Respiratory-Aware Routing for Cyclists
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Abstract

Cyclists travelling in urban areas are particularly at risk of harm from these emissions due to their increased breathing rate and proximity to vehicles. Our objective in this paper is to present a framework for routing of cyclists to mitigate the effects of pollution. However, in contrast to classical exposure based studies that are based on ambient pollution levels and travel times, the work presented here is also based on individualised fitness and physiological parameters. A key finding of this work is that statistical analysis of random synthetic commutes in London demonstrate that the impact of street-level pollution is significantly higher for less fit individuals. Further, our work suggests that pollution inhalation highly-polluted areas may be modulated through an increase of cycle velocity. These findings establish personalised travel optimisation as an effective method of reducing pollution risk, improving the net benefits of active commuting.

Keywords: PM2.5, urban commuting, bicycle routing.

Nomenclature

| Term | Definition |
|------|------------|
| PM2.5 | Particulate matter with diameter less than 2.5 µm |
| RDD | Received deposition dose, the mass of particulates deposited in the lungs |
| MMD | Mass-median diameter, the diameter of the median-weighted particle in a given sample or mass fraction |
| VR | Ventilation rate, the volume of air breathed per minute |
| HR | Heart rate, the number of beats per minute |
| P | Mechanical power required to traverse a segment |
| η_mech | Mechanical efficiency of the bicycle transmission |
| C_r | Resistance coefficient of rubber tyres on asphalt |
| C_d | Drag coefficient of the cyclist |
| m | Mass of the cyclist, bike and any luggage |
| g | Gravitational constant |
| Δh | Change in vertical height over a road segment |
| l | Length of the road segment |
| v | Travel velocity of the cyclist |
| ρ | Air density |
| A | An estimate of the frontal area of cyclist and bike |
| τ_r | Time coefficient for HR with step change in P |
| c | Gradient defining steady-state HR with increasing P |

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1 Introduction

In 2018, 417,000 deaths were attributed to PM2.5 exposure across Europe [1]. These fine pollutant particles can penetrate far into the respiratory system when inhaled, leading to an increased occurrence of cardiac arrest, stroke, asthma, reduced lung function and dementia from both long and short-term exposures [2]. Road vehicles are a significant contributor to PM2.5 concentrations in cities through emissions from incomplete combustion and tyre wear, with commuters receiving a high proportion of their daily exposure while commuting [3]. However, commute exposure can be difficult to quantify, resulting in limited awareness amongst cyclists of the potential risks of frequent or prolonged exposure while commuting [4]. Note, in contract to the prevailing narrative, vehicle electrification will not eliminate vehicle induced particulate generation as non-tailpipe emissions (tyre, road and brake emissions) are a growing problem due to the increased vehicle weight and power of electric vehicles. With urban traffic forecast to increase 51% by 2050 [5] and the cost of poor air quality to the NHS set to rise to £10 billion by 2035 [6], quantifying and mitigating the pollution risk of urban travel is critical. Interventions aimed at commuting are uniquely positioned to have huge impact on an individual’s annual exposure, with the repetition of journeys providing an ideal environment for routing-based optimisation at an individual level. Existing literature establishes two key factors affecting the pollution-routing problem: the level of pollution on each route segment and the duration of exposure. In this paper, further considerations are introduced relating to the power necessary to propel the cyclist along each route segment and the fitness of the individual. It’s well-documented that active journeys result in significantly higher breathing rates than passive ones due to their higher power requirement, and therefore the total volume of particulate pollutants inhaled is also higher across an identically-polluted route [7] of equal travel time. This higher risk can be quantified using the received deposition dose (RDD, µg) metric, which represents the mass of pollutant particles which remain in the lungs of an individual after exhalation. For an average adult male, RDD is reported to be more than 2.5 times higher for cycle than car journeys [3], however little research has been conducted into the extent to which an individual’s physiological factors can impact the validity of these generalised predictions. Therefore this paper presents an investigation into the extent that personalised commute optimisation could reduce this risk, improving the net benefit of active commuting.

