life years. There were many more benefits predicted due to improved physical fitness through walking or cycling (Xia, Nitschke et al. 2015).

3 Traffic emissions modelling: summary of the process & most commonly used models

3.1 Introduction: the need for detail

Detailed information is required to identify the locations of greatest risk to pedestrians, the "hot-spots" of concentrated pollution. The data is necessary for determining the effects of long-term exposure for those living or working near busy roads. Details of concentration and composition cannot be well represented by interpolating measurements from sparsely distributed sensors. Internet of Things (IoT) sensors that measure air quality are cheap and readily available, but these are yet to be proven in the roadside setting (Forehead, Murphy et al. 2017). The spatial and temporal resolution of traffic emissions models has been increasing over time with improvements in data collection, computational power, modelling and technology. Simulations with coarse resolution, that are simpler and quicker to use, are still commonly used for regional inventories of pollutants. However, microscopic simulations with detailed inputs are required to represent details of complex, congested traffic, (Austroads 2006). A survey of traffic emissions modelling by the US Department of Transportation identified microscopic simulations as the state of practice and that "aggregate network performance data created by traditional static assignment models is not suitable for estimating emissions accurately" (Balaji Yelchuru, Adams et al. 2011). Readers are also referred to 2 excellent earlier reviews of microscopic emissions modelling methods: (Fallah Shorshani, André et al. 2015, Fontes, Pereira et al. 2015). These models can show pollutant hot-spots and help estimate exposure for vulnerable populations, such as those in hospitals, child care, parks, aged care facilities (Batterman, Ganguly et al. 2015). Fine-scale resolution is needed to reduce uncertainty in applications such as health impact assessments (HIA), that are increasingly a part of project planning (BTRE 2005, National Research Council Committee on Health Impact 2011). Traffic emissions models can be used for other risk assessments, such as predicting increases or decreases in emissions due to infrastructure changes, roadworks or events. They can model the exposure of pedestrians to traffic pollution with different designs of intersections (Qiu and Li 2015) and the effectiveness of mitigation strategies that separate pedestrians and traffic (El-Fadel 2002).

3.2 Simpler approaches

Where detailed data are not available, a simpler macroscopic approach may be appropriate. Alternatives include the use of satellite aerosol optical depth data, in conjunction with a land use regression model, to add a temporal estimate to spatial data regarding the origins of $PM_{2.5}$. Validation of this approach in Florida, USA gave coefficient of determination of 0.63, comparable with studies that use aerodynamic-meteorological models (Mao, Qiu et al. 2012). A land use regression model was used with a simple atmospheric dispersion model to estimate the daily average particle number on a freeway. Inputs were annual averaged wind speed and annual average daily traffic counts, errors averaged 6% across 98 sites (Olvera, Jimenez et al. 2014). Traffic sources of airborne pollutants can be separated from background sources using air quality measurements from a single station and meteorological data. A freely available semi-empirical (box model) pollution model and a spreadsheet-based traffic model (Vehicle emissions prediction model) were designed for Auckland, New Zealand. Results were verified in a study, using ambient records of 2 air pollution monitors. The best estimations were achieved for nitrogen oxides; PM_{10} was difficult to distinguish due to interference from marine aerosols (Elangasinghe, Dirks et al. 2014). In developing countries, measuring traffic flow via new technologies may be too expensive or difficult to implement. A macroscopic traffic flow model can be a good choice when little traffic data is available. The Lighthill and Whitham (1955) model represents traffic in differential equations, using theories of compressible fluids. Only 6 days of data were used for estimates of density and travel times on a busy arterial road in Chennai, India. Results had mean average percentage errors ranging from 12.7% to 45.7% when checked with observations (Kumar, Vanajakshi et al. 2011). Another approach that requires little data is a seasonal Autoregressive Integrated Moving Average (SARIMA) model. A 24 hour simulation of traffic flow on an arterial roadway used only 3 days of data and errors ranged from just 4% to 10% (Kumar and Vanajakshi 2015). The publicly available Industrial Source Complex

Short Term model (ISCST3, US EPA), was used to attribute airborne PM_{10} pollution to different sources, including transport in Kanpur City, India. GIS was used to break up the study area into 2 km x 2 km grids. Resolution could be adjusted to any time and space (Behera, Sharma et al. 2011).

3.3 Microscopic traffic emissions models

Microscopic traffic emissions modelling typically comprises a series of sub-models, each generating the input data for the next (Fig. 1). First is trip and fleet generation, then the traffic model, traffic emissions and finally, the dispersion of emissions may be modelled. The number of steps used can vary according to the application. The fleet of vehicles can be built from databases, commonly from vehicle registration. Trip information can be derived from traffic sensors and demographic data, such as the census and journey to work surveys. A traffic model takes the trip data and generates the fleet activity on the road network. That information is fed into an emissions model together with vehicle emissions factors to generate the emissions data for the network. In some cases a dispersion model is added to predict the dispersion of emissions away from the vehicles and the roadway.

