

University of Wollongong

Research Online

SMART Infrastructure Facility - Papers

Faculty of Engineering and Information
Sciences

2018

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

Hugh I. Forehead

University of Wollongong, hughf@uow.edu.au

Nam N. Huynh

University of Wollongong, nhuynh@uow.edu.au

Follow this and additional works at: <https://ro.uow.edu.au/smartpapers>



Part of the [Engineering Commons](#), and the [Physical Sciences and Mathematics Commons](#)

Research Online is the open access institutional repository for the University of Wollongong. For further information contact the UOW Library: research-pubs@uow.edu.au

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

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.

Disciplines

Engineering | Physical Sciences and Mathematics

Publication Details

Forehead, H. & Huynh, N. (2018). Review of modelling air pollution from traffic at street-level - The state of the science. *Environmental Pollution*, 241 775-786.

1 **Review of modelling air pollution from traffic at street-level - the** 2 **state of the science**

3 H. Forehead¹, N. Huynh

4 SMART Infrastructure Facility, University of Wollongong, Wollongong, NSW, Australia

5 ¹corresponding author: hughf@uow.edu.au

7 **Abstract**

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

24

25 Capsule for submission:

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

28 Keywords:

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

30

31 **1 Introduction**

32 This review was prompted by the need to better understand people's exposure to traffic
33 pollution on city streets. Broad-scale, background levels of pollution are usually well monitored
34 in major cities, but it remains difficult to determine air quality data at street level in most places.
35 Concentrations can be highly variable over short distances and intervals of time, due to fleet
36 composition, congestion, weather (mainly wind) and the shape of street canyons. For examples
37 of what can be achieved with sufficient resources, readers are referred to the programmes:
38 "Dispersion of Air Pollution and its Penetration into the Local Environment" in Westminster,
39 United Kingdom (DAPPLE 2009), the "New York City Community Air Survey" in New York,
40 USA (NYCCAS 2018) and vehicle-based measurements in Oakland, USA (Apte, Messier et al.
41 2017). Low cost wireless sensors show promise for the future, but currently there are only very
42 few pollutants that can be measured well without expensive equipment. State of the science
43 traffic emissions modelling provides estimates of a comprehensive suite of pollutants with fine
44 spatial and temporal resolution, saving the considerable expense of monitoring equipment (Gois,
45 Maciel et al. 2007). The data is localised to tens of metres at street level, enabling more accurate
46 estimates of air quality for pedestrians, commuters, children and the aged. Once problems are
47 identified, they can be mitigated with barriers, spatial buffers, improved ventilation in buildings,
48 or alterations to the fleet (Batterman, Ganguly et al. 2015).

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

59

60 **2 Understanding pedestrian exposure to traffic-related air** 61 **pollutants**

62 **2.1 Traffic pollution in cities**

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

74

75 Table 1. Total annual Australian National Pollutant Inventory (NPI) emissions (kg/yr) for
 76 industry and motor vehicles (National Motor Vehicle Emissions Inventory, NMVEI) in 2010
 77 (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 $\leq 10.0 \mu\text{m}$ | 1,238,329,933 | 14,461,823 | 1.15% |
| Particulate Matter $\leq 2.5 \mu\text{m}$ | 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% |

78

79 The toxic chemicals that comprise traffic emissions are released as gases and primary particles.
 80 The two most commonly used fuels generate different mixtures of pollutants in addition to CO₂:
 81 petrol vehicles are mainly responsible for emissions of carbon monoxide (CO), volatile organic
 82 compounds (VOCs), ammonia (NH₃) and heavy metals. Diesel vehicles produce most of the

83 particles of 2.5 microns and smaller ($PM_{2.5}$) and oxides of nitrogen (NO_x) (Smit 2014). Diesel
84 particulate matter (DPM) is composed of a core of elemental carbon surrounded by organic
85 compounds including polycyclic aromatic hydrocarbons (PAHs), nitro-PAHs, small amounts of
86 sulphate, nitrate, metals and other trace elements. These particles have a large surface area,
87 making them susceptible to adsorption to lung tissue (Wichmann 2007).

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

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

102

103 2.2 Health effects of traffic pollution

104 Although traffic emissions (Table 1) are not the major fraction of airborne pollution in cities,
105 they are a major source of airborne pollution for people, because traffic occupies space close to
106 walkways, residences, workplaces and schools. The traffic intensity on the nearest road to a

107 person's home address was linked to mortality in a long-term study (Beelen, Hoek et al. 2008).
108 Diesel exhaust poses the greatest risk of cancer of any air pollutant (Wichmann 2007). An
109 extensive sampling program for volatile organic compounds (VOCs) in New York City found
110 that proximity of roads and traffic signals explained 65% of variation in atmospheric
111 concentrations of benzene (Kheirbek, Johnson et al. 2012). Commuters travelling by bicycle, bus,
112 automobile, rail, walking and ferry are exposed to concentrations of ultrafine particles that can
113 elicit acute effects in both healthy and health-compromised individuals (Knibbs, Cole-Hunter et
114 al. 2011). For a typical urban commuting journey in Alameda County, USA, personal exposure to
115 NO_x was found to increase from 29 ppb (parts per billion, 10⁻⁹) indoors to 96 ppb outdoors (Su,
116 Jerrett et al. 2015). In a study of different modes of travel to work, the greatest rates of exposure
117 to ultrafine particles were found for those walking or cycling along highly trafficked routes and
118 using buses (Spinazzè, Cattaneo et al. 2015). Some occupations are at significantly elevated risk
119 from traffic emissions. Exposure of traffic policemen in Beijing to polycyclic aromatic
120 hydrocarbons (PAH) was nearly an order of magnitude greater than regulatory limits (Liu, Tao et
121 al. 2007) (Hu, Bai et al. 2007, Liu, Tao et al. 2007). Bus drivers and mail carriers in Copenhagen,
122 Denmark were found to have elevated concentrations of biomarkers for DNA damage (Hansen,
123 Wallin et al. 2004).

124 Evidence of harm from traffic pollution is abundant and mounting, it affects multiple systems of
125 the body. For example, there are links to a range of serious damages to the heart, some fatal.
126 Emissions of NO₂ can cause a 5% enlargement of the right ventricle and 3% increase in its
127 volume after emptying (end diastolic volume). These changes are quantitatively similar to those
128 caused by diabetes or smoking (Holguin and McCormack 2014). Traffic emissions have also
129 been associated with increased levels of inflammatory nasal markers, increased urinary
130 concentrations of urea and metabolites of nitric oxide (Steenberg, Nierkens et al. 2001). Long
131 term exposure to traffic and PM_{2.5} reduced respiratory function in adults (WHO 2013, Badyda,
132 Dabrowiecki et al. 2015, Rice, Ljungman et al. 2015) and the irritant and carcinogenic chemicals

133 cause a range of morbidities including asthma. Children's rapidly growing lungs and immature
134 immune systems make them susceptible to diseases associated with airborne pollution from
135 traffic, such as asthma, allergy, bronchitis and deficits of lung function and growth (Chen, Salam
136 et al. 2015, Gehring, Beelen et al. 2015).

137 The capacity of particulate pollution to cause harm is related to its size, surface area and
138 composition. Particulate matter (PM) is usually classified into size ranges: PM₁₀ is less than or
139 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},
140 or ultrafine particles, are less than or equal to 100 nm (nanometres, 10⁻⁹ m). The smaller the size
141 of the particle, the deeper it can travel into the lungs. Ultrafine particles can reach the alveoli
142 where 50% are retained in the lung parenchyma (Valavanidis, Fiotakis et al. 2008). Linear dose-
143 response associations have been found between particulate matter (PM) pollution and mortality
144 in the United States (Daniels, Dominici et al. 2000), Canada (Requia, Higgins et al. 2018) and in
145 Europe (Samoli, Analitis et al. 2005). Most of the urban PM_{2.5} emissions are due to traffic,
146 particularly diesel-fuelled trucks and buses (Chan, Simpson et al. 1999, Salameh, Detournay et al.
147 2015). A review of adverse health effects of short-term exposure to PM_{2.5} in China showed a
148 0.40% increase in non-accident mortality with every 10 ng m⁻³ increase in concentration (Lu, Xu
149 et al. 2015). Recent work has connected urban exposure to PM_{2.5} with an increased risk of low
150 birth weight (Coker, Ghosh et al. 2015). Commonly, reports of particulate pollution have PM_{2.5}
151 as the smallest class, but this may not be adequate. Not only do ultrafine particles have the
152 capacity to penetrate deep into the airways, but their greater surface area and porosity give an
153 increased capacity to adsorb and retain toxic substances (Valavanidis, Fiotakis et al. 2008). Some
154 authors suggest that it is important to extend consideration to particles of 1 nm size, due to the
155 potential for coagulation and condensation processes at the street level. New particles can form
156 through chemical transformation processes (secondary production) over time in locations like
157 road tunnels, with prolonged residence times and increased concentrations. For example, the
158 mass of secondary nitrate was four times that of primary nitrate in fine aerosols at a site in

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

163 It is common practice to reduce PM pollution by diesel fuelled vehicles with the use of particle
164 traps. These devices can be very effective if used and maintained properly, but an undesirable by-
165 product is a substantial increase in the production of primary NO₂ (Feng, Ge et al. 2014, Tang,
166 Zhang et al. 2014, He, Li et al. 2015). The resulting effect of NO₂ on premature mortality is
167 greater than ten times that of PM_{2.5} in pre particle-trap concentrations (Harrison and Beddows
168 2017).