Our objective is to use RDD as a metric that individuals may use to determine a portfolio of routes when commuting based on RDD being below some threshold (a pollution budget). Our rationale is based on findings in [7] illustrating a trade-off between the cardiovascular benefit of cycling, and RDD, with the negative impact of RDD eventually overcoming the benefit of cycling. For every individual and every pollution exposure, there exists a risk that is dependent on both the individual’s received dose and the benefit derived from the physical activity. Moreover, the paper [7] presents a methodology for estimating a break-even point in the cost-benefit analysis of urban cycling for an average male in a city’s average level of pollution. Given the requisite physiological and environmental data, which could be gathered through real-time sensing and inference, this method could be adapted to provide an estimate of a maximum allowable pollution dose for an individual’s commute. Specifically, our idea is to allow cyclists to specify an upper limit of RDD as a function of an individual commute. This makes the route optimization not only highly personalised but also complex, depending on pollution levels along each route, average travel times, and the cyclist’s inhalation rate. This latter aspect has hitherto not been addressed in route optimization algorithms for cyclists, and offers a new dimension in route guidance. For example, a consequence of our approach is that individuals with the same origins and destinations would be offered different routes depending on their level of fitness.

![Figure 1: Proposed framework for Respiratory-Aware Routing.](image)

2 The Personalised Pollution-Routing Problem

The proposed system consists of two components. The first, a low cost sensing platform for cyclists, is depicted in Figure 2. Cyclists use the sensors to monitor pollution levels along their routes and share this information with other cyclists. The second component, which is the focus of this note, is a suite of analytics to enable personalised routing for cyclists.

A. Sensing platform

While not the focus of this present work, we refer the reader to the low cost sensing platform developed by the authors to support the personalised route guidance advocated in the note; full details of the hardware system
developed as an add-on to a standard bike can be found in the corresponding author’s thesis. Full details of the hardware design, the sensor calibration methodology, and their hardware systems validation can be found therein. We note that the feasibility of collecting cheap and accurate real-time pollution data has been demonstrated in a number of projects; see, for example, the iSCAPE citizen sensing project which deployed a large-scale, low-cost fixed air quality monitoring system. In order to overcome the issues of calibration and meteorological sensitivity seen with low-cost PM sensors, the authors derive a calibration model based on co-location to improve the validity of sensor readings. A similar method was used in this work to collect and calibrate PM2.5 measurements in real-time using a low-cost sensing module designed to be mounted onto a commuter’s bicycle, as shown in Figure 2. The remainder of this note we focus on the analytics platform that exploits data harvested from these sensors.

![Figure 2: The sensor could be mounted to the handlebars, beneath the saddle or to the bicycle frame to measure PM2.5 concentrations in real time.](https://abilangbridge.com/respiratory_aware_routing_thesis/)

B. Analytics

Calculation of an individual’s RDD on a given journey is based on the method in [10]. Four parameters are required: the mass-median diameter (MMD) of the particles inhaled; the individual’s sex; their ventilation rate; and the background exposure at the point of inhalation. MMD and background exposure vary spatio-temporally, but are not dependent on the individual. Ventilation rate is dependent on the terrain being cycled, the travel velocity, and the individual’s efficiency as an athlete. As such, the optimisation is built up using several models to capture these underlying relationships. These models are detailed in the Appendix.

B.1. Analytics - Exposure Duration and Power Cost

For the purpose of this analysis, road segments were discretised according to OpenStreetMap definitions: trun-

cated by junctions, signals and road layout changes. Each segment was assigned an expected velocity under the assumption that the cyclist’s velocity is near-uniform across the entire segment. The power required to traverse a given road segment at velocity \( v \) was calculated from first principles using the method shown in Equations 1 and 2, with parameter estimations for frontal area and drag coefficients detailed in [11]. Efficiency estimates for the bicycle transmission \( \eta_{mech} \) are from [12].

\[
\begin{align*}
P_{required} &= \frac{P_{gradient} + P_{friction} + P_{air}}{\eta_{mech}} \quad (1) \\

P_{gradient} &= mg \frac{\Delta h}{l} v \\

P_{friction} &= C_r mg v \\

P_{air} &= \frac{1}{2} C_d \rho A v^3 \quad (2)
\end{align*}
\]

Note that \( P_{gradient} \) in Equation 2 may be negative for downhill road segments, but is strictly positive in Equation 1 as it represents the human input power to traverse the edge.

B.2. Analytics - Individual Fitness

To estimate the impact of an individual’s fitness on the pollution risk of each road segment, a number of models were synthesised to facilitate the translation from the geometry of a road segment and an expected velocity to pollution dose.