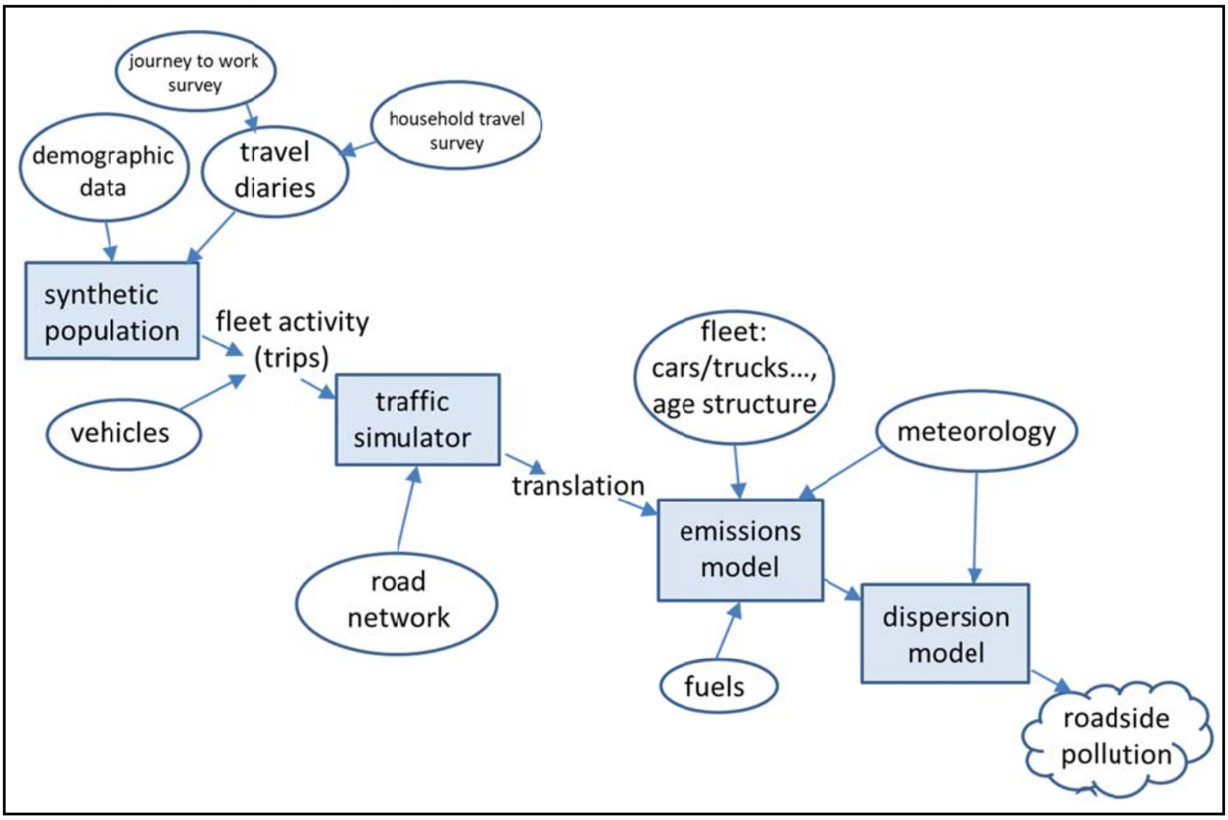

Figure 1. Modelling framework for estimating population exposure to traffic emissions. The 4 model steps are represented by the rectangles on the diagonal, the text in ovals shows the input data.

3.4 Input to traffic simulator model: trips, fleet & sensor data

A synthetic population is often used as a foundation for a traffic simulation. It populates a study area, dwelling by dwelling, with people distributed into realistic households. The population is constructed from publicly available averaged demographic information, such as a census. For details of the process, see Huynh, Namazi-Rad et al. (2013). The people in households can then be assigned vehicles in a realistic manner.

Traffic simulations need realistic 'trips,' or journeys as inputs for vehicles; these are usually compiled into origin-destination (OD) matrices. Trips are defined by their origin, destination and purpose, such as journeys to work, to school or to shops. They can be built or calculated with data from a range of sources, including: surveys of journeys to work and of household travel, census data on population, employment and residences, freight movements, parking and transport networks including road rail, bus and ferries. There are a range of models that build trips from this data, including (in order of increasing complexity) sketch-planning models, strategic-planning models, trip-based models and activity-based models (Castiglione, Bradley et al. 2015). Generally, activity-based models are used to build trips for a day, with the expectation that no variation will occur. This is, of course, unrealistic, since unexpected changes occur, due to any number of unplanned events. Rescheduling in an activity-based model allows for unexpected changes, such as car accidents or time-table changes in public transport. The FEATHERS activity-based schedule generator simulates the behaviours of mutually independent individuals or actors. The state of a transport network can be influenced by actor behaviour and external phenomena. The actors interpret changes via perception filtering and adapt their schedules accordingly. This in turn affects the network as demand changes, giving a more realistic set of behaviours for microscopic traffic models. A limitation of the framework is that it can only change routes before they are started, once a journey has begun, it is fixed (Knapen, Bellemans et al. 2014). TRANSIMS (US EPA, Federal Highway Administration) is an open-source system of models that comprises a population synthesiser, an activity generator, routing, and a microscopic traffic simulation. The system offers much, but the data requirements are large and the calibration process can be challenging (Zhang and Cai 2016).