169 Modelling of transport in Adelaide, Australia showed the benefits in reduction of pollution and
170 other health benefits of switching commuter travel from private vehicles to public transport. If
171 40% of vehicle kilometres travelled were changed to alternative transport by 2030 (projected
172 population 1.4 M), PM_{2.5} would decline by about 0.4 µg m⁻³. This was estimated to reduce
173 adverse health effects by 13 deaths/year, and 118 disability-adjusted life years. There were many
174 more benefits predicted due to improved physical fitness through walking or cycling (Xia,
175 Nitschke et al. 2015).

176

177

178 **3 Traffic emissions modelling: summary of the process & most** 179 **commonly used models**

180 3.1 Introduction: the need for detail

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

207 3.2 Simpler approaches

208 Where detailed data are not available, a simpler macroscopic approach may be appropriate.

209 Alternatives include the use of satellite aerosol optical depth data, in conjunction with a land use
210 regression model, to add a temporal estimate to spatial data regarding the origins of $PM_{2.5}$.

211 Validation of this approach in Florida, USA gave coefficient of determination of 0.63,
212 comparable with studies that use aerodynamic-meteorological models (Mao, Qiu et al. 2012). A
213 land use regression model was used with a simple atmospheric dispersion model to estimate the
214 daily average particle number on a freeway. Inputs were annual averaged wind speed and annual
215 average daily traffic counts, errors averaged 6% across 98 sites (Olvera, Jimenez et al. 2014).

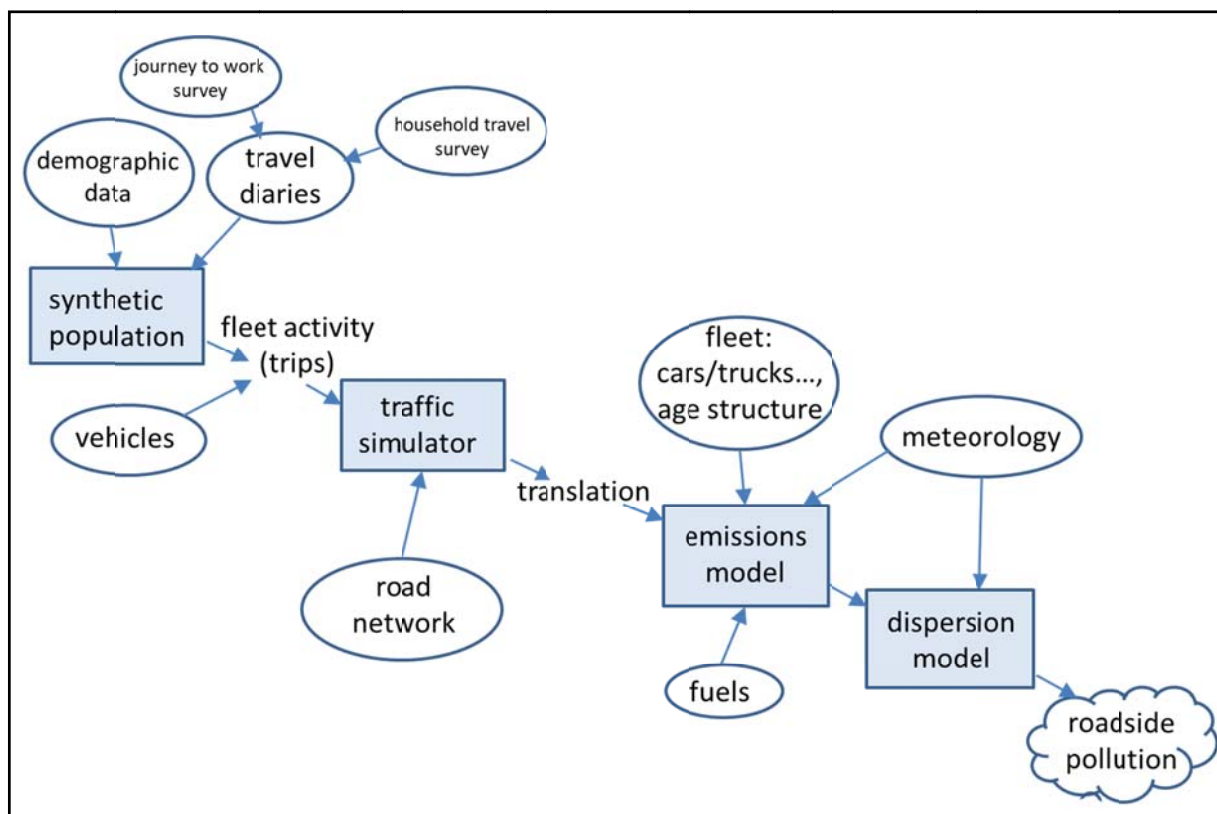
216 Traffic sources of airborne pollutants can be separated from background sources using air quality
217 measurements from a single station and meteorological data. A freely available semi-empirical
218 (box model) pollution model and a spreadsheet-based traffic model (Vehicle emissions
219 prediction model) were designed for Auckland, New Zealand. Results were verified in a study,
220 using ambient records of 2 air pollution monitors. The best estimations were achieved for
221 nitrogen oxides; PM_{10} was difficult to distinguish due to interference from marine aerosols
222 (Elangasinghe, Dirks et al. 2014). In developing countries, measuring traffic flow via new
223 technologies may be too expensive or difficult to implement. A macroscopic traffic flow model
224 can be a good choice when little traffic data is available. The Lighthill and Whitham (1955)
225 model represents traffic in differential equations, using theories of compressible fluids. Only
226 6 days of data were used for estimates of density and travel times on a busy arterial road in
227 Chennai, India. Results had mean average percentage errors ranging from 12.7% to 45.7% when
228 checked with observations (Kumar, Vanajakshi et al. 2011). Another approach that requires little
229 data is a seasonal Autoregressive Integrated Moving Average (SARIMA) model. A 24 hour
230 simulation of traffic flow on an arterial roadway used only 3 days of data and errors ranged from
231 just 4% to 10% (Kumar and Vanajakshi 2015). The publicly available Industrial Source Complex

232 Short Term model (ISCST3, US EPA), was used to attribute airborne PM₁₀ pollution to different
233 sources, including transport in Kanpur City, India. GIS was used to break up the study area into
234 2 km x 2 km grids. Resolution could be adjusted to any time and space (Behera, Sharma et al.
235 2011).

236

237 3.3 Microscopic traffic emissions models

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



248

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

252

253 3.4 Input to traffic simulator model: trips, fleet & sensor data

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

259 Traffic simulations need realistic ‘trips,’ or journeys as inputs for vehicles; these are usually
 260 compiled into origin-destination (OD) matrices. Trips are defined by their origin, destination and
 261 purpose, such as journeys to work, to school or to shops. They can be built or calculated with
 262 data from a range of sources, including: surveys of journeys to work and of household travel,

263 census data on population, employment and residences, freight movements, parking and
264 transport networks including road rail, bus and ferries. There are a range of models that build
265 trips from this data, including (in order of increasing complexity) sketch-planning models,
266 strategic-planning models, trip-based models and activity-based models (Castiglione, Bradley et
267 al. 2015). Generally, activity-based models are used to build trips for a day, with the expectation
268 that no variation will occur. This is, of course, unrealistic, since unexpected changes occur, due
269 to any number of unplanned events. Rescheduling in an activity-based model allows for
270 unexpected changes, such as car accidents or time-table changes in public transport. The
271 FEATHERS activity-based schedule generator simulates the behaviours of mutually independent
272 individuals or actors. The state of a transport network can be influenced by actor behaviour and
273 external phenomena. The actors interpret changes via perception filtering and adapt their
274 schedules accordingly. This in turn affects the network as demand changes, giving a more
275 realistic set of behaviours for microscopic traffic models. A limitation of the framework is that it
276 can only change routes before they are started, once a journey has begun, it is fixed (Knapen,
277 Bellemans et al. 2014). TRANSIMS (US EPA, Federal Highway Administration) is an open-
278 source system of models that comprises a population synthesiser, an activity generator, routing,
279 and a microscopic traffic simulation. The system offers much, but the data requirements are
280 large and the calibration process can be challenging (Zhang and Cai 2016).