B.3. Analytics - Heart and Ventilation Rate

The cyclist’s heart rate (HR) was estimated using a method presented in [13], which modelled the HR response to power steps as a first-order differential equation. By modelling the transition between route segments as a power step, this model was used to estimate the change in HR across a given route. Equation 3 was then used to calculate the HR at time \( t \) since the segment change \( t_0 \). For simplicity, a conservative calculation was adopted where the HR at \( t = t_N \), the end of the road segment, was assumed to have been constant throughout the segment. [13] also presents a method for accounting for the memory effect of power output on HR, however due to the reported moderate intensity of cycle commutes, this analysis was neglected in this implementation [14]. These simplifications resulted in an underestimation of the RDD for each segment, however they facilitated the use of linear optimisation methods, hugely reducing computation time as compared to a dynamic programming implementation. Further, for a personalised application, both historic and real-time heart rate data could easily be extrapolated from previous commutes to produce an accurate and individualised estimate of HR throughout the
journey, reducing the impact of simplifications.

\[
HR(t) = \begin{cases} 
\text{IF } HR(t) < HR_{\text{max}} \\
HR_{\text{SS}}(P(t)) + \left( HR_{\text{SS}}(P(t)) - HR(t_0) \right) e^{-\frac{t}{\tau_r}} \\
\text{ELSE } HR_{\text{max}}
\end{cases}
\]

(3)

To estimate the cyclist’s ventilation rate (VR) for each segment, an individualised model for correlation between HR and VR could be derived using historic data. \[15\] presents the results of the TRAVEL study monitoring the commutes of 34 participants, in which individual models were derived for each participant using spirometry equipment. The study also presents generalised models, stratified by sex, which were used in this optimisation to simulate generic synthetic cyclists.

B.4. Analytics - Recieved Deposition Dose

There are various models for calculating RDD, including deterministic and stochastic methods. For this study, a model outlined in \[10\] was used due to its relative simplicity, repeatability and low computational cost to facilitate real-time calculation. The PM2.5 mass-median diameter (MMD) for primary and secondary vehicle emissions at street level was estimated using data presented in the supplementary materials of \[10\]. The MMD of PM2.5 particles varies with environment, traffic distribution and time, however there is little data to support the development of a spatially-varying model and hence a constant value was used \[3\].

B.5. Analytics - Optimisation Formulation

The aim of our algorithm is to minimise the total RDD across each route as in Equation 4. This is formalised as a shortest path problem over a weighted travel graph with edge weights corresponding to the cost function. This implementation facilitated the future expansion of the cost function to account for other factors such as journey time or calorific cost which may reflect the more complex interdependencies in commuters’ priorities.

\[
\text{minimize } \sum_{e \in E} RDD(e_i, s, v) \\
\text{subject to } e_0 = O, e_N = D, e \in \mathcal{P}(E)
\]

where \( G = (V, E, \phi) \) is the directed travel graph, \( e \) the route being evaluated between origin \( O \) and destination \( D \), and \( e_i \) the \( i \)th segment of route \( e \). \( \mathcal{P}(E) \) is the power set of \( E \), i.e. all subsets of \( E \) producing a valid route \( e \). \( s \) is the subject-specific physiological parameters, and \( v \) the travel velocity.

3 Case Studies

To investigate the effects of the optimisation on routes between a fixed origin and destination for different individuals and at different velocities, two case studies were conducted. The first explored the inter-subject variation seen between ‘fit’ and ‘unfit’ subjects, while the second investigated the effect of expected velocity on optimal route for the fit subject. Both studies utilised synthetic subjects rather than real individuals as the methods for deriving these parameters from data are beyond the scope of this paper. The subjects were labelled X and Y respectively, and the physiological parameters used for the optimisation are detailed in Table 1. The \( HR_0 \), \( HR_{\text{max}} \), time coefficient \( \tau_r \) and rise constant \( c \) were selected from the ranges given in [14] to represent fit and less fit subjects respectively, though it’s not clear if these ranges are representative of the commuting population. Mass and sex were estimated from National Travel Survey 2020 data for cyclists \[16\].