GPS sensors can substantially improve traffic monitoring. A one second sampling rate was found to be required to identify events such as vehicle stops, but aggregation to a 5 second resolution was sufficient for trip identification. Identification of stops in trips could be improved by combining map information with movement data to reduce false positives, such as pauses due to traffic congestion, or false negatives such as the missing of short stops (Shen and Stopher 2013). To give correct placement of a vehicle on a road segment in real time, GPS location was matched to speed and travel time data from cars, using an algorithm that incorporated a sequence of hidden-Markov models (Szwed and Pekala 2014). Commercial software is available to translate GPS data into trips. However, a study that compared two products using the same input data showed a discrepancy of 12% of trips between results. Errors included incorrectly splitting single trips or failing to identify some trips (Stopher, Greaves et al. 2013). A Bayesian approach was used to integrate data from Bluetooth, loop detectors and GPS for real-time traffic prediction. The method dramatically improved the accuracy of information from loop detectors on an arterial corridor in Brisbane, Australia (Nantes, Ngoduy et al. 2015).

Origin-destination (OD) data was generated from archived public transport data from smart cards, in conjunction with street maps and timetables in Žilina, the Slovak republic. It was possible to infer details such as in-vehicle travel and walking times for segments of a journey (Jánošíkova, Slavík et al. 2014). Calibration software (W-SPSA) used a weighting matrix to allow for correlations between inputs to OD matrixes (Antoniou, Lima Azevedo et al. 2015). Algorithms based upon evolutionary simulations were used to make choices regarding route choices depending on time and toll cost. The result can incorporate some amount of randomness.(Nagel, Kickhöfer et al. 2014).

Technology has increased the range of options available for monitoring traffic movements. Modern traffic data collection includes technologies that range from simple inductive loop sensors to piezo-electric, magneto-resistive studs, tirtle (laser) and piezo-WIM (weight in motion) sensors. The latter instruments can give details of vehicle class, by determining the mass and number of axles of a passing vehicle. Sensors are often integrated with a traffic control system, such as the Sydney Coordinated Adaptive Traffic System (SCATS), used in 26 countries. It has a software interface, SCATSIM, to link the traffic management system to microscopic traffic models. Some authorities monitor vehicle traffic by tracking signals from Bluetooth or WiFi devices and technologies such as GPS or automatic number plate recognition (ANPR) cameras. These activities are restricted to varying degrees by privacy legislation.

ITS systems can provide cost savings, better coverage and increased accuracy over more labour-intensive methods of data collection. The integration of large collections of detailed and timely trip and locational data offer the opportunity for accurate modelling of emissions that is highly temporally and spatially resolved. (Vasantha Kumar and Vanajakshi 2014).

Bluetooth and WiFi digital radio transmitters can be used to monitor vehicle movements. Transmitters are found in many mobile electronic devices, including hands-free speaker systems for mobile phones, headsets and music players. Each device broadcasts its unique Media Access Control (MAC) address. Bluetooth transmitters have ranges from 3 m (class 3 devices) to 100 m (class 1 devices). The signal can be detected at the roadside and successive readings processed to give information relating to speed and route (Bachmann, Abdulhai et al. 2013). WiFi, signals can also be used and that system has a faster discovery time (about 1 sec) than Bluetooth (almost 10 sec) (Abedi, Bhaskar et al. 2013). There are a number of potential difficulties to be considered when using Bluetooth monitoring. There may be an uneven demographic distribution of Bluetooth devices in cars, a single device may be detected by multiple scans at busy locations and there are devices used outside motor vehicles by pedestrians, cyclists and on trains. The signals must be filtered to resolve these ambiguities (Abbott-Jard, Shah et al. 2013, Michau, Nantes et al. 2013). Early implementations of speed detection with Bluetooth were cited as problematic, with automated number-plate recognition being more reliable at higher speeds (Abbott-Jard, Shah et al. 2013). However, Bluetooth has become widely adopted for traffic monitoring and management (Aliari and Haghani 2012, Bachmann, Roorda et al. 2013, Juster, Young et al. 2014, Smith, Hainen et al. 2014). It has been used to verify the accuracy of a large dataset of probe vehicle data (Kaushik, Sharifi et al. 2014) and to give cheap & cost-effective queue measurement (Alghamdi, Nadeem et al. 2014). The technology was used in Brisbane, Australia for modelling travel times, giving much better predictions than the historical average (Khoei, Bhaskar et al. 2013) and in Lincoln, USA, increasing the accuracy of predictions over aggregated link and corridor travel times (Wu and Rilett 2014). Only limited numbers of signals from wireless devices are needed to significantly increase the understanding of traffic flows. The South Australian Bluetooth system achieves a sample rate of about 15% of vehicles, better on arterial roads, mostly due to the presence of freight vehicles. The system is good enough that the Department of Planning, Transport and Infrastructure does not buy any external traffic data. It has been used for a number of purposes, including automated incident detection (AID) and to monitoring compliance with permits for traffic controls for roadworks. The department can see if traffic is being slowed down outside the times stipulated by a permit (Southern 2015). As far back as late 2015, a number of private companies were already advertising Bluetooth systems for monitoring traffic and other purposes.

