

Vehicle emission models alone are not sufficient to understand full impact of change in traffic signal timings

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ABSTRACT

Few studies have considered the real-world impact of changes in traffic signal timings on air pollution and pedestrian exposure with most only drawing their conclusion from vehicle emission models alone. Here, we consider two distinct cycle timings at a junction in London, UK, model the impact using a traffic microsimulation and a NO_x emissions model, and compare these results with NO_x and other air pollution measurements collected during a two-week field study at the junction.

Our models predict that extending the cycle time leads to a 23% decrease in NO_x emissions within a 15 m radius of the junction itself. When the wind direction was such that our sensors were downwind of the junction a 21% decrease in traffic and background-adjusted NO_x concentrations were seen, suggesting that the intervention was successful. However, when the sensors were upwind of the junction, we observed an increase of 23% in adjusted NO_x concentrations. Similar patterns were found for the other pollutants NO₂, lung deposited surface area, black carbon and CO₂ we measured. This indicates that meteorology was by far the greatest determinant of roadside concentrations during our two-week study period.

Looking at pedestrian exposure for pedestrians waiting to cross the road, we found that their NO_x exposure increased by 46% as waiting times to cross the road increased and that potential small reductions in air pollution were offset by increases in waiting times on the main road.

The study demonstrates the need to go beyond assessing the impact of hyper-local traffic interventions on vehicle emissions. Real-world trials over extended periods are required to evaluate the impact of meteorology and changes to air pollution concentrations and pedestrian exposures.

Abbreviations: SB, southbound; NB, northbound; RT, right turn; BL, bus lane; CI, central island; TfL, Transport for London, UK; LGV, large goods vehicle; MG, medium goods vehicle; HGV, heavy goods vehicles; ULEZ, ultra low emissions zone in London, UK.

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1. Introduction

Vehicle tailpipe emissions are known to be highly variable with time and are characterised by very short emission peaks which occur during acceleration or gear change (O'Driscoll et al., 2016; Irwin et al., 2018; Peckham et al., 2020; Leach et al., 2020; Kumar and Goel, 2016; Lyu et al., 2021). This behaviour leads to emission hotspots of various pollutants at signalised junctions and pedestrian crossings. Most notable are high nitrogen oxides (NO_x) and particulate emissions where vehicles must slow down or stop before accelerating back to their regular speed (Woodward et al., 2019, 2023). These elevated emissions at junctions lead to elevated concentrations (Goel and Kumar, 2015a, 2015b; Choi et al., 2018; Krecl et al., 2020; Kim et al., 2014), and therefore higher pedestrian exposure (Zhu et al., 2020; Tan et al., 2017). Additionally, pedestrians tend to spend more time at these locations, waiting to cross the road. The significance of these hotspots causing short-term high exposures, both in terms of their contribution to longer term chronic exposure and their impact on health are not well understood. However, as ambient pollutant concentrations of nitrogen dioxide (NO_2) and particulate matter in UK cities continue to fall (Wentworth and Blake, 2023), the relative importance of these local hotspots and their contribution to pedestrian exposure may increase. As such it is important to understand the impact of traffic signal timings on air pollution concentrations and pedestrian exposure and to investigate how changes in traffic signal timings affect concentrations and exposure levels.

Many modelling studies have been conducted to inform traffic flow management at junctions and to optimize signal timings to decrease vehicle delays both at individual junctions and across networks of streets (Liang et al., 2019; Mihăița et al., 2018; Higuera et al., 2019) and also to decrease vehicle emissions (Madireddy et al., 2011; Olivera et al., 2015; Pérez et al., 2018). These studies rely on the use of a traffic model in conjunction with a vehicle emissions model where applicable. The impact of meteorological conditions on air pollution concentration levels or pedestrian exposure is, however, not generally considered in these studies even though it is known that meteorological conditions such as rain and wind affect pollution levels at the roadside (Kwak et al., 2017; Kim and Guldman, 2011). An exception is the study by Song et al. (2021) which combined particle number concentration of $\text{PM}_{2.5}$ measurements at a junction with modelling to estimate the impact of different signal timings and meteorological conditions on particle number variations. There are also only a few studies which include pedestrian exposure such as e.g. Ishaque and Noland (2008) who quantify the impact of different traffic signal timings on pedestrian exposure using modelled vehicle emissions at different parts of a junction. Zhang et al. (2013) also included an emissions dispersion model using different wind directions to determine signal timings that reduce overall modelled pedestrian exposure. Brimblecombe et al. (2021) show that cyclic traffic lights at a junction in a deep street canyon can impose a cyclic signature to the roadside NO_x signal and that pedestrians can be exposed to very high concentrations for very short periods. None of these studies found have actually measured the effect of a change in traffic signal timings on road side concentrations nor pedestrian exposure in real life though. As all models have limitations and can only give an estimate of what is happening in real life, a comparison with real life measurements is necessary to understand how well a model reflects real life conditions and to better understand traffic management and road design implications on the ground.

In this paper we aim to close this gap by combining a traffic simulation model with a vehicle emissions model to model vehicle behaviour and NO_x emissions. We then compare these results with measured changes in air pollution concentrations at a junction in central London, UK. We also consider pedestrian exposure of pedestrians waiting to cross the road at this junction. The aim of this study is not to find the optimal signal timings for this junction but rather determine whether vehicle emission models are sufficient to capture the impact of a change in traffic signal timings by comparing measured with modelled results and

by considering vehicle behaviour and emissions, air pollution measurements and pedestrian exposure.

Our objectives are to

- (i) implement two distinct traffic signal timings in a simulation and real-world environment;
- (ii) estimate changes in vehicle behaviour using a traffic micro-simulation model;
- (iii) assess NO_x vehicle emissions by using a high-resolution vehicle emissions model;
- (iv) conduct a two-week field study to measure air pollution concentrations, observe meteorological conditions, and determine traffic volumes at the junction for the two distinct traffic signal cycles;
- (v) compare our modelled with our measured results for different meteorological conditions for NO_x and;
- (vi) estimate pedestrian waiting exposure based on our real-world measurements and waiting times to cross the junction.

2. Methodology

There are two main parts to this study: the development and implementation of models and a real-world field study. We first give an overview of the field study location and signal timings. We then explain our traffic microsimulation model followed by an introduction to our instantaneous NO_x vehicle emissions model. Lastly, we describe our roadside measurements including our traffic camera set-up and the computer vision script used, the meteorological measurements and finally our air pollution analysis.

2.1. Study location and field study set-up

A two-week field study was conducted from the 16th until the 27th of September 2019 (Monday to Friday only) between 12 p.m. and 4 p.m. at the signalised junction of London Road with Garden Row in Central London, UK, near Elephant and Castle. This junction was chosen as it is a small junction and any changes in traffic signal timings during the interpeak period were unlikely to cause significant traffic disruption that propagated to other parts of the network. During our study period, two different traffic signal timings were tested on alternating weekdays between 12 p.m. and 4 p.m.

The junction in question consists of three arms, two belonging to London Road and one to Garden Row (Fig. 1). There is a single north-bound (NB) bus lane along London Road open to buses, taxis, motor-cycles and cycles only. Upstream of the junction, in the southbound (SB) direction, there are three lanes open to all traffic of which one is a right turn (RT) lane into Garden Row and the other two lanes continue south towards Elephant and Castle. Garden Row is a one-way street leading away from London Road. Additionally, there are two signalised pedestrian crossings at that junction: one to cross Garden Row and a second one to cross London Road. The London Road pedestrian crossing is south of the junction and is divided by a central island between the SB and the NB lanes. There is a left turn in the SB direction just north of the junction which is ignored in this analysis as it is not part of the signalised junction and only very few vehicles turn left there. This junction lies inside the London Ultra Low Emission Zone (ULEZ), which was introduced in April 2019 in Central London and operates 24 h a day. Vehicles that do not fulfil certain emission standards need to pay to enter this zone (GLA, 2020).

Fig. 1 shows both a schematic and a picture of the area of the monitoring campaign together with details of the traffic lanes and sensor and camera locations. It also shows the two dominant wind directions encountered during the two weeks of our study period.

2.1.1. Signal timings

The traffic signals at the London Road with Garden Row junction are

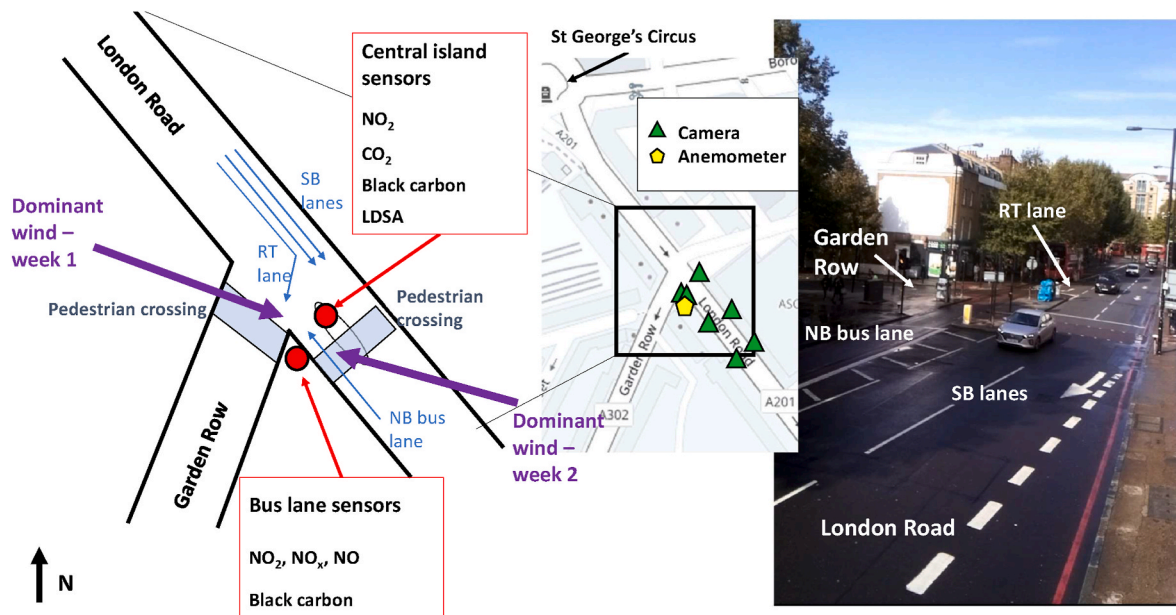


Fig. 1. Map and picture of the field study area including the location of the sensors, cameras, anemometer and pedestrian crossings at the London Road/Garden Row junction. Approximate dominant wind directions as defined in Section 3.2.2 in week 1 (northwesterly) and week 2 (southeasterly) are indicated by purple arrows. NB means northbound, RT right turn and SB southbound. LDSA stands for lung deposited surface area. Base maps and data were taken from OpenStreetMap and OpenStreetMap Foundation. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

normally part of the SCOOT traffic signal system which optimizes the signal timings across London. The traffic signals at this junction usually operate on a 48 s cycle with buses on the NB lane being given priority. For this study, on alternating weekdays between 12 p.m. and 4 p.m., two distinct traffic signal cycles were tested. The first cycle timings were in alignment with the usual cycle timings at the junction and the cycle time was set to 48 s but with fixed green times for vehicles on each arm instead of prioritising NB bus movements (denoted **A-48s** hereafter). The cycle time was increased to 96 s for the traffic intervention (denoted by **B-96s**), with the proportion of green time for buses on the NB lane more than tripled and the proportion of green time for the RT lane roughly halved. As a consequence, the decrease in green time on the RT lane led to an increase in green time for pedestrians crossing Garden Row. See Table 1 for the exact amount of green time each traffic movement was allocated and the proportion of green time of the total cycle time for each movement. As several movements can take place at the same time, these proportions do not add up to 100%.

To compare the amount of total vehicle green time between the two different signal timings, the sum of green time across all vehicle movements was calculated for a 96 s interval (one cycle time during the B-96s cycle and two cycle times during the A-48s cycle). As there is less intergreen time (time between two opposing movements where both

movements have a red signal to allow vehicles to clear the junction) during the B-96s cycle, the overall amount of vehicle green time of 146 s is higher than the 134 s for the A-48s cycle. Appendix A gives more information on when the different traffic movements were called during each traffic signal cycle. These two signal cycle timings used during the field study were decided independently by Transport for London (TfL) based on their own emission modelling.

Our hypothesis was that the B-96s cycle leads to lower emissions and hence lower air pollution concentrations as the traffic flow should be smoother. Additionally, the total green time for vehicles is higher during the B-96s cycle. Furthermore, the proportional increase of green time for NB buses during the extended cycle, which should reduce bus emissions, should also contribute to a general reduction in emissions. In order to test this hypothesis we not only modelled vehicle NO_x emissions for these two traffic signal timings but we also compared our modelled results with data collected during our two-week field study.

2.2. Modelling

We used a PTV Vissim traffic microsimulation model (PTV Group) in conjunction with an instantaneous NO_x vehicle emissions model.

2.2.1. PTV Vissim traffic simulation model

The traffic microsimulation package PTV Vissim version 9.00–12 was used in this study with the model of London Road and Garden Row having been provided and calibrated by TfL. PTV Vissim is a traffic, timestep and behaviour microsimulation model based on traffic flow and traffic signal control models. Apart from a representation of the street network and the traffic signal timings, the model uses as input vehicle counts of different vehicle classifications (e.g. cars, buses, etc.) and returns second by second individual vehicle data including speed and acceleration. The simulation for each of the two traffic signal timings was run for 4500 s including a 900 s warm-up period excluded in the final analysis.

We updated the model provided by TfL with manual junction counts collected in June 2019. We did not use any real-life camera traffic count measurements from the field study in September 2019 as the manual traffic counts provided more accurate vehicle classification information.

Table 1

Green time for each traffic and pedestrian movement during the normal A-48s and the extended B-96s traffic signal time cycles. 'Ped cross' stands for pedestrian crossing. The total vehicle green time over 96 s is the sum of all vehicle green times over one (B-96s) or two cycles (A-48s).

Movement	A-48s normal cycle		B-96s extended cycle	
	Green time (s)	% of 48s cycle	Green time (s)	% of 96s cycle
Southbound (SB)	30	62.5%	62	64.5%
Right turn (RT)	29	60.4%	30	31.2%
Bus lane (NB)	8	16.7%	54	56.2%
Ped cross (London Rd)	8	16.7%	11	11.5%
Ped cross (Garden Row)	5	10.4%	51	53.1%
Total vehicle green time over 96 s	134		146	

However, traffic counts should be similar during our study periods in June and September as neutral days as defined by DfT (2020b) (see Appendix B) were chosen for both studies. See Appendix B for further information about this traffic model.