281 GPS sensors can substantially improve traffic monitoring. A one second sampling rate was
282 found to be required to identify events such as vehicle stops, but aggregation to a 5 second
283 resolution was sufficient for trip identification. Identification of stops in trips could be improved
284 by combining map information with movement data to reduce false positives, such as pauses due
285 to traffic congestion, or false negatives such as the missing of short stops (Shen and Stopher
286 2013). To give correct placement of a vehicle on a road segment in real time, GPS location was
287 matched to speed and travel time data from cars, using an algorithm that incorporated a
288 sequence of hidden-Markov models (Szwed and Pekala 2014). Commercial software is available

289 to translate GPS data into trips. However, a study that compared two products using the same
290 input data showed a discrepancy of 12% of trips between results. Errors included incorrectly
291 splitting single trips or failing to identify some trips (Stopher, Greaves et al. 2013). A Bayesian
292 approach was used to integrate data from Bluetooth, loop detectors and GPS for real-time traffic
293 prediction. The method dramatically improved the accuracy of information from loop detectors
294 on an arterial corridor in Brisbane, Australia (Nantes, Ngoduy et al. 2015).

295 Origin-destination (OD) data was generated from archived public transport data from smart
296 cards, in conjunction with street maps and timetables in Žilina, the Slovak republic. It was
297 possible to infer details such as in-vehicle travel and walking times for segments of a journey
298 (Jánošíkova, Slavík et al. 2014). Calibration software (W-SPSA) used a weighting matrix to allow
299 for correlations between inputs to OD matrixes (Antoniou, Lima Azevedo et al. 2015).

300 Algorithms based upon evolutionary simulations were used to make choices regarding route
301 choices depending on time and toll cost. The result can incorporate some amount of
302 randomness.(Nagel, Kichhöfer et al. 2014).

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

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

317 Bluetooth and WiFi digital radio transmitters can be used to monitor vehicle movements.
318 Transmitters are found in many mobile electronic devices, including hands-free speaker systems
319 for mobile phones, headsets and music players. Each device broadcasts its unique Media Access
320 Control (MAC) address. Bluetooth transmitters have ranges from 3 m (class 3 devices) to 100 m
321 (class 1 devices). The signal can be detected at the roadside and successive readings processed to
322 give information relating to speed and route (Bachmann, Abdulhai et al. 2013). WiFi, signals can
323 also be used and that system has a faster discovery time (about 1 sec) than Bluetooth (almost 10
324 sec) (Abedi, Bhaskar et al. 2013). There are a number of potential difficulties to be considered
325 when using Bluetooth monitoring. There may be an uneven demographic distribution of
326 Bluetooth devices in cars, a single device may be detected by multiple scans at busy locations and
327 there are devices used outside motor vehicles by pedestrians, cyclists and on trains. The signals
328 must be filtered to resolve these ambiguities (Abbott-Jard, Shah et al. 2013, Michau, Nantes et al.
329 2013). Early implementations of speed detection with Bluetooth were cited as problematic, with
330 automated number-plate recognition being more reliable at higher speeds (Abbott-Jard, Shah et
331 al. 2013). However, Bluetooth has become widely adopted for traffic monitoring and
332 management (Aliari and Haghani 2012, Bachmann, Roorda et al. 2013, Juster, Young et al. 2014,
333 Smith, Hainen et al. 2014). It has been used to verify the accuracy of a large dataset of probe
334 vehicle data (Kaushik, Sharifi et al. 2014) and to give cheap & cost-effective queue measurement
335 (Alghamdi, Nadeem et al. 2014). The technology was used in Brisbane, Australia for modelling
336 travel times, giving much better predictions than the historical average (Khoei, Bhaskar et al.
337 2013) and in Lincoln, USA, increasing the accuracy of predictions over aggregated link and
338 corridor travel times (Wu and Rilett 2014). Only limited numbers of signals from wireless devices

339 are needed to significantly increase the understanding of traffic flows. The South Australian
340 Bluetooth system achieves a sample rate of about 15% of vehicles, better on arterial roads,
341 mostly due to the presence of freight vehicles. The system is good enough that the Department
342 of Planning, Transport and Infrastructure does not buy any external traffic data. It has been used
343 for a number of purposes, including automated incident detection (AID) and to monitoring
344 compliance with permits for traffic controls for roadworks. The department can see if traffic is
345 being slowed down outside the times stipulated by a permit (Southern 2015). As far back as late
346 2015, a number of private companies were already advertising Bluetooth systems for monitoring
347 traffic and other purposes.

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

364 network (Chong-White, Millar et al. 2013). The trial was abandoned due to privacy concerns with
365 the eTag data.

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

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

381

382 3.5 Traffic simulation models

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

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

401 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 |

402

403 In a traffic simulation, the smallest component of a road network is called a link. The number of
404 links must be at least equal to the number of intersections. In addition, any changes in a road,
405 such as a curve or gradient should be represented by a separate link. There is an upper limit to
406 the resolution of a traffic simulation on a network, beyond which vehicle information can be
407 missed. This is particularly the case for low traffic density. The length of a link must be sufficient
408 that all vehicles can be detected over the duration of a model's time step. The risk of a vehicle
409 being missed is proportional to the traffic's sparsity and speed; so the length of a link needs to be
410 calibrated to traffic conditions and the simulation's temporal resolution (Fontes, Pereira et al.
411 2015). Long-run estimates of large areas can be challenging to calculate with such detailed
412 models, because of the computational effort required (Fallah Shorshani, André et al. 2015).

413 Microscopic traffic simulations provide detailed representations of network behaviour by
414 modelling time-varying demand patterns and the choices and behaviours of individual drivers.
415 Simulations represent all vehicles individually, typically with a one second resolution. Algorithms
416 based upon evolutionary simulations can make decisions regarding route choices depending on
417 time and toll cost. Results can be improved by including some degree of randomness in the
418 calculations. This approach allows the fleet to respond to congestion in a realistic manner (Nagel,
419 Kickhöfer et al. 2014, Barthélemy and Carletti 2017). Models are calibrated for local driving
420 behaviours such as car-following and lane changing. Capturing details of instantaneous speeds
421 and acceleration rates increases the accuracy of emissions estimates, because the quality and
422 quantity of vehicle emissions change with deviations from a steady speed (Austroads 2006, Chen
423 and Yu 2007). As congestion increases, so does the incidence of speed changes and the emission
424 of CO and HC (Smit 2006). Lane changing behaviour can significantly change traffic flow, many
425 models simplify the manoeuvre as an instantaneous transition, but it generally takes from 1 to
426 16 s. In addition, the lane-changing behaviours of trucks and cars on arterial roads have been
427 found to be so distinct that they needed to be modelled differently (Cao, Young et al. 2013).

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

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

445 To assist in selecting from the large range of models on offer, a meta-modelling technique has
446 been used to compare and select models and to optimise parameters. Intelligent surrogate
447 modelling tested models in univariate and multivariate frameworks (Vlahogianni 2015).

448 Examination of emissions modelling of Brisbane traffic showed that the majority of errors
449 occurred not in the model specification, but the input data, particularly related to congested
450 conditions. The models performed well under free-flowing conditions, but errors increased in
451 the transitions to congested and very congested conditions (Zhu and Ferreira 2013).

452

453 3.6 Emissions models

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

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

477 Emissions factors are parameters used to calculate emissions for particular chemicals and
478 particles in vehicle exhausts. Databases for vehicle emission factors are usually specific to their
479 country or region, for example HBEFA, is a European database of emissions factors for all
480 current vehicle categories. It incorporates factors for different driving conditions, hot/cold
481 running and evaporative emissions. The emission factors are generated by emissions models
482 validated with measurements in laboratories and on roads. Originally developed by agencies in
483 Germany, Switzerland and Austria, now funded by the EU (ERMES 2015, HBEFA 2015).
484 HBEFA has also been found to be suitable for the Chinese fleet and roads. The Chinese fleet
485 has a similar composition to that of Europe, and the database was well suited to describe the
486 emissions of traffic on urban infrastructure (Sun, Schmeid et al. 2014). Many measurements of
487 vehicles are required to generate robust emissions factors, since even minor variations in testing
488 procedures can result in different outputs from the same vehicle (Franco, Kousoulidou et al.
489 2013).

490 There are a small number of publicly available microscopic emissions models. MOtor Vehicle
491 Emissions Simulator (MOVES) is the US Environmental Protection Agency (EPA) emissions
492 model for mobile sources, designed for use at scales from national to project. The latest version
493 (MOVES2014a) was released in November 2015 and there have been minor revisions since. It
494 deals with on and off-road emissions and includes calculations for emissions of over 100
495 compounds including those from fuel evaporation, brake and tyre wear. For details see
496 (<https://www.epa.gov/moves>). Three simpler microscopic emission models (VT-Micro, EMIT
497 and POLY) were ranked against CMEM, using the same input data from light-duty vehicles from
498 four vehicle classes in two Chinese cities. Different models were found to have strengths in
499 particular aspects, such as speed or better accuracy for certain pollutants (Ma, Lei et al. 2012).
500 Some microscopic emissions models, such as CMEM deal with detail such as hot and cold
501 running, but currently model only a few pollutants: NO_x, total hydrocarbons, CO₂, CO and do
502 not consider emissions due to evaporation or brake and tyre wear. COPERT Street Level is a

503 more detailed version of the European emissions inventory software, COPERT (Computer
504 Programme to calculate Emissions from Road Transport, <http://emisia.com/products/copert>).
505 It has similar resolution to MOVES and calculates the pollutants CO, CO₂, NO_x, PM and VOC.
506 PARAMICS (PARAllel MICroscopic traffic Simulator, <http://www.paramics-online.com>)
507 Monitor is an add-on for the PARAMICS traffic simulator, it models CO, CO₂, total HC, NO_x,
508 PM and fuel consumption. There is also an add-on that couples the model to CMEM. The
509 AIMSUN (Advanced Interactive Microscopic Simulator for Urban and Non-Urban networks,
510 <https://www.aimsun.com>) emissions model is easy to calibrate and implement, but the
511 calibration may not apply well to conditions that differ from those of the calibration (Bover, Zhu
512 et al. 2013). The TRANSIMS (TRansportation ANalysis and SIMulation System,
513 <https://transims-studio.soft112.com>) system of models contains an emissions simulator.