Public concerns about privacy can potentially be an obstacle to the use of location technologies that scan private wireless devices. An EU project to develop collaborative transport emphasised the need to make efforts to gain the acceptance by travellers for the sharing of information required for many of the technologies (Penttinen, Diederichs et al. 2014). In an effort to avoid privacy concerns around the collection of data from privately owned wireless devices, real-time data from buses was used to estimate travel time for other vehicles on urban arterial routes (Vasantha Kumar and Vanajakshi 2014). Public concerns can also be addressed through education and the careful design of a system. The Bluetooth scanning system in South Australia automatically truncates scanned MAC addresses to make them anonymous and deletes them at the end of each day (Southern 2015). However, local legislation may actually preclude use of the technology in some locations. For example, Bluetooth signals cannot be used to sense private vehicles in Western Australia (Maddock 2015). A recent study (Chong-White, Millar et al. 2014) examined the environmental benefits of the Sydney Coordinated Adaptive Traffic System (SCATS) system using traffic data from eTags (in-vehicle electronic wireless devices for toll system) on a stretch of Military and Spit Roads in Sydney. It was found that the system was effective in reducing travel times, but that emissions reductions were not consistent across the network (Chong-White, Millar et al. 2013). The trial was abandoned due to privacy concerns with the eTag data.

ITS can improve the reliability of data from loop detectors. The addition of information from only a few probe vehicles equipped with GPS and Bluetooth scanning can significantly improve traffic speed estimates (Bachmann, Roorda et al. 2013). The fusion of multiple mobile data sources, including sensors, probe vehicles, Bluetooth and GPS, increases the accuracy of estimates of traffic speed. With only 5% probe vehicles, the root mean square error can be reduced by up to 80%. There are a number of methods for combining data. A comparison tested five of these: distributed fusion, artificial neural networks, Kalman filters, fuzzy integrals and ordered weighting average. The methods were validated using a simulation model of a major freeway; the first three methods produced the best results (Bachmann, Abdulhai et al. 2013).

Private businesses are becoming the source of ever-increasing amounts of data. INRIX Inc. is based in the USA that provides real-time traffic information in over 40 countries. The company claimed that as of January 2015, they were collecting information about roadway speeds from "over 185 million real-time anonymous mobile phones, connected cars, trucks, delivery vans and other fleet vehicles equipped with GPS locator devices." By May 2018, this number had increased to over 300 million (INRIX 2018).

3.5 Traffic simulation models

Traffic models represent vehicle movements on a road network with varying levels of detail. There are many traffic models available, with updates and replacements constantly improving accuracy and versatility. A significant limitation to modelling efforts in many jurisdictions though, is the difficulty and expense in obtaining real traffic data for validation for more than a few major roads.

The level of detail used in traffic models depends upon the purpose of the modelling effort and the resources available. For example, in regional or national emissions inventories, results need to be comparable between jurisdictions, times and to be reproduced easily. These uses do not require resolution of seconds or tens of metres, so a strategy with a low to intermediate level of detail is generally used. Such macroscopic models may use analytical techniques such as fluid dynamics or simulations to model flows or platoons of traffic. Fine scale microscopic models (Table 2) deal with individual vehicles with second to second resolution or better. These are generally either cellular automaton models, where vehicles navigate according to rules with varying degrees of stochasticity, or car-following models, where vehicle to vehicle interactions are based upon differential equations. Mesoscopic simulations operate at an intermediate level of detail, lengths of road or groups of vehicles (Kokkinogenis, Sanchez Passos et al. 2011). Since the object of this review is the state of the science in modelling for cities, it focusses on microscopic modelling.

Table 2. Popular microscopic traffic simulation software

model name	supplier	model type
Aimsun	TTS Group, Singapore	car following
MAS-T^{2}er Lab	University of Porto, Portugal	agent-based
MITSIMLab	MIT, USA	agent-based, open source
PARAMICS	Pitney Bowes Software, UK	car following, lane changing
SUMO	ITS, Germany	car following, open source
TransModeler	Caliper Corp, USA	car following
TSIS-CORSIM	McTrans Center, USA	agent-based
VISSIM	PTV Group, Germany	car-following
TRANSIMS	US EPA, USA	agent-based, open source

In a traffic simulation, the smallest component of a road network is called a link. The number of links must be at least equal to the number of intersections. In addition, any changes in a road, such as a curve or gradient should be represented by a separate link. There is an upper limit to the resolution of a traffic simulation on a network, beyond which vehicle information can be missed. This is particularly the case for low traffic density. The length of a link must be sufficient that all vehicles can be detected over the duration of a model's time step. The risk of a vehicle being missed is proportional to the traffic's sparsity and speed; so the length of a link needs to be calibrated to traffic conditions and the simulation's temporal resolution (Fontes, Pereira et al. 2015). Long-run estimates of large areas can be challenging to calculate with such detailed models, because of the computational effort required (Fallah Shorshani, André et al. 2015).