2.2.2. NO_x emissions model

We applied the high spatial and time resolution NO_x vehicle emissions model developed by Le Cornec et al. (2020) to the results from the microsimulation traffic model. This non-linear regression (NLR) model was extended to include petrol vehicles, large goods vehicles (LGVs), heavy goods vehicles (HGVs) and buses and was used to estimate second by second NO_x vehicle emissions using instantaneous speed and acceleration information of each vehicle in the microsimulation.

As the study area forms part of the London ULEZ, the majority of the vehicles comply with strict emissions standards which are defined as Euro 4 and above for petrol cars and LGVs, Euro 6 and above for diesel cars and LGVs and at least Euro 6 for HGVs, buses and coaches. The NLR model was updated to reflect the ULEZ fleet mix (NAEI, 2018). Further information about the NLR model and how it was adapted for this study can be found in Appendix C.

2.3. Roadside measurements

A number of air pollution sensors, an anemometer and seven cameras were placed near the junction to monitor air pollution concentrations and weather and traffic conditions during our two-week field study.

2.3.1. Traffic cameras

In order to understand the traffic movements along London Road and Garden Row near the junction of interest, seven cameras were attached to lampposts at a height of about 5.20 m. The cameras were connected to Raspberry Pi computers (model Zero W) and filmed the traffic between 6 a.m. and 8 p.m. every day during the study period with a resolution of 720 p and a frame rate of 25 frames per second.

The convolutional neural network YOLO v3 (Redmon and Farhadi, 2018) was used to detect cars/LGVs, HGVs, buses and motorcycles. An intersection over union algorithm (Bochinski et al., 2017) in conjunction with the Hungarian algorithm (Clapper, 2019) were employed for vehicle tracking. If a vehicle was not detected by YOLO at a given frame, the trajectory of the vehicle was estimated using the previous detections of the vehicle to enable a matching with the correct vehicle once YOLO was able to detect that vehicle again (Schroeder et al., 2020). Traffic counts were recorded for each lane and vehicle category on a minute by minute basis. Figure D.6 shows a frame from the video footage once the computer vision script has been applied.

These traffic counts were used to scale the air pollution measurements to remove the effect on air pollution concentrations caused by changes in traffic volumes. We assumed a constant vehicle fleet mix due to having less confidence in the actual vehicle classification performed by the computer vision script.

2.3.2. Meteorology

An anemometer was placed near the air pollution sensors next to the bus lane at about roughly 1.65 m height to measure wind speed and direction at the roadside at a 4 Hz resolution. These data were averaged to a 1-min resolution to reduce noise in the measurements. The traffic camera footage was used to manually determine periods of rain.

2.3.3. Air pollution sensors

Even though our main emphasis were NO_x pollution levels at the junction, we also considered other pollutants. As shown in Fig. 1 earlier in this paper there were two sites where our air pollution sensors were placed: a) next to the NB bus lane right at the junction and b) on the central island in the centre of the junction. The sensors inlets were at a height of about 0.75 m, with the inlets of the central island sensors facing the SB lanes.

(a) NB bus lane (BL) sensors:

- (i) M200E Chemiluminescence NO/NO₂/NO_x sensor (Teledyne Instruments, USA), measuring at a 1-min resolution. We denote the NO₂ and NO_x measurements by NO₂_BL and NO_x_BL respectively; and,
- (ii) AE51 aethalometer (AETHLABS, USA), measuring black carbon at a 1-min time resolution (hereafter denoted by BC_BL).

(b) Central island (CI) sensors:

- (i) Serinus 60 NO₂ sensor (ACOEM Ecotech, Australia) using cavity attenuated phase shift spectroscopy to measure NO₂ at a 1-s resolution (hereafter called NO₂_CI). Note that the rise and fall time of this instrument is 30 s;
- (ii) AE51 aethalometer (AETHLABS, USA) measuring black carbon at a 1-min time resolution (hereafter denoted by BC_CI);
- (iii) Partector (Naneos, Switzerland) measuring lung deposited surface area of ultrafine particles at a 1 s resolution (called LDSA_CI hereafter); and,
- (vi) LI-COR LI-7815 sensor (LI-Cor, USA) measuring CO₂ at a 1 s resolution (called CO₂_CI thereafter).

All of these sensors are high resolution, high quality sensors and are expected to provide reliable readings. See Appendix E for further information about missing data due to issues with the sensors or adverse weather events which shortened the study period on some days. Appendix E also provides further information on sensor checks and data quality.

2.3.4. Analysis of air pollution data

Initial data cleaning involved removing periods where the instruments were still warming up or periods where the NO/NO₂/NO_x sensors were checked for drifts in the output values by using N₂ gas as zero gas. Furthermore, any periods where the sensors were covered by tarpaulins to protect them against heavy rainfall were ignored. Any other periods of light or heavy rain (~ 11% of all data) were also removed as rain can affect traffic speeds and emissions levels (Kwak et al., 2017; Tsapakis et al., 2013) and there was not enough data to look at the additional effect of rain. Sensors measuring with a 1 s frequency were aggregated to 1 min to enable a comparison across all sensors.

As we wanted to understand the effect caused by the change in traffic signal timings on NO_x and other air pollution concentrations, we needed to remove any other effects that could lead to differences in measurements such as background concentrations and differences in traffic volumes.

Background concentrations were removed to isolate the increments resulting from traffic emissions. We assumed that the background sources provided a more long term signal than the traffic emissions which change rapidly as vehicles drive past. For our main analysis we estimated the background of the 1-min data using the minimum concentration over a rolling 4-min window. However, we also considered other background subtraction methods and other time windows as discussed in Appendix F.

Another component that affects air pollution sensor measurements, but which might not be caused by the change in traffic signal timings, is a variation in traffic counts with higher counts usually leading to higher air pollution sensor measurements (see Appendix I). To adjust for differences in traffic volumes once the background had been subtracted from our measured air pollutant concentrations, we calculated the average traffic counts over the past 10 min for each minute within the study period (12 p.m.–4 p.m.). Then, we adjusted the background subtracted concentrations as follows:

$$X_{bg,traf,i} = X_{bg,i} \times T_{max}/T_{av,i},$$

where $X_{bg,traf,i}$ is the traffic and background adjusted air pollutant

concentration at time i , $X_{bg,i}$ is the background adjusted air pollutant concentration at time i , $T_{av,i}$ is the mean traffic count over the past 10 min, i.e. $i - 9$ to i , and T_{max} is the maximum of all traffic counts $T_{av,i}$ across all days (Monday to Friday, 12 p.m.–4 p.m.). This implies that air pollution concentrations were increased proportionally when the 10-min traffic counts were lower than the maximum count. We assumed that the traffic decomposition was the same across all 10-min periods.

A 10-min period was chosen to ensure the traffic counts from the cameras were more stable (10-min counts are significantly more reliable than 1-min counts) but also because it allowed us to capture short time period changes in traffic flows while not being such a short time period that it was affected by flow changes caused by a green or red signal. As discussed in [Appendix K](#), this scaling factor $T_{max}/T_{av,i}$ has only a small impact on our final results, the biggest impact comes from using background subtraction and adjusting for meteorological conditions.

3. Results and discussion

In this section we analyse the model outputs and field study sensor measurements and show the impact that the changes in traffic signal timings have on our modelled vehicle behaviour and NO_x emissions, on our NO_x and other air pollution measurements and finally on pedestrian exposure. For all data comparisons a two-sided Kolmogorov-Smirnov test was used to determine statistically significant differences.

3.1. Modelled results

In this section we present the results from our traffic and vehicle emissions models.

3.1.1. Vehicle behaviour

Using the PTV Vissim traffic model, we estimated some significant changes in vehicle behaviour within a radius of ± 95 m of the junction. For the SB movement we modelled lower average speeds, an increased number of stops and increased average NO_x emission factors upstream of the junction during the B-96s cycle. This indicates longer queue lengths caused by longer red periods. For the NB movement we see the opposite effect as the NB bus lane gets a significantly larger proportion of green time during the B-96s cycle. The RT movement reflects the SB picture but is more pronounced as, apart from having longer red periods in the B-96s cycle, the RT movement also gets significantly less overall green time. [Appendix G](#) contains a detailed analysis of the SB, NB and RT movements using a variety of traffic indices.

Based on our modelled results of vehicle behaviour we would expect overall lower NO_x emissions at the junction during the B-96s cycle as even though we have higher emission factors for the RT movement, this movement has a far lower traffic volume than the SB and NB movements combined ([Table B.4](#)). This supports our hypothesis that the B-96s cycle leads to lower emissions at the junction.

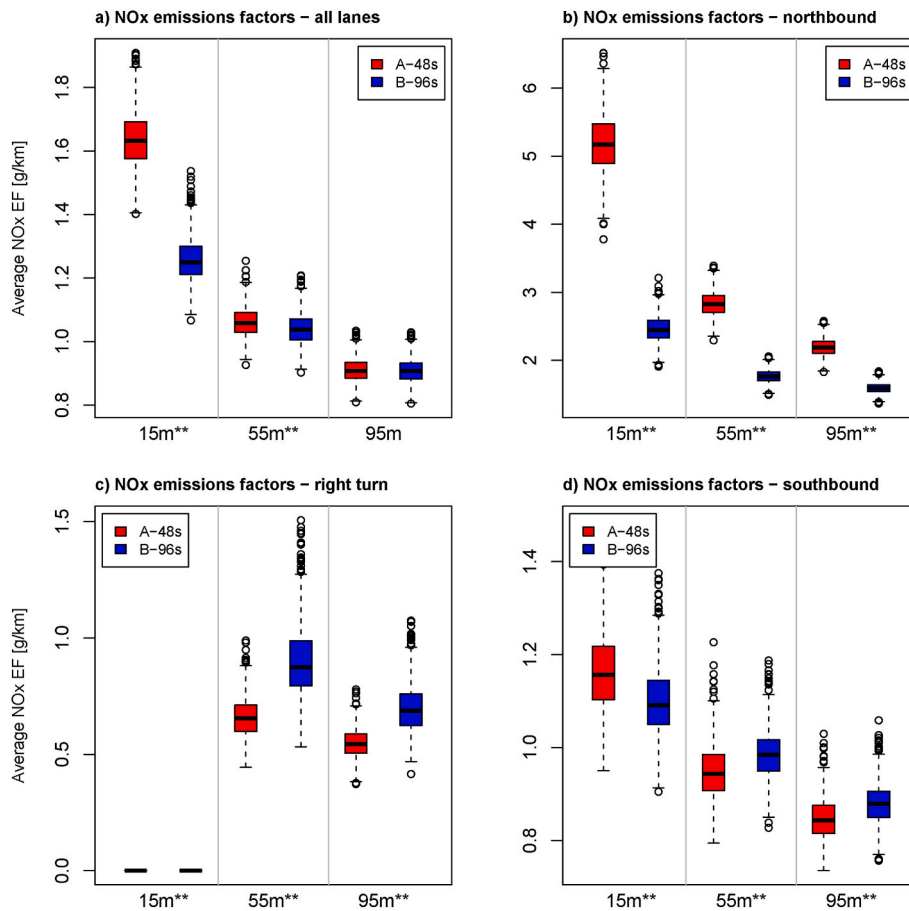


Fig. 2. Average NO_x emissions factors within a 15 m, 55 m and 95 m radius of the junction by direction. A-48s is shown in red and B-96s in blue. A “**” next to the radius indicates a statistically significant change with a p-value < 0.01 . The NB and SB stop lines are about 5 m upstream of the junction centre point, respectively, and therefore, a 15 m radius for the SB direction includes 10 m upstream of the SB stop line and 20 m downstream of it. The RT stop line is further than 15m away from the centre of the junction. The boxes contain the interquartile range (IQR), where $\text{IQR} = Q_3 - Q_1$ and Q_i stands for the i th quartile. The whiskers indicate the range between $Q_1 - 1.5 * \text{IQR}$ and $Q_3 + 1.5 * \text{IQR}$. The black central line within the boxes marks the median. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

3.1.2. Modelled vehicle NO_x emission factors

Fig. 2 shows the average NO_x emission factors within a certain radius of the junction for each of the 1000 NLR runs. Note that the NB and SB stop lines are about 5 m upstream of the junction centre point, respectively, and therefore, a 15 m radius for the SB direction includes 10 m upstream of the SB stop line and 20 m downstream of it, which for Figure G.7 would mean all estimates between -10 m and +20 m. Looking at the average NO_x vehicle emissions within a 15 m, 55 m and 95 m radius of the junction shows the impact of the changes in signal timings on different parts of the road. Recall that the B-96s cycle has proportionally more green time than the A-48s cycle (Table 1).

Fig. 2 shows that within a 15 m radius of the junction the A-48s cycle leads to significantly higher emission factors for several reasons. On the NB lane more buses are accelerating near the junction as the proportion of green time is significantly lower for the A-48s cycle. On the SB lanes the picture is not quite so pronounced as the percentage of green time is similar between the two cycle times. However, since the queues are longer for the B-96s cycle, less accelerating behaviour takes place SB near the junction which explains the higher emission factors for the A-48s cycle. Since the RT movement takes place more than 15 m away from the junction, there are no RT emission factors recorded within a 15 m radius. All results are statistically significant with a p-value < 0.01 using a two-sided Kolmogorov–Smirnov test.

Looking at a 55 m radius around the junction, the A-48s cycle still leads to statistically significantly higher NO_x emission factors, however, the difference between the two traffic signal cycles is less pronounced than within a 15 m radius. While the NB movement still causes significantly lower emission factors during the B-96s cycle times due to increased green times, the SB and RT movements show the opposite picture. As the 55 m radius captures the longer queues on the SB and RT lanes, it also captures most of the acceleration for the B-96s cycle. The reason why the vehicles on the SB lanes produce higher emission factors for the B-96s cycles is most likely caused by longer idling times caused by longer periods of a red signal. For the RT movement there is additionally only about 50% of green time during the B-96s cycle compared to the A-48s cycle.

Within a 95 m radius there is no statistically significant difference between the two cycle timings with a p-value of 0.16. On the NB lane we still observe a statistically significant reduction in emission factors for the longer B-96s cycle time but there is an increase in emission factors for the SB and RT movements. Additional information about the emission factors for the different NB, SB and RT traffic movements can be found in Appendix H.

Thus, based on our modelled results, our hypothesis that the B-96s cycle leads to lower emissions holds at the junction itself but not if we consider the effects upstream and downstream of the junction as well. This highlights the importance of considering effects not only close to the junctions themselves, but within a wider area.

These results are in line with the results in Lv and Zhang (2012), where the traffic signal cycle length was found to have a significant impact on delays but not on the number of stops or overall emissions in the vicinity of the junction.