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

519 The accuracy of all models is limited by the quality of the emissions factors used in their
520 calculations. The accuracy of predictions of some regulated pollutant measurements is better
521 than others. CO, NO_x, total VOC, PM mass and CO₂ are well understood as a function of
522 driving conditions, due to the large number of measurements. Others have been less well
523 evaluated: NO₂, NH₃, individual VOC, PAH, PM as a function of size and number, and heavy
524 metals (Fallah Shorshani, André et al. 2015). The quality and quantity of the emissions of
525 pollutants is related to the power output of a vehicle's engine. A common method takes that data
526 from a microscopic traffic simulation and uses it to calculate emissions using 'vehicle specific
527 power' (VSP) (Fontes, Fernandes et al. 2014). For example, PΔP (engine power, and change in

528 engine power) software, based on drive cycles from a large database of Australian emissions
529 tests. Validation gave average R^2 values of 0.65 for NO_x and 0.93 for CO_2 /fuel consumption
530 (Smit 2013). However, some power-based models may not be sufficiently sensitive to the small
531 changes in engine power that can have significant effects on emissions (Zhu 2015).

532 Caution is required when selecting emission factors for use in models, particularly data from
533 vehicle manufacturers. That data was suspect, even before the Volkswagen scandal (Boretti
534 2017). Engineers at an independent European tester found that manufacturers' tests
535 underestimated exhaust emissions (Schmidt and Johannsen 2010). Car makers were shown to
536 have manipulated load tests, estimates of vehicles' rolling and wind resistance, to skew emissions
537 tests by independent testers. Testers carried out alterations such as not charging the battery,
538 over-inflating tyres, disabling power steering pumps and taping the edges of windows and other
539 gaps to decrease wind and rolling resistance. When regular production vehicles were used
540 instead, fuel economy was decreased by about 12%. The gap between advertised and actual fuel
541 economy figures were as large as 50% (Dings 2013, Mock and German 2015). In the so called
542 "Dieselgate" scandal, centred around Volkswagen, it was found that cars powered by diesel
543 engines had been releasing NO_x at a rate more than 4 times that allowed by European
544 regulations. Modelling gave a median estimate of an additional 1,200 premature deaths, or 13,000
545 life-years lost and 1.9 billion EUR in associated costs, across Europe caused by the extra
546 emissions over the time these vehicles were being sold (2008-2015) (Guillaume, Robert et al.
547 2017).

548

549 3.6.1 Real time emissions data

550 Real-time data is one of the major benefits promised by Intelligent Transport Systems (ITS)
551 including connected, interacting sensors, controllers and vehicles. A service on the Google Maps
552 platform, called "Emission Map," used a combination of data from traffic loop sensors and

553 emission calculations from MOVES to give a visualisation of near real-time traffic emissions in
554 Seattle, USA. It (Ma, Yu et al. 2012).

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

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

577

578 3.7 Dispersion models

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

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

603 dispersion of a tracer gas to a large array of sensors. ADMS-Roads, AEROMOD (volume
604 source) and RLINE performed better than CALINE (Stocker, Heist et al. 2013).

605 Recently, there has been an increasing popularity of computational fluid dynamics (CFD) models
606 such as PHOENICS (Chen, Lu et al. 2017) and FLUIDITY (Aristodemou, Boganegra et al.
607 2018) over the conventional Gaussian-type dispersion models. A CFD emission model was able
608 to show detail such as eddies generated by cross-streets and increased concentrations of
609 pollutants in the lower leeward sides of street canyons (Mumovic, Crowther et al. 2006). A study
610 examined the dispersion and chemical interactions and of ultrafine particles (UFP) from vehicle
611 exhaust-pipes to the near-road environment. The study used an aerosol dynamics-CFD coupled
612 model. It was found that omitting atmospheric boundary layer conditions (wind profile and
613 turbulence quantities) from activity-based emission models resulted in an overestimate of the
614 dilution of emissions in the wake of vehicles. This led to a five-fold underestimate of the
615 nucleation rate. (Huang, Gong et al. 2014). FLUIDITY is an open source simulator that
616 incorporates an anisotropic adaptive unstructured mesh and large eddy simulations (LES). This
617 approach improves predictions by increasing resolution where required and improving the
618 representation of turbulence. The simulation was used to model the effects of increased building
619 height on the distribution of traffic pollution. It was able to reproduce wind tunnel
620 measurements well, with differences ranging from 3% to 37% (Aristodemou, Boganegra et al.
621 2018)

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

626 In an Indian study, the US EPA’s Industrial Source Complex Short Term model (ISCST3) was
627 used to attribute airborne PM₁₀ pollution in Kanpur City to different sources, including

628 transport. GIS was used to break up the study area into 2 km x 2 km grids. Resolution could be
629 adjusted to any time and space (Behera, Sharma et al. 2011).

630

631 3.8 Summary & recommendations

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

646

647 Table 3. List of recent studies using combinations of microscopic simulations to examine
648 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 |

649

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

652

653 4 Conclusions

654 The airborne emissions from traffic present significant, well established hazards to many of the
655 people in cities. The current state of the science is able to model traffic emissions with very fine
656 resolution. With the use of microsimulations, temporal resolution is typically one second and
657 spatial resolution tens of metres. This detail is necessary because the chemistry of emissions
658 changes rapidly over time and space. The most polluting phases of driving happen over short
659 intervals, such as after starts and with the acceleration and deceleration of congested traffic.

660 There are a number of software packages available for the various aspects of emissions
661 modelling, both commercial and open source. New research is applying novel approaches, such
662 as agent-based models, neural networks and ensemble learning to increase speed, detail and

663 scope. Models are used for evaluating mitigation measures, either managing the traffic to
664 improve flow and minimise emissions, or separating people from the traffic with under or
665 overpasses. The rate of data being produced from multiple types of road sensors is ever
666 increasing. Vehicles are also tracked using wireless radio signals from mobile phones and other
667 transmitting devices. Many cities integrate these multiple data streams in intelligent transport
668 systems, reducing emissions by improving the effectiveness of road and transport networks.
669 Information from ITS has also enabled the deployment of detailed real time traffic emissions
670 models, offering the possibility for people to plan travel or close windows to avoid potentially
671 harmful exposure. Spatially detailed simulations can be combined with demographic data to
672 provide targeted information and risk analyses. Traffic emissions models have grown beyond
673 only being tools for the planning of infrastructure, to versatile instruments that can inform many
674 disciplines and help to improve the health of city-dwellers.

675

676 **5 Acknowledgements**

677 This review was funded by the Clean Air and Urban Landscapes (CAUL) hub of the Australian
678 National Environmental Science Programme (NESP). We would also like to acknowledge the
679 thoughtful reviews by the anonymous reviewers whose input significantly improved this paper.