Microscopic traffic simulations provide detailed representations of network behaviour by modelling time-varying demand patterns and the choices and behaviours of individual drivers. Simulations represent all vehicles individually, typically with a one second resolution. Algorithms based upon evolutionary simulations can make decisions regarding route choices depending on time and toll cost. Results can be improved by including some degree of randomness in the calculations. This approach allows the fleet to respond to congestion in a realistic manner (Nagel, Kickhöfer et al. 2014, Barthélemy and Carletti 2017). Models are calibrated for local driving behaviours such as car-following and lane changing. Capturing details of instantaneous speeds and acceleration rates increases the accuracy of emissions estimates, because the quality and quantity of vehicle emissions change with deviations from a steady speed (Austroads 2006, Chen and Yu 2007). As congestion increases, so does the incidence of speed changes and the emission of CO and HC (Smit 2006). Lane changing behaviour can significantly change traffic flow, many models simplify the manoeuvre as an instantaneous transition, but it generally takes from 1 to 16 s. In addition, the lane-changing behaviours of trucks and cars on arterial roads have been found to be so distinct that they needed to be modelled differently (Cao, Young et al. 2013).

Software is often used to improve the calibration process; for example W-SPSA, which includes a weighting matrix to allow for correlations between inputs, such as road sensor data (Antoniou, Lima Azevedo et al. 2015). Evolutionary algorithms can also be used for calibration. A study that used evolutionary algorithms for calibration of a county-wide simulation found that there was greater benefit to the accuracy of results by allocating effort to coding of the network and traffic demand, than to the calibration process (Smith, Sadek et al. 2008).However, other researchers found that dealing with easily identifiable errors in data markedly improved the results of a city-scaled microscopic traffic model. Errors from sensors were a significant problem when using automated methods for calibrating model parameters and making estimations for OD matrixes. (Jha, Gopalan et al. 2004).

There are a number of promising new approaches to traffic modelling in the literature. A Chinese study used a deep-learning-based predictive traffic model with large traffic datasets. A stacked autoencoder model learned generic traffic flow features; the method dealt with spatial and temporal correlations (Lv, Duan et al. 2015). Real-world mobile sensing data was used on an arterial road to estimate trajectories for the entire traffic population, as input to the CMEM emissions model. Adding random noise to the model's cruise mode improved estimation results (Sun, Hao et al. 2015).

To assist in selecting from the large range of models on offer, a meta-modelling technique has been used to compare and select models and to optimise parameters. Intelligent surrogate modelling tested models in univariate and multivariate frameworks (Vlahogianni 2015). Examination of emissions modelling of Brisbane traffic showed that the majority of errors occurred not in the model specification, but the input data, particularly related to congested conditions. The models performed well under free-flowing conditions, but errors increased in the transitions to congested and very congested conditions (Zhu and Ferreira 2013).

3.6 Emissions models

Emissions models operate at the same range of scales as traffic models and similarly, over-simplification leads to inaccurate results. The emissions from a vehicle are worst when the engine is started following an extended period of inactivity, so called “cold-starts.” The severity of pollution increases with the duration of standing or “soak” time (Gao and Johnson 2009). Formation of secondary organic aerosols (SOA) decreased by a factor of 3 to 7 times between cold-start and hot-start tests in light-duty petrol passenger vehicles. To make things worse, after three hours of oxidation in the atmosphere, the concentrations of SOA from cold-start running could measure up to six times the concentrations found in the primary emissions (Gordon, Presto et al. 2014). A study of the effects of the aggregation of inputs to models found that cold start emissions contributed 67% to total road HC emissions. The next most important factors were the season and vehicle registry data, such as vehicle types and model years (Sider, Goulet-Langlois et al. 2015). Most emissions models include calculations that account for the age and structure of the fleet and meteorology.

Other sources of emissions from vehicles include brakes, particles released by the shear forces between vehicle tyres and the road and the evaporation of fuel from fuel tanks and lines at raised temperatures. These sources were often neglected in early emissions models, but are increasingly included in updated versions (European Environment Agency 2007). Evaporative emissions in Europe range from less than 3% to around 16.5% of total non-methane volatile organic compounds (NMVOCs). These losses are mainly from petrol driven vehicles and have been decreasing in recent years with the use of control systems in newer models (Mellios and Ntziachristos 2012). Wet conditions should decrease tyre wear and new road surfaces increase wear (Mellios and Ntziachristos 2012). Not all of this material is airborne, so emission factors are required in models to calculate the contribution (European Environment Agency 2007).

Emissions factors are parameters used to calculate emissions for particular chemicals and particles in vehicle exhausts. Databases for vehicle emission factors are usually specific to their country or region, for example HBEFA, is a European database of emissions factors for all current vehicle categories. It incorporates factors for different driving conditions, hot/cold running and evaporative emissions. The emission factors are generated by emissions models validated with measurements in laboratories and on roads. Originally developed by agencies in Germany, Switzerland and Austria, now funded by the EU (ERMES 2015, HBEFA 2015). HBEFA has also been found to be suitable for the Chinese fleet and roads. The Chinese fleet has a similar composition to that of Europe, and the database was well suited to describe the emissions of traffic on urban infrastructure (Sun, Schmeid et al. 2014). Many measurements of vehicles are required to generate robust emissions factors, since even minor variations in testing procedures can result in different outputs from the same vehicle (Franco, Kousoulidou et al. 2013).