3.2. Results from the two-week field study

The following section looks at the data collected during the two-week field study in September 2019. We then compare those measurements with the modelled results described in the previous section. In particular, we look at whether our modelled lower NO_x emissions during the B-96s cycle lead to lower NO_x (and other air pollution) concentrations at the junction and how changes in signal timings affect pedestrian exposure for pedestrians waiting to cross the road.

3.2.1. Traffic counts

Overall, there were generally lower traffic counts during the B-96s cycle. However, we are not aware of any reason as to why the B-96s

cycle should have led to lower traffic volumes. To account for this, our pollution concentrations were scaled linearly to adjust our air pollution measurements for different traffic volumes as explained in Section 2.3.4. See Appendix I for a detailed analysis of these traffic counts.

3.2.2. Meteorological conditions

The meteorological conditions were different between week 1 and week 2 of our field study. During week 1 we primarily experienced northwesterly wind and sunshine, whereas in week 2, the wind came mainly from the southeast and it rained on several days. For further analysis, during week 1 we defined wind with direction between 250° and 310° and wind speed between 0 and 1.5 m/s as our **dominant wind** speeds and directions. During week 2 our defined dominant wind directions were between 80° and 140° and the dominant wind speeds between 0.5 and 2 m/s (see Fig. 1). During parts of our analysis we only considered air pollution measurements during those dominant wind periods to account for meteorological conditions.

3.2.3. Measured NO_x concentrations

To look at the effect on NO_x pollution levels during our field study, we adjusted the data for background and traffic and also for meteorological conditions by restricting our analysis to periods during which the wind direction corresponded to the dominant wind direction for each week (see Section 3.2.2). As we had a different dominant wind direction in week 1 compared to week 2, this split the data neatly by week.

Table 2 shows that depending on the wind direction we either see a 23% increase or a 21% decrease in NO_x concentrations at the bus lane sensor. This clearly demonstrates that meteorological conditions have a larger effect on NO_x concentration levels than the change in traffic signal timings and need to be taken into account.

In week 1, the wind predominantly came from the west/northwest and hence, the NO_x sensor next to the bus lane was less affected by NO_x vehicle emissions at the junction itself but rather by what was happening west of the junction as can be seen in Fig. 1. This most likely explains why we see an increase in NO_x concentrations during the first week even though from both our model estimating vehicle behaviour and from our emissions model we would have expected to see a clear decrease. We think that part of this increase might have been caused by different traffic patterns on the Garden Row side road. We also suspect that we are seeing some contribution from the traffic along London Road north of the junction. The dominant wind direction during week 1 is conducive to a street canyon effect, leading to a mixing of pollutants across the width of the street while also dispersing along the SB direction (Woodward et al., 2022).

During week 2, the wind predominantly came from the southeast and so the NO_x sensor was more likely to pick up any changes in emissions from the NB lane upstream of the junction, and the SB lane downstream of the junction. Thus, we see a 21% decrease in NO_x concentrations during the B-96s cycle as expected and in line with our modelled 23% decrease in NO_x emission factors.

No absolute comparison between the modelled NO_x emission factors in Section 3.1.2 and the measured NO_x concentrations is possible as different entities were measured and we also have slightly different traffic volumes and most likely also a slightly different vehicle

Table 2

Measured NO_x concentrations (ppb) at the bus lane adjusted for background, traffic and by dominant wind direction, showing the mean concentrations for each traffic signal cycle, the percentage difference and the p-value using a two-sided Kolmogorov–Smirnov test.

Week	Dominant wind	A-48s mean NO _x (ppb)	B-96s mean NO _x (ppb)	% diff	p-value
Week 1	west/northwest	35.9	44.0	22.6%	< 1%
Week 2	southeast	18.0	14.3	-20.7%	< 1%

decomposition in our model than was observed during our two-week field study. Additionally, the NLR NO_x emissions model was mainly built using emissions from well maintained vehicles which does not necessarily reflect real emissions on the road (Jiang et al., 2021; Wilde et al., 2024). Despite this we saw a similar average NO_x concentration decrease compared to our average modelled decrease in NO_x emissions in week 2 which shows that the intervention was working.

It should be noted that if we do not account for background, traffic and meteorological conditions but consider the measured NO_x concentrations across both weeks as they are, we do indeed see a statistically significant reduction of 18% during the B-96s cycle (Table J.12). However, there is a high degree of heterogeneity between the days even when looking at the same intervention, i.e. even between days of the same intervention there is a large difference between the measured NO_x concentrations. Subtracting the background and adjusting for meteorological conditions and differences in traffic volume decreases this heterogeneity. A detailed description of this analysis can be found in Appendix K. So, adjusting for background, traffic and meteorological conditions is necessary to establish the impact of the change in signal timings.

Additionally, our study took place during the interpeak period and not during peak times. As such, queues were usually cleared in one traffic signal cycle and vehicles only had to stop and start once at most. The results might well look different during peak times when it might take several traffic signal cycles for a vehicle to pass through the junction, especially during the A-48s cycle. In this case, there might be a clearer benefit in extending the cycle time to the B-96s cycle as vehicles would have to stop and start less times.

Even though we only consider two wind directions and two different traffic signal cycles here, we are confident that our results are more generalisable for different locations and wind directions even though we cannot make any predictions about actual concentration levels encountered in different situations. But this study clearly demonstrates that vehicle emissions models alone are not sufficient to predict roadside concentration levels at specific locations at the junction which is in line with the study by Kim and Guldman (2011) which showed that wind directions have a large impact on roadside concentration levels.

3.2.4. NO_x pedestrian exposure

To estimate waiting pedestrian exposure at the junction, the 1-min NO_x concentrations measured across the two weeks for each traffic signal cycle were multiplied by the average time spent waiting at the junction as the waiting time is a major contributor to pedestrian exposure at a junction (Pan et al., 2022). We did not adjust for background, meteorological conditions or traffic in this part of the analysis. If a pedestrian signal is green, then pedestrians can cross immediately without spending any time waiting at the junction. If the pedestrian signal is red, then the average waiting time is the total red time between two green pedestrian signals divided by 2. All results in this section are statistically significant with a p-value < 1% using a two-sided Kolmogorov-Smirnov test.

At the London Road (main road) crossing the time pedestrians spent waiting during the A-48s cycle was on average 16.7 s and during the B-96s cycle 37.6 s. As the total waiting time during the B-96s cycle is more than twice as long as during the A-48s cycle, the small decreases in NO_x concentrations at the junction itself do not lead to decreased pedestrian exposure but has the opposite effect. At the Garden Row (side road) pedestrian crossing, the average waiting times for the two cycles A-48s and B-96s were 19.3 s and 10.5 s respectively with the waiting time of

Table 3

Average pedestrian NO_x (ppb) waiting exposure at both the London Road and the Garden Row crossing during the two signal cycles A-48s and B-96s. A two-sided Kolmogorov-Smirnov test was used.

Location	A-48s mean NO _x (ppb)	B-96s mean NO _x (ppb)	% diff	p-value
London Road (main road)	12.9	23.9	46%	< 1%
Garden Row (side road)	15.0	6.7	-123%	< 1%

the B-96s cycle being nearly half of the A-48s cycle. We therefore see a different effect compared with the London Road crossing as here there is a reduction in pedestrian exposure during the B-96s cycle as can be seen in Table 3.

Hence, in order to determine the effect on pedestrian exposure at a junction not only overall concentrations but also waiting times need to be taken into account. Longer waiting times are likely to lead to higher pedestrian exposure even if air pollution concentrations are lower overall. Here, we saw an overall decrease of non-adjusted NO_x levels of 18% during the B-96s cycle at the bus lane, whereas we saw a 46% increase in pedestrian waiting exposure at the London Road crossing. This was also shown by Ishaque and Noland (2008) who demonstrated in their modelling study that longer cycle times can lead to higher pedestrian exposure for pedestrians waiting to cross the main road but lower exposure for side roads. This clearly demonstrates that just using an emissions model to predict the impact of a change in traffic signal timings is not sufficient to capture the full effects these changes might have on real-life pedestrian exposure as changes in pedestrian waiting times might well play a far larger role than changes in emissions and air pollution levels.

As these waiting times are fairly short, the impact of hyperlocal junctions on overall pedestrian exposure is likely to be small. Nevertheless, traffic interventions such as changes in traffic signal timings are considered useful tools when it comes to reducing pedestrian exposure in London (WSP, 2018). Furthermore, junctions are pollution hotspots with high spikes in air pollution levels (Woodward et al., 2023) and as such add disproportionately to the total exposure. Additionally, as discussed in Woodward et al. (2023), we do not yet understand the mechanism of harm caused by chronic exposure. Harm from chronic exposure may in fact be a result of repeated “acute” exposures such as those which can be experienced by a pedestrian at an intersection. These high level exposures might therefore be not insignificant for population health.

Additionally, it should be noted that longer waiting times to cross a junction can be detrimental to people choosing walking as their mode of transport (Ferrer et al., 2015) and can tempt pedestrians to cross the junction without waiting for a green signal which might increase the likelihood of accidents (Brosseau et al., 2013).

3.2.5. Additional air pollution concentrations at the junction

We also considered the effect of the change in traffic signal timings on the other air pollutants we measured during the two-week field study to show that our measured results are not unique to NO_x. To compare between the different sensors, the data from each sensor were normalised to a scale between 0 and 1 using the minimum and maximum measurements across all data for each analyser. For all the statistical comparisons in this section a two-sided Kolmogorov-Smirnov test was used.

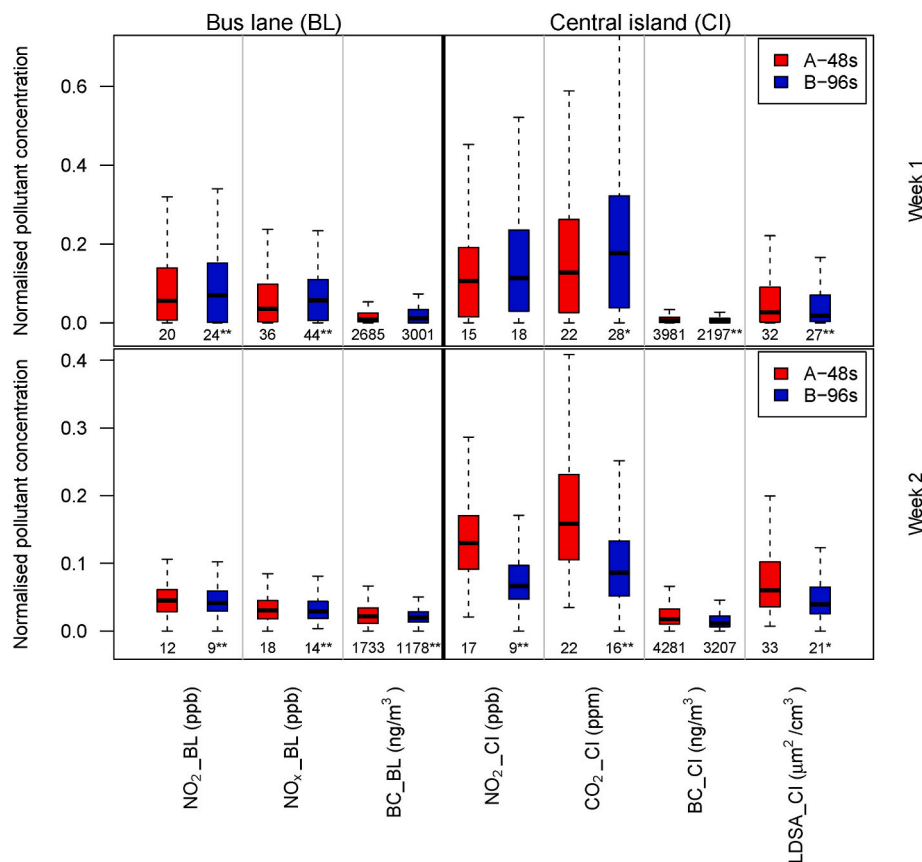


Fig. 3. Normalised junction concentrations with background subtracted and adjusted for traffic and meteorology split by intervention and week. The plots show the normalised concentrations during week 1 (top) and week 2 (bottom). Numbers below the whiskers give the mean concentration for each sensor, intervention and week. A-48s is shown in red and B-96s in blue. A *** next to the mean value indicates a statistically significant change between the two cycle times with a p-value of $< 1\%$, a ** indicates a statistically significant change with a p-value of $< 5\%$. BC stands for black carbon and LDSA for lung deposited surface area. The boxes contain the interquartile range (IQR), where $IQR = Q_3 - Q_1$ and Q_i stands for the i th quartile. The whiskers indicate the range between $Q_1 - 1.5 * IQR$ and $Q_3 + 1.5 * IQR$. The black central line within the boxes marks the median. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Similarly to our NO_x concentrations, we adjusted the data for background and traffic and also for meteorological conditions by only considering data points during dominant wind episodes (see Section 3.2.2). This was to remove as much noise as possible from the data and, as discussed for the NO_x concentrations, this leads to lower heterogeneity between measurements of days during the same signal cycle (see Appendix K). For figures showing the results across all (non-adjusted) data or for the data split by week, please see Figures J.12 and J.13 respectively.

Fig. 3, shows the effect of the changes in traffic signal timings once the data has been adjusted for background, traffic and by dominant wind. We note that the increase in CO_2 measurements at the central island during week 2 were only statistically significant at the 5% but not at the 1% level.

Once these adjustments have been made, the B-96s cycle only shows a statistically significant improvement in week 1 for the black carbon and LDSA concentrations measured on the central island. For all other sensors, there is no statistically significant difference or the A-48s cycle leads to lower concentrations. In week 2, we generally see an improvement in concentrations during the B-96s cycle, although the BC concentration changes on the central island are not statistically significant and the LDSA changes are only significant at the $< 5\%$ level.

As discussed before, in week 1 the wind predominantly came from the west/northwest and hence, the bus lane sensors were less affected by vehicle emissions at the junction itself but rather by what was happening west of the junction, by differences in traffic patterns on Garden Row and by a potential street canyon effect. During this week the central island sensors were downwind of the RT and NB bus lane and therefore likely to be detecting emissions from those lanes. Black carbon and ultrafine particles on the central island seem to be less affected by changes in meteorological conditions as we see a statistically significant decrease in concentration levels during the B-96s cycle even in week 1. However, this could possibly also be explained by the fact that the sensors on the central island primarily detect bus emissions coming from the NB bus lane during week 1. As the buses are at least of Euro 6 standard, NO_2 and particle tailpipe emissions should be fairly low but brake and tyre wear and road dust re-suspension, which are likely lower during the B-96s cycle as buses have to stop less, could influence the black carbon and ultrafine particle measurements (Kim et al., 2021, 2022; Lyu and Olofsson, 2020).

In week 2, the dominant wind came from the east/southeast and hence the sensors were more likely to detect changes in vehicle emissions at the junction itself. Thus, the improved concentration levels during the B-96s cycle were likely to be due to the changes in traffic

signal timings.