680

681

682 **8 References**

683

- 684 Abbott-Jard, M., H. Shah and A. Bhaskar (2013). Empirical evaluation of Bluetooth and Wifi scanning for
685 road transport. 36th Australasian Transport Research Forum, ATRF 2013, Australasian Transport
686 Research Forum.
- 687 Abedi, N., A. Bhaskar and E. Chung (2013). Bluetooth and Wi-Fi MAC address based crowd data
688 collection and monitoring: Benefits, challenges and enhancement. 36th Australasian Transport Research
689 Forum, ATRF 2013, Australasian Transport Research Forum.
- 690 Alghamdi, A., T. Nadeem and M. Cetin (2014). BlueEye: A bluetooth-based vehicle location identification
691 system for queue length estimation at signalized intersections. 21st World Congress on Intelligent

- 692 Transport Systems: Reinventing Transportation in Our Connected World, ITSWC 2014, Intelligent
693 Transport Systems (ITS).
- 694 Aliari, Y. and A. Haghani (2012). Bluetooth sensor data and ground truth testing of reported travel times.
695 Transportation Research Record: 167-172.
- 696 Amirjamshidi, G., T. S. Mostafa, A. Misra and M. J. Roorda (2013). "Integrated model for
697 microsimulating vehicle emissions, pollutant dispersion and population exposure." Transportation
698 Research Part D: Transport and Environment **18**(1): 16-24.
- 699 Antoniou, C., C. Lima Azevedo, L. Lu, F. Pereira and M. Ben-Akiva (2015). "W-SPSA in practice:
700 Approximation of weight matrices and calibration of traffic simulation models." Transportation Research
701 Part C: Emerging Technologies.
- 702 Apte, J. S., K. P. Messier, S. Gani, M. Brauer, T. W. Kirchstetter, M. M. Lunden, J. D. Marshall, C. J.
703 Portier, R. C. H. Vermeulen and S. P. Hamburg (2017). "High-Resolution Air Pollution Mapping with
704 Google Street View Cars: Exploiting Big Data." Environmental Science & Technology **51**(12): 6999-7008.
- 705 Aristodemou, E., L. M. Boganegra, L. Mottet, D. Pavlidis, A. Constantinou, C. Pain, A. Robins and H.
706 ApSimon (2018). "How tall buildings affect turbulent air flows and dispersion of pollution within a
707 neighbourhood." Environmental Pollution **233**: 782-796.
- 708 Auld, J., D. Karbowski, V. Sokolov and N. Kim (2016). A Disaggregate Model System for Assessing the
709 Energy Impact of Transportation at the Regional Level. 95th Annual Meeting of the Transportation
710 Research Board. Washington DC.
- 711 Aust, N., P. Watkiss, P. Boulter and K. Bawden (2013). Methodology for Valuing the health impacts of
712 changes in particle emissions- final report, NSW Environment Protection Authority.
- 713 Austroads (2006). The use and application of microsimulation traffic models. Sydney, Australia: 103.
- 714 Bachmann, C., B. Abdulhai, M. J. Roorda and B. Moshiri (2013). "A comparative assessment of multi-
715 sensor data fusion techniques for freeway traffic speed estimation using microsimulation modeling."
716 Transportation Research Part C: Emerging Technologies **26**: 33-48.
- 717 Bachmann, C., M. J. Roorda, B. Abdulhai and B. Moshiri (2013). "Fusing a bluetooth traffic monitoring
718 system with loop detector data for improved freeway traffic speed estimation." Journal of Intelligent
719 Transportation Systems: Technology, Planning, and Operations **17**(2): 152-164.
- 720 Badyda, A. J., P. Dabrowiecki, P. O. Czechowski and G. Majewski (2015). "Risk of bronchi obstruction
721 among non-smokers-review of environmental factors affecting bronchoconstriction." Respiratory
722 Physiology and Neurobiology **209**: 39-46.
- 723 Balaji Yelchuru, B., V. Adams, E. Hurley and V. Bonifera (2011). AERIS: State-of-the-Practice Scan of
724 Environmental Models. Washington DC, USA, Research and Innovative Technology Administration
725 (RITA): 74.
- 726 Barthélemy, J. and T. Carletti (2017). An adaptive agent-based approach to traffic simulation.
727 Transportation Research Procedia.
- 728 Batterman, S., R. Ganguly and P. Harbin (2015). "High resolution spatial and temporal mapping of
729 traffic-related air pollutants." International Journal of Environmental Research and Public Health **12**(4):
730 3646-3666.
- 731 Beelen, R., G. Hoek, P. A. van den Brandt, R. A. Goldbohm, P. Fischer, L. J. Schouten, M. Jerrett, E.
732 Hughes, B. Armstrong and B. Brunekreef (2008). "Long-term effects of traffic-related air pollution on
733 mortality in a Dutch cohort (NLCS-AIR study)." Environmental Health Perspectives **116**(2): 196-202.
- 734 Behera, S. N., M. Sharma, O. Dikshit and S. P. Shukla (2011). "GIS-based emission inventory, dispersion
735 modeling, and assessment for source contributions of particulate matter in an urban environment."
736 Water, Air, and Soil Pollution **218**(1-4): 423-436.
- 737 Boretti, A. (2017). "The Future of the Internal Combustion Engine after "diesel-Gate"." **2017-July**(July).
- 738 Boriboonsomsin, K. and M. Barth (2008). "Impacts of freeway high-occupancy vehicle lane configuration
739 on vehicle emissions." Transportation Research Part D: Transport and Environment **13**(2): 112-125.
- 740 Bover, P., S. Zhu and L. Ferreira (2013). "Modelling vehicle emissions for Australian conditions." Road
741 and Transport Research **22**(4): 15-29.
- 742 BTRE (2005). Health impacts of transport emissions in Australia: economic costs. B. o. T. a. R.
743 Economics, Department of Transport and Regional Services.
- 744 Cao, X., W. Young and M. Sarvi (2013). Exploring duration of lane change execution. 36th Australasian
745 Transport Research Forum, ATRF 2013, Australasian Transport Research Forum.
- 746 Castiglione, J., M. Bradley and J. Gliebe (2015). Activity-based travel demand models: a primer. The
747 second strategic highway research program. Washington D.C., Transportation Research Board.

- 748 Chan, Y. C., R. W. Simpson, G. H. McTainsh, P. D. Vowles, D. D. Cohen and G. M. Bailey (1999).
 749 "Source apportionment of PM_{2.5} and PM₁₀ in Brisbane (Australia) by receptor modelling." Atmospheric
 750 Environment **33**(19): 3251-3268.
- 751 Chen, K. and L. Yu (2007). "Microscopic Traffic-Emission Simulation and Case Study for Evaluation of
 752 Traffic Control Strategies." Journal of Transportation Systems Engineering and Information Technology
 753 **7**(1): 93-99.
- 754 Chen, S., S. Bekhor, Yuval and D. M. Broday (2016). "Aggregated GPS tracking of vehicles and its use as
 755 a proxy of traffic-related air pollution emissions." Atmospheric Environment **142**: 351-359.
- 756 Chen, S. L., J. Lu and W. W. Yu (2017). "A quantitative method to detect the ventilation paths in a
 757 mountainous urban city for urban planning: A case study in guizhou, China." Indoor and Built
 758 Environment **26**(3): 422-437.
- 759 Chen, Z., M. T. Salam, S. P. Eckel, C. V. Breton and F. D. Gilliland (2015). "Chronic effects of air
 760 pollution on respiratory health in Southern California children: Findings from the Southern California
 761 Children's Health Study." Journal of Thoracic Disease **7**(1): 46-58.
- 762 Chen, Z., C. Yang and A. Chen (2014). "Estimating fuel consumption and emissions based on
 763 reconstructed vehicle trajectories." Journal of Advanced Transportation **48**(6): 627-641.
- 764 Chong-White, C., G. Millar, F. Johnson and S. Shaw (2014). The SCATS and the environment study:
 765 Introduction and preliminary results. 34th Australasian Transport Research Forum, ATRF 2011,
 766 Australasian Transport Research Forum.
- 767 Chong-White, C., G. Millar and S. Shaw (2013). SCATS and the environment study: An indication of road
 768 customer value. 36th Australasian Transport Research Forum, ATRF 2013, Australasian Transport
 769 Research Forum.
- 770 Coker, E., J. Ghosh, M. Jerrett, V. Gomez-Rubio, B. Beckerman, M. Cockburn, S. Liverani, J. Su, A. Li,
 771 M. L. Kile, B. Ritz and J. Molitor (2015). "Modeling spatial effects of PM_{<inf>2.5</inf>} on term low
 772 birth weight in Los Angeles County." Environmental Research **142**: 354-364.
- 773 Daniels, M. J., F. Dominici, J. M. Samet and S. L. Zeger (2000). "Estimating particulate matter-mortality
 774 dose-response curves and threshold levels: An analysis of daily time-series for the 20 largest US cities."
 775 American Journal of Epidemiology **152**(5): 397-406.
- 776 DAPPLE. (2009). "Dispersion of Air Pollution and its Penetration into the Local Environment." from
 777 <http://www.dapple.org.uk>.
- 778 Dekoninck, L., D. Botteldooren and L. Int Panis (2015). "Using city-wide mobile noise assessments to
 779 estimate bicycle trip annual exposure to Black Carbon." Environment International **83**: 192-201.
- 780 Dia, H. and N. Boongrapue (2015). "Vehicle emission models using Australian fleet data." Road and
 781 Transport Research **24**(1): 14-26.
- 782 Dings, J. (2013) "Mind the Gap! Why official car fuel economy figures don't match up to reality."
- 783 El-Fadel, M. (2002). "Grade separations for traffic congestion relief: Air quality and noise implications."
 784 International Journal of Environmental Studies **59**(6): 689-705.
- 785 Elangasinghe, M. A., K. N. Dirks, N. Singhal, S. B. Costello, I. Longley and J. A. Salmond (2014). "A
 786 simple semi-empirical technique for apportioning the impact of roadways on air quality in an urban
 787 neighbourhood." Atmospheric Environment **83**: 99-108.
- 788 ERMES. (2015). "Leading EU Models." 2015, from [http://www.ermes-](http://www.ermes-group.eu/web/leading_EU_models)
 789 [group.eu/web/leading_EU_models](http://www.ermes-group.eu/web/leading_EU_models).
- 790 European Environment Agency (2007). EMEP/EEA air pollutant emission inventory guidebook,
 791 Technical guidance to prepare national emission inventories. EEA Technical reports. Office for Official
 792 Publications of the European Communities, Luxembourg.
- 793 Fallah Shorshani, M., M. André, C. Bonhomme and C. Seigneur (2015). "Modelling chain for the effect of
 794 road traffic on air and water quality: Techniques, current status and future prospects." Environmental
 795 Modelling and Software **64**: 102-123.
- 796 Feng, X., Y. Ge, C. Ma, J. Tan, L. Yu, J. Li and X. Wang (2014). "Experimental study on the nitrogen
 797 dioxide and particulate matter emissions from diesel engine retrofitted with particulate oxidation catalyst."
 798 Science of the Total Environment **472**: 56-62.
- 799 Fontes, T., P. Fernandes, H. Rodrigues, J. M. Bandeira, S. R. Pereira, A. J. Khattak and M. C. Coelho
 800 (2014). "Are HOV/eco-lanes a sustainable option to reducing emissions in a medium-sized European
 801 city?" Transportation Research Part A: Policy and Practice **63**: 93-106.