There are a small number of publicly available microscopic emissions models. MOtor Vehicle Emissions Simulator (MOVES) is the US Environmental Protection Agency (EPA) emissions model for mobile sources, designed for use at scales from national to project. The latest version (MOVES2014a) was released in November 2015 and there have been minor revisions since. It deals with on and off-road emissions and includes calculations for emissions of over 100 compounds including those from fuel evaporation, brake and tyre wear. For details see (https://www.epa.gov/moves). Three simpler microscopic emission models (VT-Micro, EMIT and POLY) were ranked against CMEM, using the same input data from light-duty vehicles from four vehicle classes in two Chinese cities. Different models were found to have strengths in particular aspects, such as speed or better accuracy for certain pollutants (Ma, Lei et al. 2012). Some microscopic emissions models, such as CMEM deal with detail such as hot and cold running, but currently model only a few pollutants: NO_x, total hydrocarbons, CO_2, CO and do not consider emissions due to evaporation or brake and tyre wear. COPERT Street Level is a more detailed version of the European emissions inventory software, COPERT (COmputer Programme to calculate Emissions from Road Transport, http://emisia.com/products/copert). It has similar resolution to MOVES and calculates the pollutants CO, CO_2, NO_x, PM and VOC. PARAMICS (PARAllel MICroscopic traffic Simulator, http://www.paramics-online.com) Monitor is an add-on for the PARAMICS traffic simulator, it models CO, CO_2, total HC, NO_x, PM and fuel consumption. There is also an add-on that couples the model to CMEM. The AIMSUN (Advanced Interactive Microscopic Simulator for Urban and Non-Urban networks, https://www.aimsun.com) emissions model is easy to calibrate and implement, but the calibration may not apply well to conditions that differ from those of the calibration (Bover, Zhu et al. 2013). The TRANSIMS (TRansportation ANalysis and SIMulation System, https://transims-studio.soft112.com) system of models contains an emissions simulator.

A preliminary study of an artificial neural network (ANN) approach to fuel and emissions modelling used 26 vehicles. (Dia and Boongrapue 2015). Results for fuel consumption had 96% to 98% accuracy; emissions data 70% to 97% accuracy; depending upon the pollutant modelled and the vehicle. To realise the potential of ANN in emissions modelling, it needs to be integrated with microscopic traffic models.

The accuracy of all models is limited by the quality of the emissions factors used in their calculations. The accuracy of predictions of some regulated pollutant measurements is better than others. CO, NO_x, total VOC, PM mass and CO_2 are well understood as a function of driving conditions, due to the large number of measurements. Others have been less well evaluated: NO_2, NH_3, individual VOC, PAH, PM as a function of size and number, and heavy metals (Fallah Shorshani, André et al. 2015). The quality and quantity of the emissions of pollutants is related to the power output of a vehicle's engine. A common method takes that data from a microscopic traffic simulation and uses it to calculate emissions using 'vehicle specific power' (VSP) (Fontes, Fernandes et al. 2014). For example, PΔP (engine power, and change in engine power) software, based on drive cycles from a large database of Australian emissions tests. Validation gave average R^2 values of 0.65 for NO_x and 0.93 for CO_2/fuel consumption (Smit 2013). However, some power-based models may not be sufficiently sensitive to the small changes in engine power that can have significant effects on emissions (Zhu 2015).

Caution is required when selecting emission factors for use in models, particularly data from vehicle manufacturers. That data was suspect, even before the Volkswagen scandal (Boretti 2017). Engineers at an independent European tester found that manufacturers' tests underestimated exhaust emissions (Schmidt and Johannsen 2010). Car makers were shown to have manipulated load tests, estimates of vehicles' rolling and wind resistance, to skew emissions tests by independent testers. Testers carried out alterations such as not charging the battery, over-inflating tyres, disabling power steering pumps and taping the edges of windows and other gaps to decrease wind and rolling resistance. When regular production vehicles were used instead, fuel economy was decreased by about 12%. The gap between advertised and actual fuel economy figures were as large as 50% (Dings 2013, Mock and German 2015). In the so called "Dieselgate" scandal, centred around Volkswagen, it was found that cars powered by diesel engines had been releasing NO_x at a rate more than 4 times that allowed by European regulations. Modelling gave a median estimate of an additional 1,200 premature deaths, or 13,000 life-years lost and 1.9 billion EUR in associated costs, across Europe caused by the extra emissions over the time these vehicles were being sold (2008-2015) (Guillaume, Robert et al. 2017).

3.6.1 Real time emissions data

Real-time data is one of the major benefits promised by Intelligent Transport Systems (ITS) including connected, interacting sensors, controllers and vehicles. A service on the Google Maps platform, called "Emission Map," used a combination of data from traffic loop sensors and emission calculations from MOVES to give a visualisation of near real-time traffic emissions in Seattle, USA. It (Ma, Yu et al. 2012).