We also performed a similar pedestrian exposure analysis to Section 3.2.4 for all the other pollutants which confirmed our findings for NO_x (see Appendix L).

4. Conclusion

Changing the traffic signal timings at the London Road/Garden Row junction in London from a shorter 48s to a longer 96s cycle had various effects on vehicle behaviour, emissions, roadside concentrations, and pedestrian exposure.

Whilst we modelled a significant decrease in NO_x emissions at the junction itself during the extended cycle, we also found that longer queues during the extended cycle just moved the emissions away from the junction and overall emissions within a 95m radius did not change. This shows that the impact of such changes needs to be considered for a wider area.

Despite the significant modelled decrease at the junction, during our two-week field study we found that meteorology dominated locally measured concentrations at the roadside when adjusting our data for background and traffic conditions. When the wind direction was such that the sensors were downwind of the junction we saw statistically significant decreases for NO_x (−21%) and the other pollutants during the extended cycle which was in line with our modelled decrease in NO_x emissions of −23% at the junction itself. When the sensors were upwind of the junction, however, we saw a mixed picture with statistically significant increases of up to 23% for NO_x and decreases of up to 45% for black carbon.

We also found that waiting times to cross the road can have a far larger impact on pedestrian waiting exposure than any changes in concentrations. At the main road crossing we saw a significant increase of up to 46% in NO_x pedestrian exposure while waiting to cross the road as the waiting times at the junction more than doubled during the extended cycle time. At the side road crossing we saw statistically significant decreases of up to 123% in NO_x pedestrian waiting exposure as the waiting times nearly halved.

It is clear from this study that purely looking at vehicle emission models is not sufficient to capture the effects of a change of traffic signal timings as meteorology and pedestrian waiting times play a significant role. Studies should at least consider the impact of the prevalent wind direction at the junction and the effect on the locations where the pedestrians spend time waiting to cross as well as the actual waiting times. A longer study period would be needed to quantify the full impact of the intervention on vehicle emissions, roadside concentrations and pedestrian exposure for a wider range of meteorological and traffic flow conditions.

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Engineering and Physical Sciences Research Council, UK (EP/

Appendices.

Appendix A. Traffic signal timings

In this appendix more information about the different traffic signal movements and at which stage of the traffic signal cycle they are called is given in Figure A.4 and Figure A.5.

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CRedit authorship contribution statement

Anna K. Schroeder: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Huw Woodward:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Clémence M.A. Le Cornec:** Writing – review & editing, Software, Methodology, Investigation, Formal analysis, Data curation. **Thomas Proust:** Writing – review & editing, Software, Methodology, Formal analysis. **Peter J. Benie:** Writing – review & editing, Software. **Shiwei Fan:** Writing – review & editing, Investigation, Data curation. **Elsa Aristodemou:** Writing – review & editing, Resources, Funding acquisition. **Roderic L. Jones:** Writing – review & editing, Supervision, Resources, Funding acquisition. **P.F. Linden:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Audrey de Nazelle:** Writing – review & editing, Supervision, Funding acquisition. **Adam M. Boies:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Marc E.J. Stettler:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Most data are available in the University of Cambridge data repository (<https://doi.org/10.17863/CAM.99720> (Schroeder et al., 2024)) and will be available for at least 10 years from the last access. All the data are stored in accordance with the Data Protection Act 1998. For privacy reasons, video files of the traffic cannot be shared but aggregated traffic count data are available. For commercial reasons, only partial outputs of the PTV Vissim model can be made available.

Acknowledgements

With many thanks to TfL for providing us with their PTV Vissim model of the London Road area and for their signalling support. Many thanks also to London South Bank University for allowing us the use of their buildings to store our equipment.

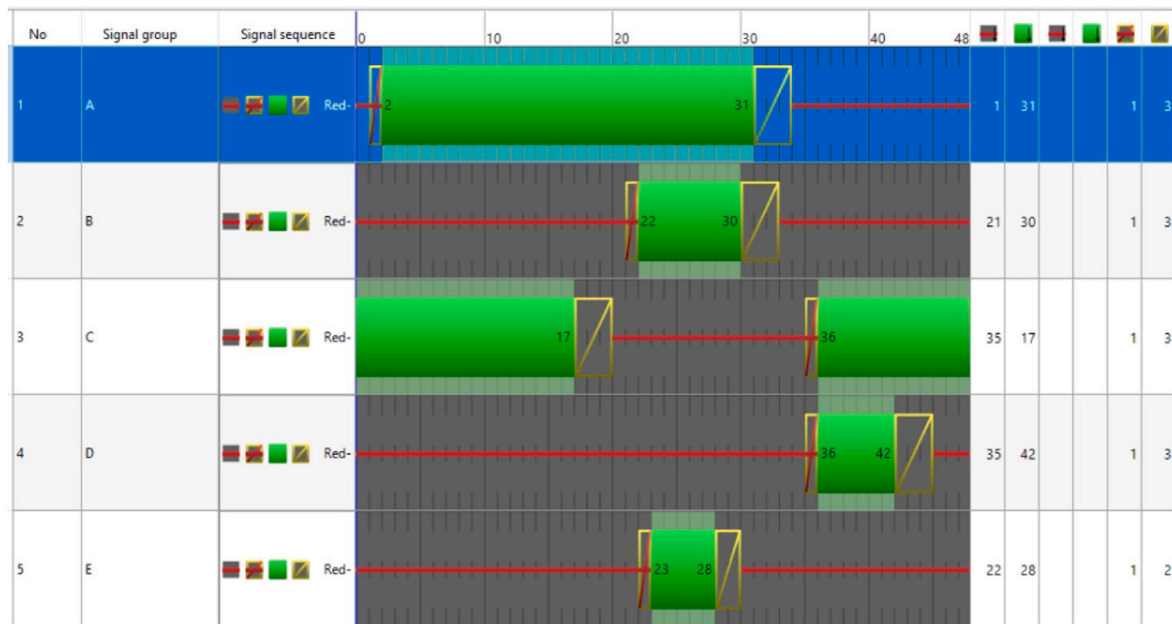


Fig. A.4. Traffic movements during the A-48s cycle. Signal group A indicates the southbound (SB) movement, group B the northbound (NB) and group C the right turn (RT) traffic movement. Groups D and E show the pedestrian crossings on London Road and Garden Row respectively. Green bars indicate green time for each movement, the yellow boxes at either end of the green bars show the amber period and the red lines indicate when the signal for the respective movement was on red.

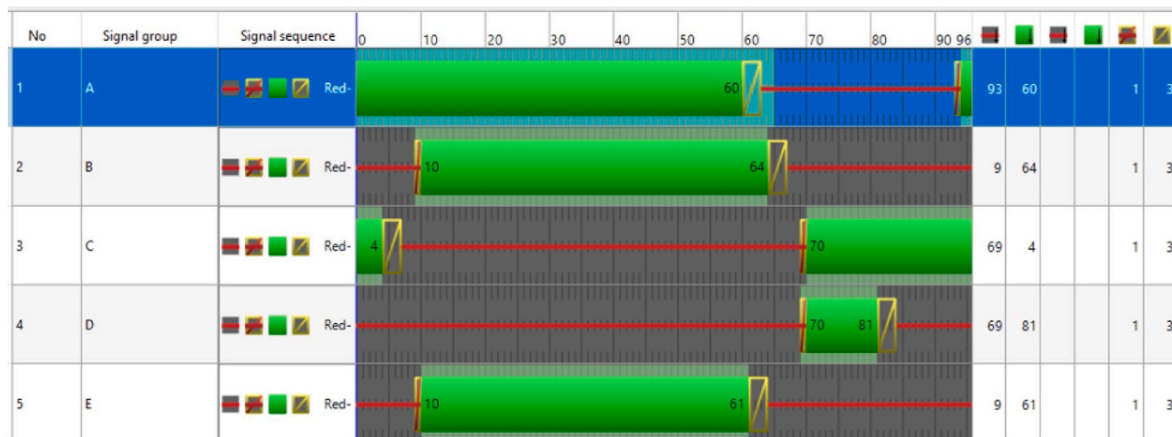


Fig. A.5. Traffic movements during the B-96s cycle. Signal group A indicates the southbound (SB) movement, group B the northbound (NB) and group C the right turn (RT) traffic movement. Groups D and E show the pedestrian crossings on London Road and Garden Row respectively. Green bars indicate green time for each movement, the yellow boxes at either end of the green bars show the amber period and the red lines indicate when the signal for the respective movement was on red.

Appendix B. PTV Vissim traffic model

The PTV Vissim model ([PTV Group, Germany](#)) of London Road obtained from Transport for London, UK, was calibrated using manual junction turning counts collected between 12 p.m. and 2 p.m. on three neutral days in June 2019 for cars/LGVs (large goods vehicles), taxis, MGVs (medium goods vehicles), HGVs (heavy goods vehicles) and buses. Days for traffic counting were chosen to be neutral days (Mondays to Thursdays from March through to November excluding holiday periods) as defined by the Department for Transport, UK ([DfT, 2020b](#)), and should therefore represent the general traffic volume as observed during the field study period which also took place on neutral days. Additionally, based on private communication with TfL, the traffic counts are fairly invariant between 12 p.m. and 4 p.m. on Tuesdays, Wednesdays and Thursdays.

Table B.4 shows the average hourly traffic counts used within the model. Due to the nature of PTV Vissim to better represent real-life variations in traffic flows the actual vehicle numbers differ slightly in each model run.

Table B.4

Manual traffic counts used in PTV Vissim traffic model. SB means southbound, RT right turn, NB northbound, LGV large goods vehicle, MGV medium goods vehicle and HGV heavy good vehicle.

Vehicle	Vissim type	Hourly manual counts			
		SB	RT	NB	Total
Car/LGV	100	369	150	0	519
Taxi	1000	22	19	0	41
MGV	1010	50	10	0	60
HGV	200	14	10	0	24
Bus	300, 900	136	2	79	217
Total		591	191	79	861

Appendix C. NLR emissions model

The high spatial and time resolution NO_x vehicle emissions model NLR developed by Le Cornec (Le Cornec et al., 2020) was applied to the outputs from the PTV Vissim model in order to model instantaneous second by second NO_x vehicle emissions for cars/LGVs (large goods vehicles), HGVs (heavy goods vehicles)/MGVs (medium goods vehicles), buses and taxis.

The underlying passenger car datasets detailing instantaneous vehicle emissions used to build the NLR model were provided by Emissions Analytics (Emissions Analytics) and the Driver and Vehicle Standards Agency (Driver and Vehicle Standards Agency). The LGV and HGV datasets were obtained from TfL (Transport for London, UK) with the respective vehicles being tested under different loads (Moody and Tate, 2017). The bus data were also provided by TfL and consist of ten Euro 5 retrofitted TfL buses with unknown loads tested under real-driving conditions using a portable emissions measurement systems. Nine of these buses were double-decker buses and one bus a single-decker bus (Phantawesak et al., 2021).

Second by second vehicle speed and acceleration behaviour of cars/LGVs, taxis, MGVs, HGVs and buses were modelled in the PTV Vissim network. For emission calculations MGVs were treated as HGVs. These modelled vehicles were then randomly assigned a respective vehicle type in the NLR model in line with the following rules.

Vehicles in the car/LGV category in the PTV Vissim model were randomly assigned as cars or LGVs using the National Atmospheric Emissions Inventory (NAEI) vehicle fleet composition (in terms of vehicle kilometers travelled) for the ULEZ (ultra low emissions zone, London, UK) area with 22% being LGVs (NAEI, 2018). The final distribution of the fuel type and Euro standard distribution for passenger cars was also taken from the NAEI for the ULEZ area (NAEI, 2018) and the engine distribution of the cars follows the engine size distribution in the UK (DfT, 2020a) (see Table C.5). Note that it was assumed that all petrol cars are ULEZ compliant due to a lack of emission data for non-compliant petrol cars. As 99% of petrol cars in central London are ULEZ compliant however, this has no significant impact on the final results. For diesel passenger cars, 85% were assumed to be ULEZ compliant (NAEI, 2018) and the emissions for the remaining 15% were approximated using a range of diesel Euro 5 vehicles. LGVs were assumed to be 82% compliant and all LGVs were assumed to be diesel vehicles. As according to the National Emissions Factor Inventory (NAEI, 2018) 97.4% of LGVs are diesel vehicles this assumption should again not cause any significant issues.

Petrol taxis were assumed to be ULEZ compliant whereas diesel taxis were assumed not to be compliant. That implies that 31% of taxis were assumed to be ULEZ compliant (NAEI, 2018). All diesel taxis were assumed to be Euro 5 diesel vehicles. MGVs and HGVs were assumed to be 90% compliant (NAEI, 2018). Buses and coaches were assumed to be 100% compliant again due to a lack of data but as all TfL buses are ULEZ compliant this should again not impact the final results significantly. Furthermore, all buses were assumed to be double-decker buses in line with the observations from the field study.

The following table, Table C.5, shows the overall engine size and fuel type distribution used for cars.

Table C.5

Distribution of fuel types and engine sizes of cars used in the NLR model

Engine size	< 1000 cc	1001 - 1550 cc	1551 - 2000 cc	2001 - 2500 cc	2501 - 3000 cc	>3001 cc	Total
Petrol	9.3%	27.9%	18.2%	1.0%	1.2%	1.5%	59.1%
Diesel	0%	5.8%	26.1%	5.2%	3.8%	0%	40.9%

Appendix D. Traffic cameras

Figure D.6 shows both a picture of one of the Raspberry Pi cameras used to film the traffic and a frame from the recorded video footage once the computer vision script has been applied. The video frame shows the location of the two traffic counting areas on each lane (in light red, light yellow and yellow) and the individual cumulative counts for each area and vehicle category at the top of the frame. Total counts were taken to be the average across the two counting areas on each lane. Detected vehicles are surrounded by a box where the colour of the box represents the detected vehicle category (turquoise represents motorcycles, purple cars and LGVs and red buses). The number in each vehicle box is a unique number assigned to each vehicle by the computer vision script.



Fig. D.6. Image of one of the cameras attached to a lamppost and frame from video footage showing traffic counting areas on each lane and cumulative traffic counts. Mbike stands for motorbike, NBf stands for front counter on the NB lane and NBb for the back counter. Similarly for the other lanes. SB stands for southbound.

Each of the seven cameras along London Road and Garden Row had a different count accuracy for different lanes looking at 10-min counts which varied between approximately -26% and $+7\%$. These statistics were calculated by comparing 10-min counts from all cameras against manually counting vehicles on the footage. As not all cameras were working at all times, the counts from different cameras had to be used to cover all the lanes during the field study period. This led to an approximate 10-min count bias across all lanes of -1% on most days with the exception of the 17th of September, where we had a count accuracy of approximately -8% , the 18th of September with a count accuracy of -2% and the 25th of September with a count accuracy of -4% . The camera vehicle counts were adjusted accordingly for each day.