- 802 Fontes, T., S. R. Pereira, P. Fernandes, J. M. Bandeira and M. C. Coelho (2015). "How to combine
803 different microsimulation tools to assess the environmental impacts of road traffic? Lessons and
804 directions." Transportation Research Part D: Transport and Environment **34**: 293-306.
- 805 Forehead, H. I., C. Murphy, P. Perez and I. Wadlow (2017). Quiet Streets, Clean Air. International
806 Symposium on Next Generation Infrastructure. London, UK.
- 807 Franco, V., M. Kousoulidou, M. Muntean, L. Ntziachristos, S. Hausberger and P. Dilara (2013). "Road
808 vehicle emission factors development: A review." Atmospheric Environment **70**: 84-97.
- 809 Gao, H. O. and L. S. Johnson (2009). "Methods of analysis for vehicle soak time data." Transportation
810 Research Part A: Policy and Practice **43**(8): 744-754.
- 811 Garcia-Castro, A. and A. Monzon (2014). "Using floating car data to analyse the effects of ITS measures
812 and Eco-driving." Sensors (Switzerland) **14**(11): 21358-21374.
- 813 Gehring, U., R. Beelen, M. Eeftens, G. Hoek, K. De Hoogh, J. C. De Jongste, M. Keuken, G. H.
814 Koppelman, K. Meliefste, M. Oldenwening, D. S. Postma, L. Van Rossem, M. Wang, H. A. Smit and B.
815 Brunekreef (2015). "Particulate matter composition and respiratory health the PIAMA birth cohort
816 study." Epidemiology **26**(3): 300-309.
- 817 Gois, V., H. Maciel, L. Nogueira, C. Almeida, P. Torres, S. Mesquita and F. Ferreira (2007). A detailed
818 urban road traffic emissions inventory model using aerial photography and GPS surveys EPA's 16th
819 Annual International Emission Inventory Conference. Raleigh, NC.
- 820 Gordon, T. D., A. A. Presto, A. A. May, N. T. Nguyen, E. M. Lipsky, N. M. Donahue, A. Gutierrez, M.
821 Zhang, C. Maddox, P. Rieger, S. Chattopadhyay, H. Maldonado, M. M. Maricq and A. L. Robinson
822 (2014). "Secondary organic aerosol formation exceeds primary particulate matter emissions for light-duty
823 gasoline vehicles." Atmospheric Chemistry and Physics **14**(9): 4661-4678.
- 824 Grumert, E., X. Ma and A. Tapani (2015). "Analysis of a cooperative variable speed limit system using
825 microscopic traffic simulation." Transportation Research Part C: Emerging Technologies **52**: 173-186.
- 826 Guillaume, P. C., M. Robert, A. Akshay, C. D. Irene, D. E. Sebastian, L. S. Raymond and R. H. B. Steven
827 (2017). "Public health impacts of excess NO_x emissions from Volkswagen diesel passenger vehicles in
828 Germany." Environmental Research Letters **12**(3): 034014.
- 829 Hansen, Å. M., H. Wallin, M. L. Binderup, M. Dybdahl, H. Autrup, S. Loft and L. E. Knudsen (2004).
830 "Urinary 1-hydroxypyrene and mutagenicity in bus drivers and mail carriers exposed to urban air
831 pollution in Denmark." Mutation Research - Genetic Toxicology and Environmental Mutagenesis **557**(1):
832 7-17.
- 833 Harrison, R. M. and D. C. Beddows (2017). "Efficacy of Recent Emissions Controls on Road Vehicles in
834 Europe and Implications for Public Health." Scientific Reports **7**(1).
- 835 HBEFA. (2015). "Handbook of Emission Factors for Road Transport (HBEFA)." from
836 <http://www.hbefa.net/e/index.html>.
- 837 He, C., J. Li, Z. Ma, J. Tan and L. Zhao (2015). "High NO₂/NO_x emissions downstream of the catalytic
838 diesel particulate filter: An influencing factor study." Journal of Environmental Sciences (China) **35**: 55-
839 61.
- 840 Holguin, F. and M. C. McCormack (2014). "Right from wrong: The effect of traffic-related pollution on
841 the right heart." American Journal of Respiratory and Critical Care Medicine **189**(9): 1018-1019.
- 842 Houghton, N., J. McRobert, S. Patrick and D. Tsolakis (2003). Planning for freight in urban areas,
843 Austrroads: 79.
- 844 Hu, Y., Z. Bai, L. Zhang, X. Wang, L. Zhang, Q. Yu and T. Zhu (2007). "Health risk assessment for
845 traffic policemen exposed to polycyclic aromatic hydrocarbons (PAHs) in Tianjin, China." Science of the
846 Total Environment **382**(2-3): 240-250.
- 847 Huang, L., S. L. Gong, M. Gordon, J. Liggiio, R. Staebler, C. A. Stroud, G. Lu, C. Mihele, J. R. Brook and
848 C. Q. Jia (2014). "Aerosol-computational fluid dynamics modeling of ultrafine and black carbon particle
849 emission, dilution, and growth near roadways." Atmospheric Chemistry and Physics **14**(23): 12631-12648.
- 850 Huynh, N., M. R. Namazi-Rad, P. Perez, M. J. Berryman, Q. Chen and J. Barthelemy (2013). Generating a
851 synthetic population in support of agent-based modeling of transportation in Sydney. 20th International
852 Congress on Modelling and Simulation. Adelaide, Australia.
- 853 INRIX. (2018). "INRIX Traffic." Retrieved 15/5/2017, from <http://inrix.com/products/traffic/>.
- 854 Int Panis, L., S. Broekx and R. Liu (2006). "Modelling instantaneous traffic emission and the influence of
855 traffic speed limits." Science of the Total Environment **371**(1-3): 270-285.
- 856 Jánošíkova, L., J. Slavík and M. Koháni (2014). "Estimation of a route choice model for urban public
857 transport using smart card data." Transportation Planning and Technology **37**(7): 638-648.