An ever increasing range of technologies are being used in creative ways to calculate emissions. Radar speed detectors were used to reconstruct vehicle trajectories, which became the input to CMEM, to calculate the resulting emissions and fuel consumption (Chen, Yang et al. 2014). The GPS trajectories of 32,000 taxis over 2 months on a road network in Beijing were used to generate instantaneous information on fuel consumption and emission of vehicles. Where data was sparse, a Bayesian Network model, Traffic Volume Inference (TVI) was used to interpolate (Shang, Zheng et al. 2014). NO_x was estimated from GPS tracks of vehicle movements via non-linear optimisation (Chen, Bekhor et al. 2016). A Spanish study collected signals from on-board diagnostic systems in cars via mobile phones. The phones also collected GPS coordinates and the information was combined to give second by second trip and emissions data (Garcia-Castro and Monzon 2014).

In a Belgian study, exposure of cyclists to black carbon was found to correlate with noise measurements (Dekoninck, Botteldooren et al. 2015). Another study measured personal exposure to microfine particles with personal monitoring. The measurements were made on repeated traverses (on different times of day, different days and different seasons) of a route that included well frequented urban microenvironments. It found the highest exposures from walking or biking along highly-trafficked routes and using public buses. Exposure to ultrafine particles was significantly lower in modern cars, with efficient filters and recirculated air (Spinazzè, Cattaneo et al. 2015). Personal exposure monitors are expensive, may be inaccurate or may not record locational information. To overcome these limitations, a study used smart phone tracking combined with estimates of ambient pollution concentrations to estimate personal exposure (Su, Jerrett et al. 2015).

3.7 Dispersion models

Dispersion modelling is a complex science and the models can be very computationally intensive. For accurate prediction of the fate of the products of combustion, models must calculate not just dispersion, but also the complex chemical and physical transformations that occur over time. Dispersion of emissions near a source can be modelled by Gaussian models; these are of two main types, plume or puff. Plume models assume steady-state conditions; puff models simulate instantaneous releases in a changing environment and are computationally more demanding. A combination of the two approaches can give good results (Fallah Shorshani, André et al. 2015).

The US EPA have a number of freely available atmospheric dispersion models, developed for a range of purposes. These include AEROMOD (continuously updated), a steady-state plume model that can deal with surface and elevated sources on all types of terrain. CALPUFF is a non-steady-state puff dispersion model that includes the effects of terrain and meteorology and various transformations of emissions over time. CALINE3, a steady-state Gaussian dispersion model for highway pollution in relatively uncomplicated terrain and has calculations for traffic hot-spots and queuing; it allows for meteorological data input. CAL3QHCR is a carbon monoxide model with queuing at signalised intersections and hot spot calculations; it includes meteorological data as an input. The EPA also produces 15 alternative emission dispersion models of varying complexity. AEROMOD uses CAL3QHCR as a meteorological data pre-processor and AERMAP as a terrain pre-processor. The Operational Street Pollution Model (OSPM, Aarhus University, Denmark) is a street canyon circulation model that accounts for building geometry and wind (Kakosimos, Hertel et al. 2010). Atmospheric Dispersion Modelling System - Roads (ADMS-Roads, Cambridge Environmental Research Consultants, Cambridge, UK) is an advanced dispersion model. R-LINE is a freely available research-grade dispersion model produced by the University of North Carolina and US EPA. MyAir is an EU model evaluation toolkit, it was used to compare the performance of four models in predicting the dispersion of a tracer gas to a large array of sensors. ADMS-Roads, AEROMOD (volume source) and RLINE performed better than CALINE (Stocker, Heist et al. 2013).

Recently, there has been an increasing popularity of computational fluid dynamics (CFD) models such as PHOENICS (Chen, Lu et al. 2017) and FLUIDITY (Aristodemou, Boganegra et al. 2018) over the conventional Gaussian-type dispersion models. A CFD emission model was able to show detail such as eddies generated by cross-streets and increased concentrations of pollutants in the lower leeward sides of street canyons (Mumovic, Crowther et al. 2006). A study examined the dispersion and chemical interactions and of ultrafine particles (UFP) from vehicle exhaust-pipes to the near-road environment. The study used an aerosol dynamics-CFD coupled model. It was found that omitting atmospheric boundary layer conditions (wind profile and turbulence quantities) from activity-based emission models resulted in an overestimate of the dilution of emissions in the wake of vehicles. This led to a five-fold underestimate of the nucleation rate. (Huang, Gong et al. 2014). FLUIDITY is an open source simulator that incorporates an anisotropic adaptive unstructured mesh and large eddy simulations (LES). This approach improves predictions by increasing resolution where required and improving the representation of turbulence. The simulation was used to model the effects of increased building height on the distribution of traffic pollution. It was able to reproduce wind tunnel measurements well, with differences ranging from 3% to 37% (Aristodemou, Boganegra et al. 2018)

A microscopic dispersion model used the "Random Forest" ensemble learning method for predicting roadside concentrations of CO and NO_x on four urban roads with 5 minutely resolution. This approach gave better results than an artificial neural network, which could not determine the relationship between the traffic and roadside air quality (Song, Wu et al. 2014).