Appendix E. Air pollution sensors

The following list gives an overview of the various sensor checks that were carried out to ensure the collected data was as accurate as possible. For a description of the sensors see Section 2.3.3.

M200E Chemiluminescence NO/NO₂/NO_x sensor:

- Sensor was calibrated before the field study.
- Sensor was left running overnight to ensure it was warmed up sufficiently for our study period.
- We used nitrogen gas as zero gas on five occasions during the field study to check for sensor drifts.

Serinus 60 NO₂ sensor:

- Sensor was calibrated before the field study.
- Sensor was switched on 2 h before each study period to ensure the instrument was warmed up.
- We used nitrogen gas as zero gas on five occasions during the field study to check for sensor drifts.

LI-COR LI-7815 sensor:

- Sensor was calibrated before the field study.

AE51 aethalometer black carbon sensors:

- Sensors were factory calibrated but not directly before the field study.

- The two aethalometers used were compared against each other to ensure they were showing similar readings.
- The filters were changed every day.

Naneos Partector LDSA sensor:

- Sensor was factory calibrated but not directly before the field study.

In addition to the above sensor checks, we also performed the following data checks:

- We plotted all data to look for any abnormalities.
- Small negative numbers were set to zero
- We removed any data collected during rain periods
- For some extreme NO₂ values measured on the central island, we checked the camera footage to see whether we could identify any high emitting vehicles that could have caused the spike which was usually the case.

Table Appendix E gives an overview for which days data was missing for the various sensors.

Table E.6

Air pollution sensors used during field study from the 16th until the 27th of September 2019 (Monday to Friday only). BC stands for black carbon and LDSA for lung deposited surface area.

Location	Sensor	Pollutant	Time resolution	Data issues
Bus lane	M200e	NO ₂	1 min	17th missing, 23rd/24th partial
	M200e	NO _x	1 min	17th missing, 23rd/24th partial
	AethB	BC	1 min	17th/20th/23rd/24th partial
Central island	Caps	NO ₂	1 s	18th/23rd/24th partial
	Licor	CO ₂	1 s	23rd/24th missing
	AethCi	BC	1 min	19th missing, 24th partial
	Naneos	LDSA	1 s	19th missing, 24th partial

Appendix F. Background subtraction methods

There are many different ways in which the background concentration of air pollution data can be estimated. We generally estimated the background of the 1-min data using the minimum concentration over a rolling 4-min window.

Background concentrations for NO₂ were plotted for 4-min to 16-min rolling averages in 2-min increments to look at the effect of these different time periods. As there was no big difference between the time periods, we decided that the 4-min period was the most appropriate time period to capture variations caused by changes in the traffic signal timings whilst also filtering out more long-term pollution sources.

Whenever possible we also estimated the background in a different way for comparison as there is no universally agreed method to estimate background concentrations:

- Background estimation for 1-min data:
 - Minimum measured concentration* over rolling 4-min window.
 - London Air Quality Network (LAQN)* sensor data from Elephant and Castle, Horseferry Road and Covent Garden was used to find the minimum measurement for any 15-min time period across those three nearest LAQN background sensors during the study period - for NO₂ only ([London Air](#)).
- Background estimation for 1-s data:
 - 5th percentile* of the measured concentrations on a rolling 4-min window ([Popoola et al., 2018](#)).
 - London Air Quality Network (LAQN)* data same as for the 1-min data - for NO₂ only ([London Air](#)).

Appendix G. Modelled changes in vehicle behaviour

This appendix gives more detail about the modelled changes in vehicle behaviour between the A-48s and the B-96s cycle discussed in Section 3.1.1. All analysis is based on considering a 95 m radius around the junction, the vehicle behaviour was modelled using PTV Vissim and the vehicle emissions are the average results from 1000 runs of the NLR model. Traffic indices reflecting changes in vehicle behaviour were taken from ([Smit et al., 2008](#)). These indices are defined in [Table G.7](#).

Table G.7

Traffic indices used to understand differences in vehicle behaviour

Traffic index	Definition
Mean speed [km/h]	Average vehicle speed
# of stops	Number of vehicles with a speed of less than 5 km/h for at least 2 consecutive seconds during the 1 h simulation run
Total time [s]	Amount of time each vehicle spends in a given area
Idle time [%]	Proportion of time vehicles spend idling with speed equal to 0 km/h
Prop speed fluctuation [%]	Average proportion of time vehicles spend either accelerating > 3 m/s ² or decelerating < - 3 m/s ²

(continued on next page)

Table G.7 (continued)

Traffic index	Definition
Acceleration noise [m/s ²]	Average across all vehicles of $\sqrt{\frac{\sum (a_t - a)^2}{t_{\text{area}}}}$, where a_t is the acceleration at each second, a gives the average acceleration for the respective vehicle and t_{area} is the total time the vehicle spends in the area with speed > 0 km/h
Dec time (< -1 m/s ²) [%]	Average proportion of time vehicles spend decelerating with < -1 m/s ²
Acc time (> x m/s ²) [%]	Average proportion of time vehicles spend accelerating with given acceleration

To understand microscale changes upstream and downstream of the junction, the traffic indices were considered for nine 10 m distance bands upstream and nine bands downstream of the junction. Figure G.7 shows the overall changes for each movement within 10 m distance bands. On the x-axis the distance from the stop lines for each of these movements is given. Distances upstream of the stop lines for each movement are denoted by negative numbers whereas downstream distances are denoted by positive numbers.

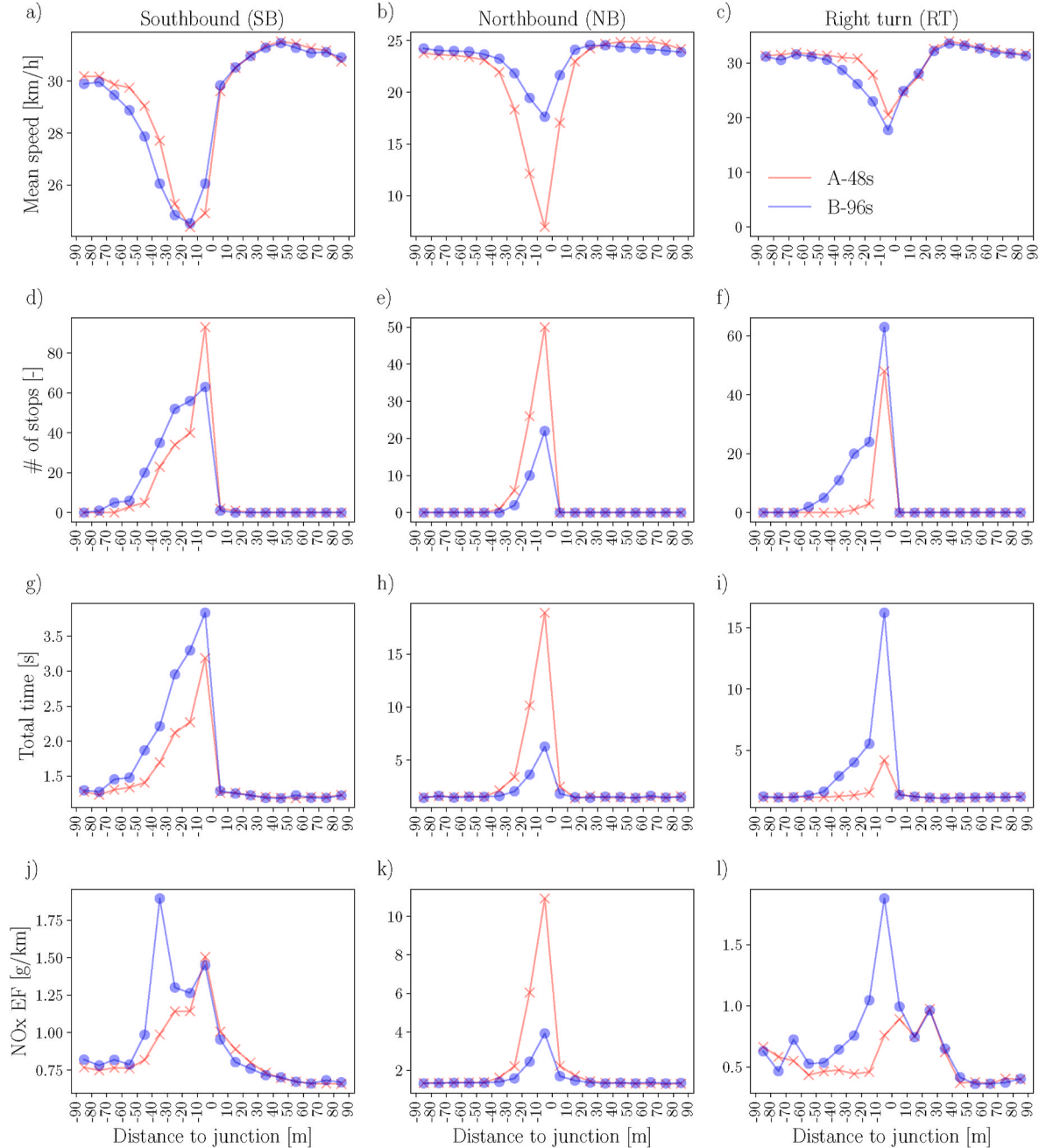


Figure G.7. Modelled differences in vehicle behaviour between the A-48s and the B-96s cycle times by distance to junction. Negative distances on the x-axis show distances upstream of the respective stop lines. Graphs a), b), c) show average vehicle speeds [km/h] for each distance band in the SB, NB and RT direction respectively, d), e) and f) the total number of times vehicles stop, g), h), i) the average time each vehicle spends in each distance band and j), k) and l) show the average NO_x emission factors.

It can be seen in Figure G.7 that for the SB movement the average speed is slightly lower upstream of the junction for the B-96s cycle time which indicates longer queue lengths caused by longer red periods. This is also reflected in the increased number of stops upstream of the junction and the longer time periods each vehicle spends upstream. The increased average NO_x emission factors further away upstream of the junction also support this as acceleration is a large contributor to emissions; as stops occur further away from the junction during the B-96s cycle, acceleration also takes place further away.

For the NB movement we see the opposite effect as the NB bus lane gets a significantly larger proportion of green time during the B-96s cycle. The RT movement reflects the SB picture but is more pronounced as, apart from having longer red periods in the B-96s cycle, the RT movement also gets significantly less overall green time.

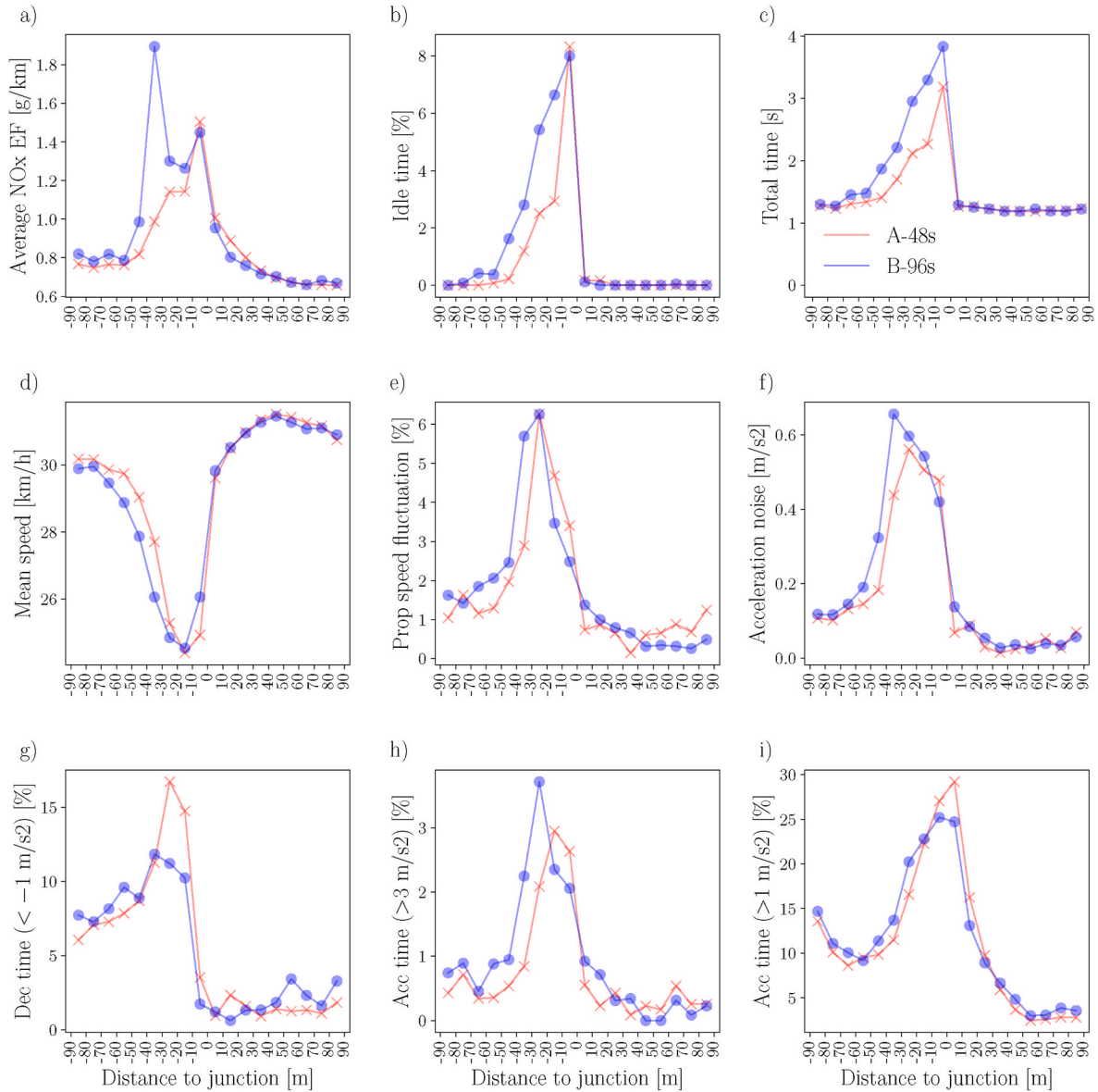


Figure G.8. Traffic indices for the southbound (SB) movement by distance to junction (in meters) based on the modelled vehicle trajectories. Negative distances on the x-axis show distances upstream of the SB stop line. Plot a) gives the mean NO_x vehicle emission factors, plot b) the percentage of time spent idling, plot c) the total mean time a vehicle spends in each distance band, plot d) the mean vehicle speed, plot e) the proportion of speed fluctuation, plot f) the mean time spent accelerating/decelerating $> 3\text{m/s}^2 / < -3\text{m/s}^2$, and plots g), h) and i) the mean time spent decelerating or accelerating. Red and blue lines represent the A-48s and B-96s signal cycles respectively.