- 858 Jha, M., G. Gopalan, A. Garms, B. P. Mahanti, T. Toledo and M. E. Ben-Akiva (2004). Development and
859 calibration of a large-scale microscopic traffic simulation model. Transportation Research Record: 121-
860 131.
- 861 Juster, R. M., S. E. Young and E. Sharifi (2014). Measuring performance on interrupted flow facilities
862 with GPS probe and bluetooth traffic monitoring data. 21st World Congress on Intelligent Transport
863 Systems: Reinventing Transportation in Our Connected World, ITSWC 2014, Intelligent Transport
864 Systems (ITS).
- 865 Kakosimos, K. E., O. Hertel, M. Ketznel and R. Berkowicz (2010). "Operational Street Pollution Model
866 (OSPM) - A review of performed application and validation studies, and future prospects."
867 Environmental Chemistry 7(6): 485-503.
- 868 Kaushik, K., E. Sharifi, S. E. Young and B. Baghaei (2014). Comparison of national performance measure
869 data set (NPMRDS) with bluetooth traffic monitoring (BTM) data and I-95 corridor coalition Vehicle
870 Probe Project (VPP) data. 21st World Congress on Intelligent Transport Systems: Reinventing
871 Transportation in Our Connected World, ITSWC 2014, Intelligent Transport Systems (ITS).
- 872 Kheirbek, I., S. Johnson, Z. Ross, G. Pezeshki, K. Ito, H. Eisl and T. Matte (2012). "Spatial variability in
873 levels of benzene, formaldehyde, and total benzene, toluene, ethylbenzene and xylenes in New York City:
874 A land-use regression study." Environmental Health: A Global Access Science Source 11(1).
- 875 Khoei, A. M., A. Bhaskar and E. Chung (2013). Travel time prediction on signalised urban arterials by
876 applying SARIMA modelling on Bluetooth data. 36th Australasian Transport Research Forum, ATRF
877 2013, Australasian Transport Research Forum.
- 878 Knapen, L., T. Bellemans, M. Usman, D. Janssens and G. Wets (2014). "Within day rescheduling
879 microsimulation combined with macrosimulated traffic." Transportation Research Part C: Emerging
880 Technologies 45: 99-118.
- 881 Knibbs, L. D., T. Cole-Hunter and L. Morawska (2011). "A review of commuter exposure to ultrafine
882 particles and its health effects." Atmospheric Environment 45(16): 2611-2622.
- 883 Kokkinogenis, Z., L. Sanchez Passos, R. Rossetti and J. Gabriel (2011). "Towards the next-generation
884 traffic simulation tools: A first evaluation." Proc. of DSIE2011 6th Doctoral Symposium in Informatics
885 Engineering.
- 886 Kumar, P., M. Ketznel, S. Vardoulakis, L. Pirjola and R. Britter (2011). "Dynamics and dispersion
887 modelling of nanoparticles from road traffic in the urban atmospheric environment-A review." Journal of
888 Aerosol Science 42(9): 580-603.
- 889 Kumar, S. V. and L. Vanajakshi (2015). "Short-term traffic flow prediction using seasonal ARIMA model
890 with limited input data." European Transport Research Review 7(3).
- 891 Kumar, S. V., L. Vanajakshi and S. C. Subramanian (2011). Location-based data for estimated traffic on
892 urban arterial in heterogeneous traffic conditions. Transportation Research Record: 16-22.
- 893 Lighthill, M. J. and G. B. Whitham (1955). "On kinematic waves II: A theory of traffic flow on long
894 crowded roads." Proceedings of the Royal Society 229(1178): 317-345.
- 895 Liu, Y., S. Tao, Y. Yang, H. Dou, Y. Yang and R. M. Coveney (2007). "Inhalation exposure of traffic
896 police officers to polycyclic aromatic hydrocarbons (PAHs) during the winter in Beijing, China." Science
897 of The Total Environment 383(1-3): 98-105.
- 898 Lu, F., D. Xu, Y. Cheng, S. Dong, C. Guo, X. Jiang and X. Zheng (2015). "Systematic review and meta-
899 analysis of the adverse health effects of ambient PM2.5 and PM10 pollution in the Chinese population."
900 Environmental Research 136: 196-204.
- 901 Lv, Y., Y. Duan, W. Kang, Z. Li and F. Y. Wang (2015). "Traffic Flow Prediction with Big Data: A Deep
902 Learning Approach." IEEE Transactions on Intelligent Transportation Systems 16(2): 865-873.
- 903 Ma, X., J. Jin and W. Lei (2014). "Multi-criteria analysis of optimal signal plans using microscopic traffic
904 models." Transportation Research Part D: Transport and Environment 32: 1-14.
- 905 Ma, X., W. Lei, I. Andréasson and H. Chen (2012). "An Evaluation of Microscopic Emission Models for
906 Traffic Pollution Simulation Using On-board Measurement." Environmental Modeling and Assessment
907 17(4): 375-387.
- 908 Ma, X., R. Yu and Y. Wang (2012). Developing regional map-based platform for spatial and temporal
909 assessment of traffic emission inventory. 12th COTA International Conference of Transportation
910 Professionals: Multimodal Transportation Systems - Convenient, Safe, Cost-Effective, Efficient, CICTP
911 2012, Beijing.
- 912 Maddock, J. (2015). Traffic Data Manager, Main Roads Western Australia.

- 913 Mao, L., Y. Qiu, C. Kusano and X. Xu (2012). "Predicting regional space-time variation of PM2.5 with
914 land-use regression model and MODIS data." Environmental Science and Pollution Research **19**(1): 128-
915 138.
- 916 Marquez, L. and V. Salim (2007). "Assessing impacts of urban freight measures on air toxic emissions in
917 Inner Sydney." Environmental Modelling and Software **22**(4): 515-525.
- 918 Mellios, G. and L. Ntziachristos (2012). Gasoline evaporation from vehicles. EMEP/EEA emission
919 inventory guidebook. Luxembourg, European Environment Agency.
- 920 Michau, G., A. Nantes and E. Chung (2013). Towards the retrieval of accurate od matrices from
921 bluetooth data: Lessons learned from 2 years of data. 36th Australasian Transport Research Forum,
922 ATRF 2013, Australasian Transport Research Forum.
- 923 Mock, P. and J. German (2015). The future of vehicle emissions testing and compliance, The
924 International Council on Clean Transportation.
- 925 Mumovic, D., J. M. Crowther and Z. Stevanovic (2006). "Integrated air quality modelling for a designated
926 air quality management area in Glasgow." Building and Environment **41**(12): 1703-1712.
- 927 Nagel, K., B. Kickhöfer and J. W. Joubert (2014). Heterogeneous tolls and values of time in multi-agent
928 transport simulation. 5th International Conference on Ambient Systems, Networks and Technologies,
929 ANT 2014 and 4th International Conference on Sustainable Energy Information Technology, SEIT 2014,
930 Hasselt, Elsevier.
- 931 Nantes, A., D. Ngoduy, A. Bhaskar, M. Miska and E. Chung (2015). "Real-time traffic state estimation in
932 urban corridors from heterogeneous data." Transportation Research Part C: Emerging Technologies.
933 National Research Council Committee on Health Impact, A. (2011). The National Academies Collection:
934 Reports funded by National Institutes of Health. Improving Health in the United States: The Role of
935 Health Impact Assessment. Washington (DC), National Academies Press (US)
- 936 National Academy of Sciences.
- 937 NYCCAS. (2018). "New York City Community Air Survey." from
938 <http://www1.nyc.gov/site/doh/data/data-publications/air-quality-nyc-community-air-survey.page>.
- 939 Olvera, H. A., O. Jimenez and E. Provencio-Vasquez (2014). "Modeling particle number concentrations
940 along Interstate 10 in El Paso, Texas." Atmospheric Environment **98**: 581-590.
- 941 Penttinen, M., F. Diederichs, K. Pagle, E. Portouli and P. Rämä (2014). Impact evaluation methodology
942 for collaborative transport applications. 21st World Congress on Intelligent Transport Systems:
943 Reinventing Transportation in Our Connected World, ITSWC 2014, Intelligent Transport Systems (ITS).
- 944 Pu, Y., C. Yang, H. Liu, Z. Chen and A. Chen (2015). "Impact of license plate restriction policy on
945 emission reduction in Hangzhou using a bottom-up approach." Transportation Research Part D:
946 Transport and Environment **34**: 281-292.
- 947 Qiu, Z. and X. Li (2015). "At-grade intersection configuration influences on pedestrian exposure to
948 PM2.5." Clean Technologies and Environmental Policy.
- 949 Qu, L., M. Li, D. Chen, K. Lu, T. Jin and X. Xu (2015). "Multivariate analysis between driving condition
950 and vehicle emission for light duty gasoline vehicles during rush hours." Atmospheric Environment **110**:
951 103-110.
- 952 Requia, W. J., C. D. Higgins, M. D. Adams, M. Mohamed and P. Koutrakis (2018). "The health impacts
953 of weekday traffic: A health risk assessment of PM2.5 emissions during congested periods." Environment
954 International **111**: 164-176.
- 955 Rice, M. B., P. L. Ljungman, E. H. Wilker, K. S. Dorans, D. R. Gold, J. Schwartz, P. Koutrakis, G. R.
956 Washko, G. T. O'Connor and M. A. Mittleman (2015). "Long-term exposure to traffic emissions and fine
957 particulate matter and lung function decline in the Framingham Heart Study." American Journal of
958 Respiratory and Critical Care Medicine **191**(6): 656-664.
- 959 Ruckerl, R., A. Schneider, S. Breitner, J. Cyrys and A. Peters (2011). "Health effects of particulate air
960 pollution: A review of epidemiological evidence." Inhalation Toxicology **23**(10): 555-592.
- 961 Ryu, Y. H., J. J. Baik, K. H. Kwak, S. Kim and N. Moon (2013). "Impacts of urban land-surface forcing
962 on ozone air quality in the Seoul metropolitan area." Atmospheric Chemistry and Physics **13**(4): 2177-
963 2194.
- 964 Salameh, D., A. Detournay, J. Pey, N. Pérez, F. Liguori, D. Saraga, M. C. Bove, P. Brotto, F. Cassola, D.
965 Massabò, A. Latella, S. Pillon, G. Formenton, S. Patti, A. Armengaud, D. Piga, J. L. Jaffrezo, J. Bartzis, E.
966 Tolis, P. Prati, X. Querol, H. Wortham and N. Marchand (2015). "PM2.5 chemical composition in five
967 European Mediterranean cities: A 1-year study." Atmospheric Research **155**: 102-117.