| Subject | X   | Y   |
|---------|-----|-----|
| Mass (kg) | 90  | 100 |
| Sex     | M   | M   |
| \( HR_0 \) (bpm) | 60  | 100 |
| \( HR_{\text{max}} \) (bpm) | 180 | 180 |
| \( \tau_r \) (s) | 30  | 24  |
| \( c \) (bpm\cdot W^{-1}) | 0.15 | 0.45 |

3.0.1 Real-Time Calculation

The RDD model was also modified to calculate pollution risk for commutes in real-time using data collected from \[https://github.com/gboeing/osmnx\].
the sensing module. GPS data from the sensing module was used to calculate the travel velocity between each pair of measurements and the power exerted by the subject over that interval. HR and VR were then calculated by estimating the physiological parameters of the cyclist as in the optimisation model, with RDD calculated by combining these with the real-time PM2.5 measurement from the low-cost sensor. The Python code used to produce the results in the following section is available on the author’s GitHub.

4 Results

4.1 Inter-Subject Variation

Very high inter-subject variation was seen across RDD, with the less fit subject Y experiencing 175% more RDD compared to subject X over only a 6% longer journey. Subject Y’s journey also required more energy to be exerted as summarised in Table 2. The different optimal routes are illustrated in Figure 3. Statistical analysis of Table 2: Summary metrics for the optimal routes calculated for each subject.

| Subject | Time (mm) | Distance (km) | RDD (µg) | Energy (kJ) |
|---------|-----------|---------------|----------|-------------|
| X       | 27.1      | 9.03          | 28.40    | 90.7        |
| Y       | 28.9      | 9.63          | 78.17    | 102.3       |
| %age Δ  | 6.64      | 6.64          | 175      | 12.8        |

Figure 3: Illustration of the optimal routes for subject X (green) and subject Y (blue).

500 pairs of routes revealed that the optimal route RDD is significantly higher for subject Y ($P < 0.001$), with the mean RDD for the fit subject 28.3177 µg and for the unfit subject 79.8307 µg, as shown in Figure 4.

To investigate the effect of small variance in individual fitness between these fit and unfit subjects, nine synthetic subjects were designed to produce a uniform interpolation between subject X and Y. The average RDD across 500 routes for each subject was then compared, showing strong positive correlation in Figure 5.

4.2 Intra-Subject Variation

To further explore the effects of power output on RDD, the effect of modifying the travel velocity from 15 to 25 kph for the fit subject was investigated. While the optimal routes in this study varied less significantly, likely due to constraints imposed by the travel graph, some origin-destination pairs showed notable contrast between subjects. One example is summarised in Table 3 and illustrated in Figure 6. The faster route was less direct, however the total distances are similar. By travelling 10 kph faster, the fast route reduced journey time by 7 minutes and RDD by more than a third, though the energy required was almost twice that of the slow route. An analysis of 500 routes was conducted, with optimal RDD higher at lower velocity ($P < 0.001$). The mean RDD for the 15 kph commute was 37.3959 µg and for the 25 kph commute 23.0348 µg.
Table 3: Summary metrics for the optimal routes calculated for subject X at 15 and 25 kph.

| Subject | Time (mins) | Distance (km) | RDD (µg) | Energy (kJ) |
|---------|-------------|---------------|----------|-------------|
| X (15 kph) | 18.4 | 4.60 | 19.29 | 44.6 |
| X (25 kph) | 11.7 | 4.86 | 12.24 | 78.8 |
| %age ∆ | -36.4 | 5.65 | -36.5 | 76.7 |

Figure 6: Optimal routes for the 25 kph (red) and 15 kph (green) cases.

4.3 Real-Time RDD Calculation

In this experiment, pollution data collected by a series of low-cost sensors over 32 commutes is used to investigate the efficacy of using mean exposure as a proxy for RDD. Four routes were cycled throughout the study, either ending (AM) or beginning (PM) at Imperial College London’s South Kensington campus. The individualised parameters used for this analysis are those of the idealised fit commuter from Table 1, to enable comparison of pollution risk between the four routes as if they were an individual’s commute alternatives.