A closer look at the SB movement shows longer queues, more stops and higher emission factors upstream of the junction during the B-96s cycle, as can be seen in Figure G.8. The idle time in subplot b) shows the proportion of time spent idling with speed equal to 0 km/h, which again is higher upstream of the junction during the B-96s cycle due to longer queues. This is supported by longer times spent in each band upstream of the junction in subplot c). The proportion of speed fluctuation plot d) shows again more variability in speeds upstream of the junction during the B-96s cycle. The acceleration noise plot f) and the acceleration and deceleration time plots also show higher variability upstream of the junction during the B-96s cycle.

For the RT movement, the patterns observed for the SB movement are even more pronounced as there is significantly less green time during the B-96s cycle (see Figure G.9). As there is significantly more green time for NB buses during the B-96s cycle, we see shorter queues and lower emissions during this extended cycle time (see Figure G.10).

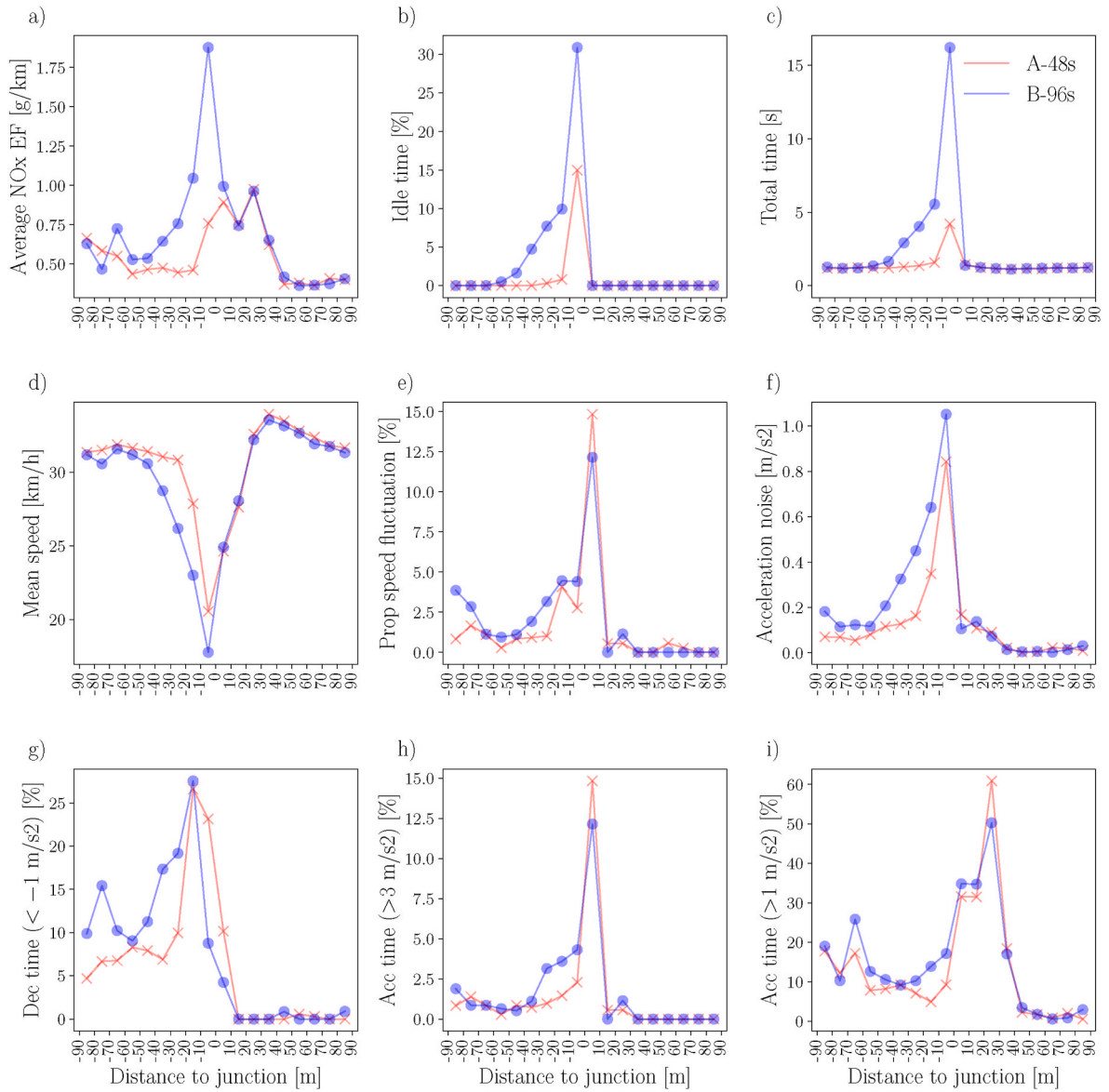


Figure G.9. Traffic indices for the right turn movement (RT) by distance to junction (in meters). Negative distances on the x-axis show distances upstream of the RT stop line. Plot a) gives the mean NO_x vehicle emission factors, plot b) the percentage of time spent idling, plot c) the total mean time a vehicle spends in each distance band, plot d) the mean vehicle speed, plot e) the proportion of speed fluctuation, plot f) the mean time spent accelerating/decelerating $> 3\text{m/s}^2 / < -3\text{m/s}^2$, and plots g), h) and i) the mean time spent decelerating or accelerating. Red and blue lines represent the A-48s and B-96s signal cycles respectively.

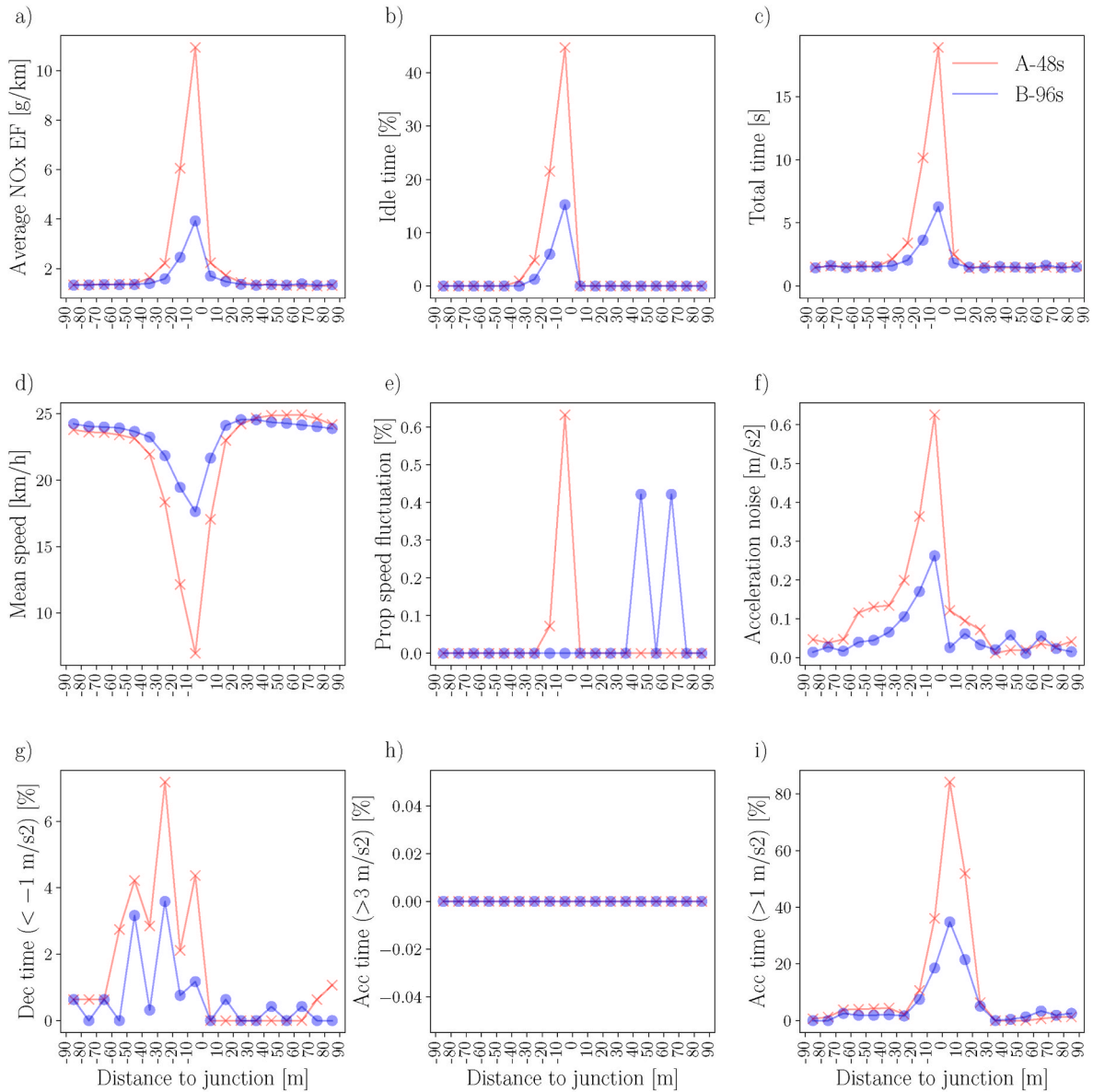


Figure G.10. Traffic indices for the northbound (NB) movement by distance to junction (in meters). Negative distances on the x-axis show distances upstream of the NB stop line. Plot a) gives the mean NO_x vehicle emission factors, plot b) the percentage of time spent idling, plot c) the total mean time a vehicle spends in each distance band, plot d) the mean vehicle speed, plot e) the proportion of speed fluctuation, plot f) the mean time spent accelerating/decelerating $> 3\text{m/s}^2 / < -3\text{m/s}^2$, and plots g), h) and i) the mean time spent decelerating or accelerating. Red and blue lines represent the A-48s and B-96s signal cycles respectively.

Appendix H. Modelled NO_x emission factors

To understand differences in the NO_x emissions of vehicles between the A-48s and the B-96s cycle, the NLR model was run 1000 times, each time assigning a different vehicle make and hence slightly different emission factor to each vehicle in the PTV Vissim model. The p-values quoted are based on two-sided Kolmogorov-Smirnov tests.

Table H.8 shows the NO_x emission factors summary statistics for the two cycle times for all vehicles within a 15 m, 55 m and 95 m radius from the junction. It gives the statistics behind Fig. 2.

Table H.8

Average emissions factors within a 15 m, 55 m and 95 m radius of the junction by direction. The p-values were calculated using a two-sided Kolmogorov-Smirnov test.

Radius	Movement	Mean NO _x EF A-48s (g/km)	Mean NO _x EF B-96s (g/km)	p-value	B-96s < A-48s?
15 m	Total	1.64	1.26	<1%	yes
15 m	SB	1.16	1.10	<1%	yes
15 m	RT	na	na	na	–
15 m	NB	5.18	2.46	<1%	yes

(continued on next page)

Table H.8 (continued)

Radius	Movement	Mean NO _x EF A-48s (g/km)	Mean NO _x EF B-96s (g/km)	p-value	B-96s < A-48s?
55 m	Total	1.06	1.04	<1%	yes
55 m	SB	0.95	0.99	<1%	no
55 m	RT	0.66	0.90	<1%	no
55 m	NB	2.83	1.76	<1%	yes
95 m	Total	0.91	0.91	0.164	no diff
95 m	SB	0.85	0.88	<1%	no
95 m	RT	0.55	0.70	<1%	no
95 m	NB	2.19	1.59	<1%	yes

Looking at the emissions on the SB lanes a bit more closely, it can be seen that different vehicle types lead to different changes in average emissions as can be seen in [Table H.9](#). Within a 15 m radius, the buses and HGVs produce statistically significantly lower emissions during the extended B-96s cycle timings whereas the opposite is true for cars. For buses and HGVs the pattern can most likely be explained by fewer vehicles accelerating near the junction due to longer queues during the B-96s cycle timings. However, for cars we see a different behaviour because cars do not produce such high emissions when accelerating and the time spent idling near the junction, which is higher for the B-96s cycle, is likely to play a larger part.

Considering a larger 55 m radius, the picture changes slightly in that we now have higher bus emissions for the B-96s cycle as well, whereas HGV emissions still show the opposite effect. As most queues are captured within a 55 m radius, differences in acceleration emissions play less of a part when looking at the difference between the two cycle times and increased idling time in the B-96s cycle becomes more important. As buses are at least of Euro 6 standard, whereas only about 90% of HGVs are of at least Euro 6 standard, HGVs have most likely proportionally higher emissions when accelerating which means that slight differences in acceleration behaviour cause lower emissions during the B-96s cycle times. Looking at HGV emissions within a 95 radius, the results are not statistically significant at a 1% level any longer but only at a 5% level.

Table H.9

Average NO_x emission factors (EF) within a 15 m, 55 m and 95 m radius in the southbound direction by mode. The p-values were calculated using a two-sided Kolmogorov-Smirnov test.

Distance	Movement	Mean NO _x EF A-48s (g/km)	Mean NO _x EF B-96s (g/km)	p-value	B-96s < A-48s?
15 m	SB - Car/LGV	0.53	0.56	<1%	no
15 m	SB - HGV	3.43	2.88	<1%	yes
15 m	SB - Bus	1.93	1.81	<1%	yes
55 m	SB - Car/LGV	0.40	0.45	<1%	no
55 m	SB - HGV	2.82	2.70	<1%	yes
55 m	SB - Bus	1.65	1.74	<1%	no
95 m	SB - Car/LGV	0.35	0.38	<1%	no
95 m	SB - HGV	2.52	2.49	<5%	yes
95 m	SB - Bus	1.48	1.56	<1%	no

[Table H.11](#) shows the emissions factors in the NB direction, whereas [Table H.10](#) shows the NO_x emission factors in the RT direction.

Table H.10

Average NO_x emission factors (EF) within a 15 m, 55 m and 95 m radius in the right turn direction by mode. The p-values were calculated using a two-sided Kolmogorov-Smirnov test.

Distance	Movement	Mean NO _x EF A-48s (g/km)	Mean NO _x EF B-96s (g/km)	p-value	B-96s < A-48s?
15 m	RT - Car/LGV	na	na	na	–
15 m	RT - HGV	na	na	na	–
15 m	RT - Bus	na	na	na	–
55 m	RT - Car/LGV	0.44	0.60	<1%	no
55 m	RT - HGV	2.63	3.57	<1%	no
55 m	RT - Bus	na	na	na	–
95 m	RT - Car/LGV	0.36	0.45	<1%	no
95 m	RT - HGV	2.28	2.84	<1%	no
95 m	RT - Bus	na	na	na	–

Table H.11

Average NO_x emission factors (EF) within a 15 m, 55 m and 95 m radius in the northbound direction by mode. The p-values were calculated using a two-sided Kolmogorov-Smirnov test.