- 968 Samoli, E., A. Analitis, G. Touloumi, J. Schwartz, H. R. Anderson, J. Sunyer, L. Bisanti, D. Zmirou, J. M.
 969 Vonk, J. Pekkanen, P. Goodman, A. Paldy, C. Schindler and K. Katsouyanni (2005). "Estimating the
 970 exposure-response relationships between particulate matter and mortality within the APHEA multicity
 971 project." Environmental Health Perspectives **113**(1): 88-95.
- 972 Schmidt, H. and R. Johannsen (2010). Future Development of the EU Directive for Measuring the CO₂
 973 Emissions of Passenger Cars - Investigation of the Influence of Different Parameters and the
 974 Improvement of Measurement Accuracy, Federal Environment Agency, Germany.
- 975 Schrank, D., B. Eisele, T. Lomax and J. Bak (2015). 2015 Urban mobility scorecard, Texas Transportation
 976 Institute, The Texas A&M University System, INRIX Inc: 81.
- 977 Shang, J., Y. Zheng, W. Tong, E. Chang and Y. Yu (2014). Inferring gas consumption and pollution
 978 emission of vehicles throughout a city. 20th ACM SIGKDD International Conference on Knowledge
 979 Discovery and Data Mining, KDD 2014, New York, NY, Association for Computing Machinery.
- 980 Shen, L. and P. R. Stopher (2013). Should we change the rules for trip identification for GPS travel
 981 records? 36th Australasian Transport Research Forum, ATRF 2013, Australasian Transport Research
 982 Forum.
- 983 Sider, T., G. Goulet-Langlois, N. Eluru and M. Hatzopoulou (2015). "Quantifying the effects of input
 984 aggregation and model randomness on regional transportation emission inventories." Transportation.
 985 Smit, R. (2006). An examination of congestion in road traffic emission models and their application to
 986 urban road networks. PhD, Griffith University.
- 987 Smit, R. (2013). "Development and performance of a new vehicle emissions and fuel consumption
 988 software (PΔP) with a high resolution in time and space." Atmospheric Pollution Research **4**(3): 336-345.
- 989 Smit, R. (2014). Australian Motor Vehicle Emission Inventory for the National Pollutant Inventory
 990 (NPI). St Lucia, Australia, UniQuest Pty Ltd: 45.
- 991 Smith, M. C., A. W. Sadek and S. Huang (2008). "Large-Scale microscopic simulation: Toward an
 992 increased resolution of transportation models." Journal of Transportation Engineering **134**(7): 273-281.
- 993 Smith, W. B., A. M. Hainen, S. M. Remias, R. S. Freije and D. M. Bullock (2014). Assessing network
 994 changes attributed to opening a new 67 mile segment of I-69 using field data from bluetooth probe
 995 vehicles. 21st World Congress on Intelligent Transport Systems: Reinventing Transportation in Our
 996 Connected World, ITSWC 2014, Intelligent Transport Systems (ITS).
- 997 Song, B., J. Wu, Y. Zhou and K. Hu (2014). "Fine-scale prediction of roadside CO and NO_x
 998 concentration based on a random forest model." Journal of Residuals Science and Technology **11**(3): 83-
 999 89.
- 1000 Southern, M. (2015). Traffic Management Centre Supervisor at Department of Planning, Transport and
 1001 Infrastructure (DPTI).
- 1002 Spinazzè, A., A. Cattaneo, D. R. Scocca, M. Bonzini and D. M. Cavallo (2015). "Multi-metric
 1003 measurement of personal exposure to ultrafine particles in selected urban microenvironments."
 1004 Atmospheric Environment **110**: 8-17.
- 1005 Steerenberg, P. A., S. Nierkens, P. H. Fischer, H. Van Loveren, A. Opperhuizen, J. G. Vos and J. G. C.
 1006 Van Amsterdam (2001). "Traffic-related air pollution affects peak expiratory flow, exhaled nitric oxide,
 1007 and inflammatory nasal markers." Archives of Environmental Health **56**(2): 167-174.
- 1008 Stevanovic, A., J. Stevanovic, J. So and M. Ostojic (2015). "Multi-criteria optimization of traffic signals:
 1009 Mobility, safety, and environment." Transportation Research Part C: Emerging Technologies **55**: 46-68.
- 1010 Stocker, J., D. Heist, C. Hood, V. Isakov, D. Carruthers, S. Perry, M. Snyder, A. Venkatram and S.
 1011 Arunachalam (2013). H15-78: Road source model intercomparison study using new and existing datasets.
 1012 15th International Conference on Harmonisation within Atmospheric Dispersion Modelling for
 1013 Regulatory Purposes, HARMO 2013, Environmental Software and Modelling Group.
- 1014 Stopher, P. R., S. P. Greaves and L. Shen (2013). Comparing two processing routines for GPS traces -
 1015 Lessons learnt. 36th Australasian Transport Research Forum, ATRF 2013, Australasian Transport
 1016 Research Forum.
- 1017 Su, J. G., M. Jerrett, Y.-Y. Meng, M. Pickett and B. Ritz (2015). "Integrating smart-phone based
 1018 momentary location tracking with fixed site air quality monitoring for personal exposure assessment."
 1019 Science of The Total Environment **506–507**: 518-526.
- 1020 Sun, S., M. Schmeid, D. Bongardt, P. Wüthrich and U. Eichhorst (2014). Modelling energy consumption
 1021 and GHG emissions of road transport in China: technical paper on GIZ CRTEM/HBEFA-China model,
 1022 Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety, Federal
 1023 Republic of Germany: 37.

- 1024 Sun, Z., P. Hao, X. Ban and D. Yang (2015). "Trajectory-based vehicle energy/emissions estimation for
1025 signalized arterials using mobile sensing data." Transportation Research Part D: Transport and
1026 Environment **34**: 27-40.
- 1027 Szwed, P. and K. Pekala (2014). Map-Matching in a Real-Time Traffic Monitoring Service.
1028 Communications in Computer and Information Science, Springer Verlag. **424**: 425-434.
- 1029 Tang, T., J. Zhang, D. Cao, S. Shuai and Y. Zhao (2014). "Experimental study on filtration and
1030 continuous regeneration of a particulate filter system for heavy-duty diesel engines." Journal of
1031 Environmental Sciences (China) **26**(12): 2434-2439.
- 1032 UN-Habitat (2013). Planning and design for sustainable urban mobility. Global report on human
1033 settlements 2013, United Nations Human Settlements Programme.
- 1034 Valavanidis, A., K. Fiotakis and T. Vlachogianni (2008). "Airborne particulate matter and human health:
1035 Toxicological assessment and importance of size and composition of particles for oxidative damage and
1036 carcinogenic mechanisms." Journal of Environmental Science and Health - Part C Environmental
1037 Carcinogenesis and Ecotoxicology Reviews **26**(4): 339-362.
- 1038 Vasantha Kumar, S. and L. Vanajakshi (2014). "Urban Arterial Travel Time Estimation Using Buses as
1039 Probes." Arabian Journal for Science and Engineering **39**(11): 7555-7567.
- 1040 Vlahogianni, E. I. (2015). "Optimization of traffic forecasting: Intelligent surrogate modeling."
1041 Transportation Research Part C: Emerging Technologies **55**: 14-23.
- 1042 WHO (2013). Review of evidence on health aspects of air pollution – REVIHAAP project: final technical
1043 report.
- 1044 Wichmann, H. E. (2007). "Diesel exhaust particles." Inhalation Toxicology **19**(SUPPL. 1): 241-244.
- 1045 Wijayaratna, K., V. Dixit, T. Mao and S. T. Waller (2013). Emissions impacts of transit signal
1046 prioritisation. 36th Australasian Transport Research Forum, ATRF 2013, Australasian Transport
1047 Research Forum.
- 1048 Wu, Z. and L. R. Rilett (2014). Predicting corridor travel time reliability in real time using bluetooth data.
1049 21st World Congress on Intelligent Transport Systems: Reinventing Transportation in Our Connected
1050 World, ITSWC 2014, Intelligent Transport Systems (ITS).
- 1051 Xia, T., M. Nitschke, Y. Zhang, P. Shah, S. Crabb and A. Hansen (2015). "Traffic-related air pollution and
1052 health co-benefits of alternative transport in Adelaide, South Australia." Environment International **74**:
1053 281-290.
- 1054 Xiong, C., Z. Zhu, X. He, X. Chen, S. Zhu, S. Mahapatra, G. L. Chang and L. Zhang (2015). "Developing
1055 a 24-hour large-scale microscopic traffic simulation model for the before-and-after study of a new tolled
1056 freeway in the Washington, DC-Baltimore region." Journal of Transportation Engineering **141**(6).
- 1057 Zhang, H. and H. Cai (2016). Integrating regional travel forecasting model and microscopic traffic model
1058 to assist highway work zone mobility analysis. 2nd International Conference on Geographical
1059 Information Systems Theory, Applications and Management, GISTAM 2016, SciTePress.
- 1060 Zhu, S. (2015). Development of vehicle emissions models for Australian conditions. PhD, University of
1061 Queensland.
- 1062 Zhu, S. and L. Ferreira (2013). "Quantifying errors in micro-scale emissions models using a case-study
1063 approach." Transportation Research Part D: Transport and Environment **21**: 19-25.

1064