In an Indian study, the US EPA's Industrial Source Complex Short Term model (ISCST3) was used to attribute airborne PM_{10} pollution in Kanpur City to different sources, including transport. GIS was used to break up the study area into 2 km x 2 km grids. Resolution could be adjusted to any time and space (Behera, Sharma et al. 2011).

3.8 Summary & recommendations

There are a number of microscopic models that will perform well, as long as the required input data is available. Table 3 lists shows combinations of models used in studies to estimate emissions and to evaluate methods to reduce exposure. For simulating traffic, SUMO is an open-source model with excellent capabilities; it can represent car-following, lane-changing and signalised intersections. Commercial models, such as AIMSUN, VISSIM and PARAMICS also perform well and tend to have more polished user interfaces. There are fewer choices for emissions simulators; MOVES is very capable, well supported, comprehensive and widely used. Its popularity is in part due to its being required for compliance purposes in the US. There are also commercial emissions models; COPERT Street Level, PΔP and others built for the above commercial traffic simulators. Dispersion models are available for a range of applications from the US EPA website; for example: AEROMOD can be used for scales of up to 50 km. Commercial offerings include OSPM, to model dispersion in street canyons and there are versions of ADMS models for different scales. Promising developments include data-driven approaches to modelling emissions and CFD methods for dispersion.

Table 3. List of recent studies using combinations of microscopic simulations to examine strategies to mitigate pollution

topic related to emissions	models used	citation	reduction in pollution
effects of different driving behaviours	VISSIM and CMEM	(Chen and Yu 2007)	2.6 to 16.5%

strategies for high-occupancy vehicle (HOV) lanes	PARAMICS and CMEM	(Boriboonsomsin and Barth 2008)	3 to 17%
strategies for high-occupancy vehicle (HOV) lanes	VISSIM and VSP	(Fontes, Fernandes et al. 2014)	37 to 43%
Transit Signal Priority (TSP) system that prioritised buses	PARAMICS and PARAMICS Monitor (emissions application)	(Wijayaratna, Dixit et al. 2013)	-11%
optimise signal timing on a large intersection	VISSIM / SUMO and CMEM	(Ma, Jin et al. 2014)	2.5 to 6.3%
optimisation of signal timing	VISSIM and CMEM	(Stevanovic, Stevanovic et al. 2015).	4.5% (fuel consumed)
active speed management	DRACULA* and non-linear multiple regression	(Int Panis, Broekx et al. 2006).	-1.1 to 1.2%
active speed management	SUMO and CMEM	(Grumert, Ma et al. 2015)	3.8 to 8.0%
use of ITS: variable message signs, highway advisory radio	VISSIM, POLARIS	(Auld, Karbowski et al. 2016)	2.5% (fuel consumed)
different designs of intersections	MOVES and AEROMOD	(Qiu and Li 2015)	81.7%
traffic pollution and dispersion	PARAMICS, CMEM and AERMET	(Amirjamshidi, Mostafa et al. 2013)	1 to 12%
license plate restrictions	VISSUM and MOVES	(Pu, Yang et al. 2015)	6.9%
different lane configurations, traffic management strategies	TransModeler and MOVES	(Xiong, Zhu et al. 2015)	0.22 to 0.72%
mitigation of harm to vulnerable populations	MOVES and RLINE (10 m spatial resolution)	(Batterman, Ganguly et al. 2015)	measures not quantified

* Dynamic Route Assignment Combining User Learning and microsimulAtion, Institute for Transport Studies, University of Leeds, UK

4 Conclusions

The airborne emissions from traffic present significant, well established hazards to many of the people in cities. The current state of the science is able to model traffic emissions with very fine resolution. With the use of microsimulations, temporal resolution is typically one second and spatial resolution tens of metres. This detail is necessary because the chemistry of emissions changes rapidly over time and space. The most polluting phases of driving happen over short intervals, such as after starts and with the acceleration and deceleration of congested traffic. There are a number of software packages available for the various aspects of emissions modelling, both commercial and open source. New research is applying novel approaches, such as agent-based models, neural networks and ensemble learning to increase speed, detail and scope. Models are used for evaluating mitigation measures, either managing the traffic to improve flow and minimise emissions, or separating people from the traffic with under or overpasses. The rate of data being produced from multiple types of road sensors is ever increasing. Vehicles are also tracked using wireless radio signals from mobile phones and other transmitting devices. Many cities integrate these multiple data streams in intelligent transport systems, reducing emissions by improving the effectiveness of road and transport networks. Information from ITS has also enabled the deployment of detailed real time traffic emissions models, offering the possibility for people to plan travel or close windows to avoid potentially harmful exposure. Spatially detailed simulations can be combined with demographic data to provide targeted information and risk analyses. Traffic emissions models have grown beyond only being tools for the planning of infrastructure, to versatile instruments that can inform many disciplines and help to improve the health of city-dwellers.

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