Distance	Movement	Mean NO _x EF A-48s (g/km)	Mean NO _x EF B-96s (g/km)	p-value	B-96s < A-48s?
15 m	NB - Car/LGV	na	na	na	–
15 m	NB - HGV	na	na	na	–
15 m	NB - Bus	5.18	2.46	<1%	yes
55 m	NB - Car/LGV	na	na	na	–
55 m	NB - HGV	na	na	na	–
55 m	NB - Bus	2.83	1.76	<1%	yes
95 m	NB - Car/LGV	na	na	na	–
95 m	NB - HGV	na	na	na	–
95 m	NB - Bus	2.19	1.59	<1%	yes

Appendix I. Traffic counts

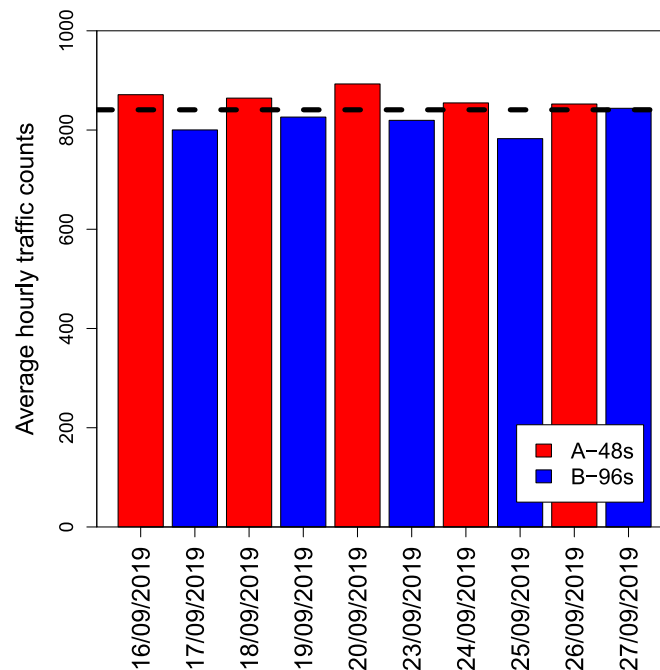


Fig. I.11. Average hourly junction counts between 12 p.m. and 4 p.m. on the 16th to 20th and on the 23rd to 27th of September 2019. The horizontal dotted line indicates the average hourly count across the 10 days.

We adjusted our camera traffic counts depending on from which cameras the traffic counts were used as explained in [Appendix D](#). As can be seen in [Fig. I.11](#) the traffic counts are generally lower on days where the B-96s cycle was in place. However, there is no obvious reason as to why the B-96s cycle should have led to lower traffic volumes as there were no long queues which might have tempted drivers to re-route and given the geography of the area there were no obvious alternative routes. Furthermore, we see the opposite behaviour for vehicle counts between 10 a.m. and 12 p.m. where average hourly counts are higher for days where the B-96s cycle was in place later during the day as the change in traffic signal timings only took place between 12 p.m. and 4 p.m. Since this behaviour between 10 a.m. and 12 p.m. was certainly not caused by changes in traffic signal timings, we are confident that the observed pattern in traffic counts between 12 p.m. and 4 p.m. was just a coincidence. As described earlier in [Section 2.3.4](#), we account for variation in traffic by linearly scaling the pollution concentration by the traffic counts.

Appendix J. Air pollution measurements

This appendix gives more details about the air pollution concentrations measured at the junction during the two-week field study discussed in [Section 3.2.5](#). All p-values are based on two-sided Kolmogorov-Smirnov tests.

Air pollution sensor data at a 1-min resolution show a statistically significant decrease in concentrations for the B-96s cycle (not accounting for traffic or meteorological conditions). To compare between the different sensors, the data from each sensors were normalised to a scale between 0 and 1 using the minimum and maximum measurements across all data for each analyser. [Figure J.12](#) shows the resulting statistics.

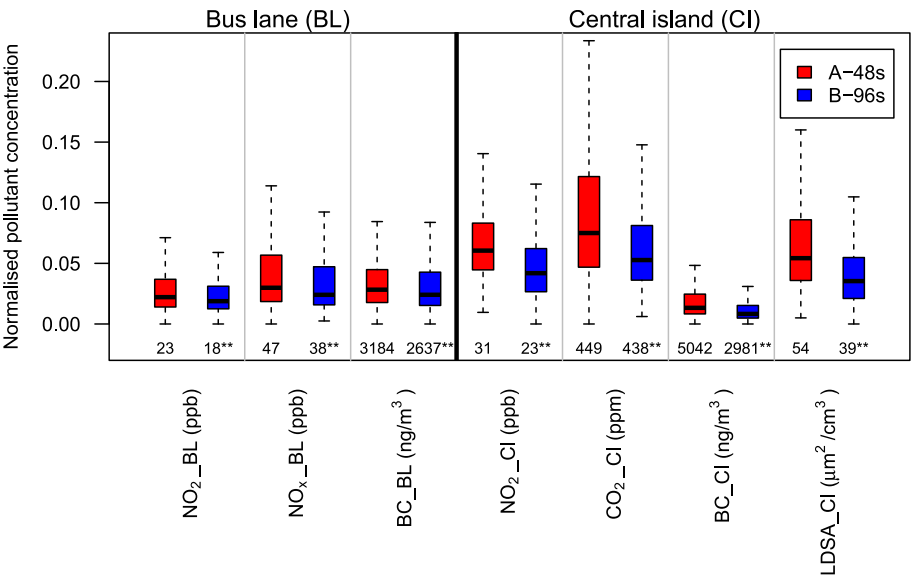


Figure J.12. Normalised junction concentrations across both weeks split by intervention. Numbers below the whiskers give the mean concentration for each sensor and intervention. A-48s is shown in red and B-96s in blue. A “**” next to the mean value indicates a statistically significant change between the two cycle times with a p-value of < 1%. BC stands for black carbon and LDSA for lung deposited surface area. The boxes contain the interquartile range (IQR), where $IQR = Q_3 - Q_1$ and Q_i stands for the i th quartile. The whiskers indicate the range between $Q_1 - 1.5 * IQR$ and $Q_3 + 1.5 * IQR$. The black central line within the boxes marks the median.

Table J.12 shows the average measured minute by minute concentrations for all sensors across both weeks. It corresponds to Figure J.12. It does not account for either weather conditions, nor traffic and background concentrations.

Table J.12

Junction concentrations across both weeks split by intervention. For B-96s we see a statistically significant reduction with a p-value < 0.01 relative to A-48s. Std stands for standard deviation, BC for black carbon and LDSA for lung deposited surface area.

Location	Pollutant	Unit	A-48s mean	B-96s mean	% diff	A-48s std	B-96s std	p-value
Bus lane	NO2	ppb	22.7	18.5	−18.7	34.7	25.8	<1%
	NOx	ppb	46.6	38.1	−18.1	56.8	48.4	<1%
	BC	ng/m3	3183.7	2637.3	−17.2	4904.6	3640.9	<1%
Central island	NO2	ppb	31.3	22.7	−27.4	21.4	13.2	<1%
	CO2	ppm	449.4	438.5	−2.4	28.7	19.5	<1%
	BC	ng/m3	5041.8	2980.5	−40.9	11049.5	6322.3	<1%
	LDSA	μm2/cm3	54.1	38.6	−28.6	51.3	40.9	<1%

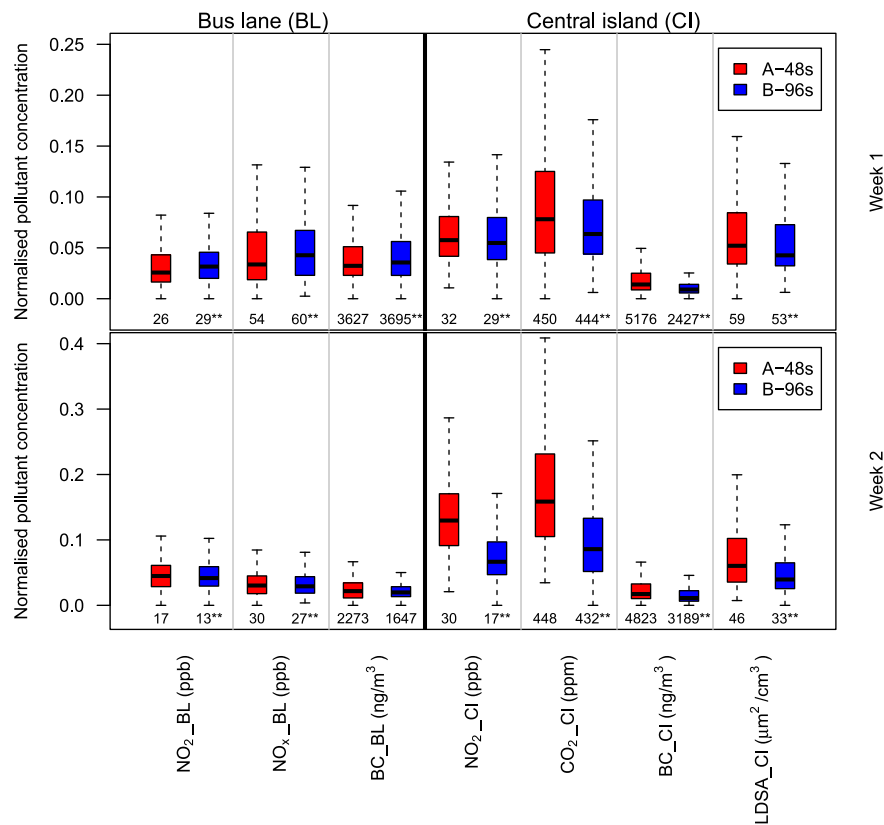


Figure J.13. Normalised junction concentrations split by intervention and week. The plots show the normalised concentrations during week 1 (top) and week 2 (bottom). Numbers below the whiskers give the mean concentration for each sensor, intervention and week. A-48s is shown in red and B-96s in blue. A ‘***’ next to the mean value indicates a statistically significant change between the two cycle times with a p-value of $< 1\%$. BC stands for black carbon and LDSA for lung deposited surface area. The boxes contain the interquartile range (IQR), where $IQR = Q_3 - Q_1$ and Q_i stands for the i th quartile. The whiskers indicate the range between $Q_1 - 1.5 * IQR$ and $Q_3 + 1.5 * IQR$. The black central line within the boxes marks the median.

Examining the data by week, as there were significant differences in the meteorological conditions between the two weeks (see Section 3.2.2), the data show a slightly different picture in each week, see Figure J.13. In week 1, we observe an increase in concentrations at the bus lane sensors during the B-96s cycle but a decrease on the central island. In week 2, the aethalometer at the bus lane does not show any statistically significant differences between the two interventions but for all other sensors the B-96s cycle leads to a reduction.

Generally, the concentrations in week 1 were higher than in week 2 with the exception of the black carbon concentrations at the central island during the B-96s cycle. These differences are most likely caused by changes in the meteorological conditions. The B-96s cycle was run for three days during the second week but only two days during the first week, whereas the A-48s cycle was run for two days during the second but three days during the first week. As the concentrations in week 2 were generally lower, you would expect lower average concentrations during the B-96s cycle if you consider all the data (without splitting by week) purely caused by changes in meteorology between the two weeks. In order to understand the impact caused by the change in traffic signal timings it is therefore important to look at each week independently.

Table J.13 shows the average minute by minute air pollution concentrations split by week. It does not account for either weather conditions, nor traffic and background concentrations and corresponds to Figure J.13.

Table J.13

Junction concentrations split by intervention and week. The top half shows the concentrations during week 1 and the bottom half during week 2. The p-values were calculated using a two-sided Kolmogorov-Smirnov test. Std stands for standard deviation, BC for black carbon and LDSA for lung deposited surface area.

Location	Pollutant	Unit	Week	A-48s mean	B-96s mean	% diff	A-48s std	B-96s std	p-value
Bus lane	NO2	ppb	Week 1	25.6	29.5	15.3	37.7	39.6	<1%
	NOx	ppb		54.3	59.9	10.3	63.1	65.3	<1%
	BC	ng/m3		3626.7	3694.7	1.9	5035.1	4826.2	<1%
Central island	NO2	ppb	Week 1	31.9	29.4	-8	22.9	14.1	<1%
	CO2	ppm		450.1	443.6	-1.4	30.4	21.2	<1%
	BC	ng/m3		5176.3	2427.5	-53.1	11717.4	2481.3	<1%
	LDSA	µm2/cm3		59.2	52.7	-11	53.2	50.4	<1%
Bus lane	NO2	ppb	Week 2	16.5	12.9	-22.2	26.1	10.9	<1%
	NOx	ppb		29.9	27.1	-9.3	34.6	31.8	<1%
	BC	ng/m3		2272.8	1646.9	-27.5	4497.4	1361.8	0.14
Central island	NO2	ppb	Week 2	30.4	17.2	-43.3	18.7	9.4	<1%
	CO2	ppm		447.6	432	-3.5	23.3	14.8	<1%
	BC	ng/m3		4822.7	3189.3	-33.9	9875.6	7253.1	<1%
	LDSA	µm2/cm3		45.6	33.3	-27.1	47	35.2	<1%

Importantly though, there is a high degree of heterogeneity between the days even when looking at the same intervention, i.e. even between days of the same intervention there is a large difference between the measured air pollution concentrations. However, subtracting the background, and adjusting for meteorological conditions and differences in traffic volume decreases this heterogeneity. A detailed description of this analysis can be found in [Appendix K](#).

[Table J.14](#) gives the average minute concentrations once the background has been subtracted using the 4-min minimum concentration and the data has been adjusted for different traffic volumes. Furthermore, only data points where the wind came from the dominant direction in week 1 and week 2 (see [Section 3.2.2](#)) were considered.

Table J.14

Junction concentrations with background subtracted, adjusted for traffic, split by intervention and week and only using dominant wind measurements. The top half shows the concentrations during week 1 and the bottom half during week 2. The p-values were calculated using a two-sided Kolmogorov-Smirnov test. Std stands for standard deviation, BC for black carbon and LDSA for lung deposited surface area.

Location	Pollutant	Unit	Week	A-48s mean	B-96s mean	% diff	A-48s std	B-96s std	p-value
Bus lane	NO2	ppb	Week 1	20.2	24.4	20.7	28.1	34.7	<1%
	NOx	ppb		35.9	44	22.6	58.7	66.8	<1%
	BC	ng/m3		2685.1	3000.7	11.8	7423.2	7991.5	0.06
Central island	NO2	ppb	Week 1	15.2	18.2	19.7	16.9	19.1	0.1
	CO2	ppm		21.8	27.7	27.4	22.3	26.9	<5%
	BC	ng/m3		3980.7	2196.7	-44.8	16377.8	3920.1	<1%
	LDSA	µm2/cm3		31.8	27.4	-13.8	58.4	52.6	<1%
Bus lane	NO2	ppb	Week 2	11.9	9.2	-23.2	24	14.6	<1%
	NOx	ppb		18	14.3	-20.7	32.8	24.1	<1%
	BC	ng/m3		1733.2	1178.2	-32	2596.5	1789.9	<1%
Central island	NO2	ppb	Week 2	16.5	8.8	-46.5	25	11.8	<1%
	CO2	ppm		21.7	15.8	-27.1	23.1	20.5	<1%
	BC	ng/m3		4281.4	3206.9	-25.1	12461.9	6199.6	0.42
	LDSA	µm2/cm3		32.9	21.2	-35.6	65.9	45.6	<5%

Appendix K. Homogeneity of air pollution measurements

In this appendix we look at the homogeneity of air pollution concentrations measured on different days but during the same intervention. [Table K.15](#), shows the percentage of pairs of days where there is no statistically significant difference between the concentrations of the two days in question. If we have sensor data for three days (day1, day2, day3) of intervention e.g. A-48s, then there are 3 day pairs (day1 with day2, day1 with day3 and day2 with day3) to consider. If one of these pairs has concentrations that are statistically significantly different from each other but the other two pairs show no difference, then the table entry would be 67 (%). A 100 (%) for all sensors and interventions would imply that all days for that sensor and intervention showed similar pollution levels. Thus, if the difference between the A-48s and the B-96s interventions were statistically significantly different, then this difference would be purely due to changes in the traffic signal timings.

Table K.15

Percentage of homogeneity between days of the same intervention for different sensors and data. Red indicates low homogeneity whereas blue indicates high homogeneity. The 'BG method' show whether the data has been adjusted by subtracting the background using either the 4 min minimum method ('4min'), LAQN data ('LAQN') or the 5th percentile method ('5th perc') or not ('-'). The 'Traffic adj' column shows whether the data has been adjusted for traffic. 'Time res' indicates the time resolution of the data and 'Data' shows whether the data has been adjusted for wind conditions, where 'All Data' means no adjustment, 'Mat wind' indicates that data points were matched by wind conditions and 'Dom wind' shows that only dominant wind data points were used.

				Bus Lane						Central Island							
				BC		NO ₂		NO _x		BC		LDSA		NO ₂		CO ₂	
BG method	Traffic adj	Time res	Data	48s	96s	48s	96s	48s	96s	48s	96s	48s	96s	48s	96s	48s	96s
-	no	1min	All data	0	0	10	17	0	17	20	0	20	0	50	10	0	17
-	no	1min	Mat wind	20	0	20	17	20	17	30	67	30	33	50	10	50	67
-	no	1min	Dom wind	25	0	25	33	75	33	25	33	75	33	50	75	33	50
4min	no	1min	All data	20	10	20	17	20	17	60	17	50	83	30	30	50	17
4min	no	1min	Mat wind	50	50	60	50	40	33	80	67	90	100	60	30	50	100
4min	no	1min	Dom wind	50	25	25	33	75	33	100	33	75	100	75	100	100	100
LAQN	no	1min	All data			10	17							40	20		
LAQN	no	1min	Mat wind			30	50							50	20		
LAQN	no	1min	Dom wind			75	33							50	100		
4min	yes	1min	All data	20	10	20	17	20	17	60	17	60	83	30	20	50	33
4min	yes	1min	Mat wind	50	50	60	50	40	33	80	67	90	100	60	20	50	100
4min	yes	1min	Dom wind	50	25	25	33	75	33	100	33	75	100	75	75	100	100
LAQN	yes	1min	All data			10	17							30	20		
LAQN	yes	1min	Mat wind			30	33							50	10		
LAQN	yes	1min	Dom wind			75	33							50	75		
-	no	1s	All data									0	0	0	0	0	0
-	no	1s	Mat wind									0	0	0	0	0	0
-	no	1s	Dom wind									25	67	0	0	33	50
5th perc	no	1s	All data									0	0	0	0	0	0
5th perc	no	1s	Mat wind									10	0	0	0	0	17
5th perc	no	1s	Dom wind									0	33	0	0	33	50
5th perc	yes	1s	All data									0	0	0	0	0	0
5th perc	yes	1s	Mat wind									0	0	0	0	0	0
5th perc	yes	1s	Dom wind									0	33	0	0	33	50

Table K.15 is structured as follows: The *BG method* columns shows if no background has been subtracted '-' or if the background has been subtracted which method was used ('4min' - 4 min minimum, 'LAQN' - LAQN data, '5th perc' - 5th percentile method (see Appendix F)). The column *Traffic adj* indicates whether the data has been adjusted for traffic and the column *Time res* which time resolution the underlying data had. The *Data* column shows whether all data was used or whether the data was adjusted for wind directions. 'Mat wind' means that for each entry from day 1 an entry was found (without replacement) on day 2 with a wind direction within $\pm 20^\circ$ of the day 1 measurement and within ± 0.3 m/s of the wind speed of the day 1 measurement. 'Dom wind' only uses data points that fall within the dominant wind categories as discussed in Section 3.2.2. It should be noted that for the dominant wind there were at most 4 day pairs to be considered as there were only at most two days of one intervention during one week (1 pair) and three days during the other week (3 pairs). For the other comparisons, there were at most 10 pairs. However, as we did not collect data on all sensors on all days, there were often fewer pairs. It can be seen that adjusting for wind (green rows in table) always improves the homogeneity of the data.

The left hand columns indicate the percentage of homogeneity for the different sensors and traffic signal cycles. The B-96s cycle shows slightly more homogeneity but there is not much difference between the two cycle timings.

It can be seen that there is very low homogeneity between the days when we consider the raw data, i.e. without any adjustments for background, traffic or wind, and with each additional adjustment made, the homogeneity improves. Interestingly, for the 1 min data, the 4-min minimum subtraction method seems to work slightly better for the NO₂ concentrations measured at the central island, whereas using measurements from the London Air Quality Network as background seems to work better for the NO₂ concentrations measured at the bus lane. For consistency we only considered the 4-min minimum method in our further analysis.

Adjusting for traffic once the background has been subtracted does not make much difference to the results, probably because subtracting the background already adjusts for differences in traffic volume to a large extent. It should also be noted that there is a lower homogeneity between the days at the bus lane, most likely because wind plays an important role in whether the bus lane sensors primarily pick up the vehicle emissions from London Road or not. As the central island sensors were placed in the centre of the junction, they always picked up the signal from the road.

As can be seen there is significantly lower homogeneity between the days when considering the 1 s data which justifies our approach to only consider the 1-min data in our analysis.

Appendix L. Pedestrian exposure tables

In this section we look at pedestrian exposure for all pollutants. Pedestrian exposure was calculated by determining the average waiting times at each of the pedestrian crossings and then multiplying this waiting time by the average 1-min concentrations observed during the two-week field study. We did not adjust for background, traffic or meteorological conditions in this analysis. As discussed in Section 3.2.4, at London Road the pedestrians

spent on average 16.7 s waiting during the A-48s cycle and 37.6 s during the B-96s cycle. As the total waiting time during the B-96s cycle is significantly longer, this leads to increased pedestrian exposure as can be seen in Figure L.14 and the corresponding Table L.16.

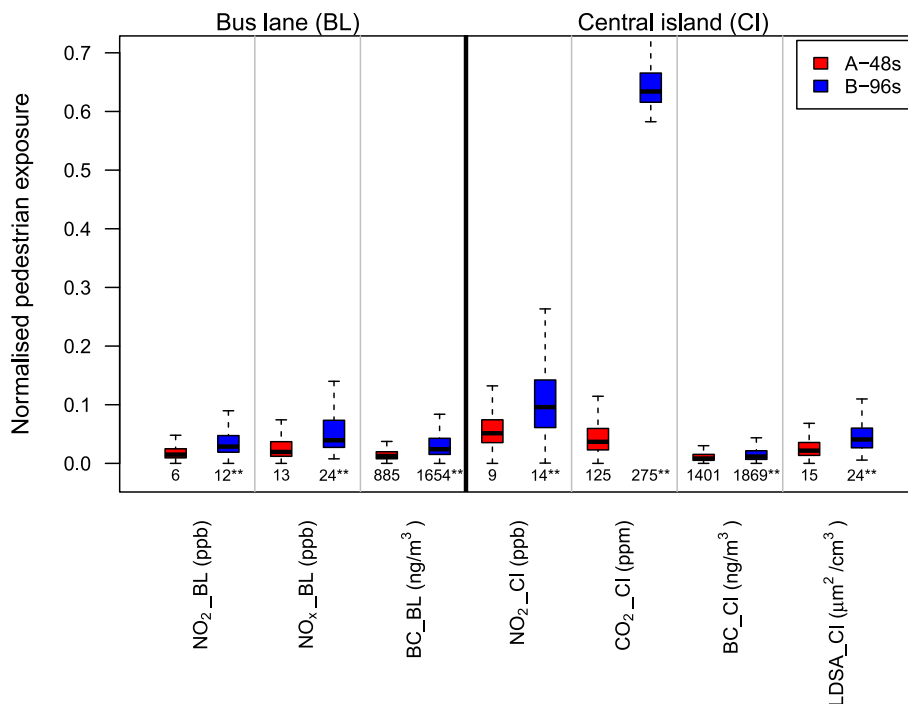


Figure L.14. Pedestrian waiting exposure at London Road crossing. Numbers below the whiskers give the mean exposure for each sensors and intervention. A-48s is shown in red and B-96s in blue. A *** next to the mean value indicates a statistically significant change between the two cycle times with a p-value of < 1%. BC stands for black carbon and LDSA for lung deposited surface area. The boxes contain the interquartile range (IQR), where $IQR = Q_3 - Q_1$ and Q_i stands for the i th quartile. The whiskers indicate the range between $Q_1 - 1.5 * IQR$ and $Q_3 + 1.5 * IQR$. The black central line within the boxes marks the median.

Table L.16

Average pedestrian waiting exposure at London Road crossing. The p-values were calculated using a two-sided Kolmogorov-Smirnov test. BC stands for black carbon and LDSA for lung deposited surface area.

Location	Pollutant	Unit	A-48s mean	B-96s mean	% diff
Bus lane	NO ₂	ppb	6.3	11.6	46%
	NO _x	ppb	12.9	23.9	46%
	BC	ng/m ³	884.4	1654.0	47%
Central island	NO ₂	ppb	8.7	14.2	39%
	CO ₂	ppm	124.8	275.0	55%
	BC	ng/m ³	1400.5	1869.3	25%
	LDSA	μm ² /cm ³	15.0	24.2	38%

The reason why there is such a large difference in the CO₂ measurements on the central island is because there is very little impact caused by the two traffic signal timings (i.e. there is only a −2.4% reduction during the B-96s cycle) and therefore the effect of increased waiting times is larger than for the other pollutants where we saw a larger decrease in pollutant concentrations of between −17% and −41% during the B-96s cycle (see Table J.12). So, for most pollutants except CO₂ the increase in waiting times is partially offset by a decrease in air pollution levels.

At the Garden Row pedestrian crossing, we estimated a 19.3 s waiting time during the A-48s cycle and a 10.5 s waiting time during the B-96s cycle leading to a clear reduction in pedestrian exposure as can be seen in Figure L.15 and the corresponding Table L.17. Note that only the concentrations at the bus lane sensors are shown as they were closest to the Garden Row crossing. Further information about the pedestrian exposure statistics can be found in Appendix L.

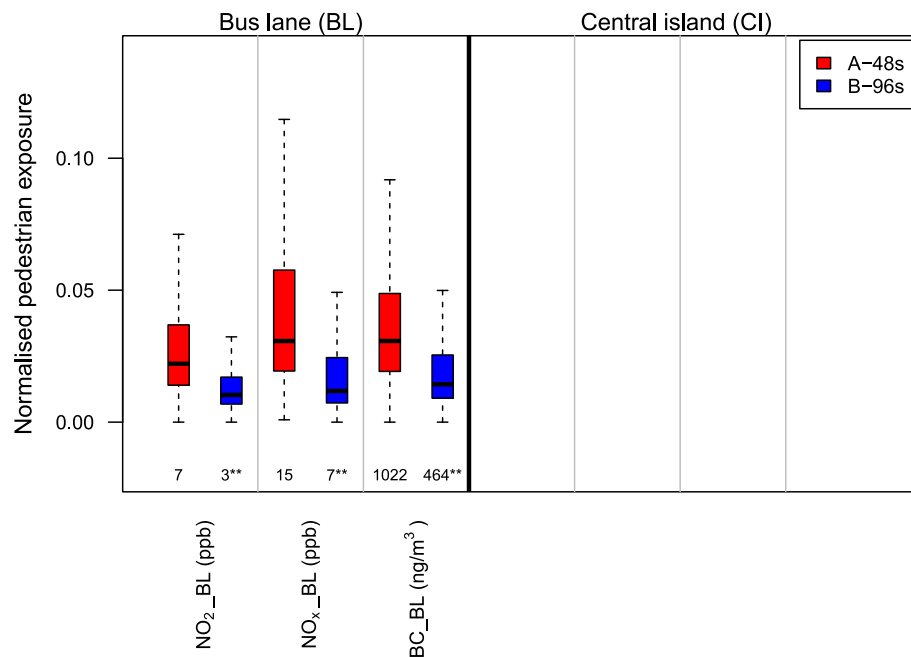


Figure L.15. Pedestrian waiting exposure at Garden Row crossing. Numbers below the whiskers give the mean exposure for each sensors and intervention. A-48s is shown in red and B-96s in blue. A “***” next to the mean value indicates a statistically significant change between the two cycle times with a p-value of < 1%. BC stands for black carbon. The boxes contain the interquartile range (IQR), where $IQR = Q_3 - Q_1$ and Q_i stands for the i th quartile. The whiskers indicate the range between $Q_1 - 1.5 * IQR$ and $Q_3 + 1.5 * IQR$. The black central line within the boxes marks the median.

Table L.17

Average pedestrian waiting exposure at Garden Row crossing. The p-values were calculated using a two-sided Kolmogorov-Smirnov test. BC stands for black carbon.

Location	Pollutant	Unit	A-48s mean	B-96s mean	% diff
Bus lane	NO2	ppb	7.3	3.3	-124%
	NOx	ppb	15.0	6.7	-123%
	BC	ng/m3	1022.0	463.6	-120%

As discussed before, this clearly demonstrates the need to consider pedestrian waiting times and the location of where pedestrians spend the most time waiting to cross a road in any traffic signal analysis to avoid any unintended consequences.

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