Table 4: RDD for an idealised commuter with parameters equal to those of subject X was calculated for each of four routes and stratified by direction.

| Route | AM | PM |
|-------|----|----|
|       | Mean Exposure (µgm⁻³) | Mean RDD (µg) | Mean Exposure (µgm⁻³) | Mean RDD (µg) |
| A     | 11.07 | 56.10 | 10.34 | 59.39 |
| B     | 10.75 | 56.74 | 11.68 | 67.94 |
| C     | 14.97 | 53.15 | 13.75 | 61.87 |
| D     | 18.67 | 45.08 | 9.601 | 11.53 |

As Table 4 shows, there is little correlation between the mean exposure and the mean RDD experienced on a given route, with the RDD metric providing evidence that there is different risk associated with each of the four routes.

Figure 7: Histograms and probability density functions showing the difference in characteristics between the slow and fast journeys’ RDD.

Despite the similar mean PM2.5 concentration recorded in the PM direction, the RDD on route D is significantly lower due to the shorter length of the commute, which is not reflected in the exposure metric.

5 Discussion

All case studies support the proposed need for a highly individualised routing system that accounts for both physiological parameters and journey characteristics. The results presented here show the significant difference between the cleanest route for two individuals. While it’s intuitive that a less fit individual will experience higher RDD on a given journey due to their higher HR for a given power output, the magnitude of the difference is considerable. This result was made even more surprising considering that both subjects’ parameters were taken from a study of endurance athletes, suggesting that people who don’t exercise frequently could experience even higher RDD on a cycle commute. This result also highlighted the importance of using accurate models and parameters for calculating RDD, however the results in Figure 5 demonstrate the smoothness of the correlation between RDD and unfitness, and suggest that even approximations of fitness parameters may yield sufficiently accurate pollution estimates. The results of the second case study show significant but lower variation between RDD for the same individual at different velocities. This result highlights the importance of modelling route velocity accurately when predicting RDD and suggests that using speed limits to estimate cyclist velocity may be inappropriate depending on the individual’s journey characteristics. This conclusion is supported by data from the commute monitoring sensors, which showed little correlation between differential velocity and edge speed limit for each measurement. This result also suggests that PM2.5 inhalation could be further reduced by increasing travel velocity through highly polluted areas. While at present this may not be feasible due to speed limits, infrastructural limitations and congestion, it raises an interesting
question for local authorities regarding the location of cycle-specific infrastructure to mitigate both physical and pollution risk. Further, the RDD analysis summarised in Table 4 demonstrates the inadequacy of using exposure alone as a metric for route cleanliness due to the limited correlation between exposure and RDD. Similarly, neither distance or time were linearly correlated with the calculated RDD, which varied significantly with route. This supports the need for an individualised optimisation as none of these metrics are adequate for defining the optimal route. Ultimately, this provides the necessary proof of concept to show that the implementation of an individualised routing system is possible, both post-hoc and in real time, using measurements taken by the designed sensor modules. While in this analysis the subjects were treated as physiologically identical, the authors of [13] present a method for fitting physiological parameters from heart rate and power output data which could be gathered through recordings of commute journeys using a fitness watch. For the purpose of this study, considering the subjects as identical allowed direct comparison between the four routes as if they were an individual’s commute alternatives.

5.1 Methodology Limitations
As noted, the cost function in Equation 4 was sensitive to small changes in physiological parameters. Consequently, the validity of the suggested route strongly depends on the estimated physiological parameters. Initial work suggests that these parameters could be inferred from activity data from a smart watch or a platform such as Strava. Furthermore, the proposed optimisation did not account for the variation in exposure across the travel graph that was demonstrated in the commute monitoring study. Thus, implementing spatial variation in the background concentration would improve the accuracy of the calculated RDD, which could be achieved in real-time with calibrated measurements or by using a prediction model. In addition, this work did not investigate the correlation between the results of the optimisation and real-world exposure. This validation would require extensive real-time measurement of exposure levels using a gravimetric-flow-rate PM2.5 sensor and spirometer during a cycle commute.

6 Conclusion
A proof-of-concept system for the optimisation of pollution inhalation was proposed in this work. The work highlights the remarkable variation of RDD between cyclists travelling between the same origin and destination. In particular, individuals’ pollution inhalation is strongly dependent on their fitness, with up to three times more RDD experienced by the less fit subject. Additionally, significant variation was seen with travel velocity. These findings demonstrate that personalised commute optimisation could be hugely beneficial in reducing pollution risk. A logical continuation of the work presented here would involve a large-scale pollution monitoring study to facilitate the development of more accurate RDD predictions for individuals. A study such as this would provide more insight into the spatial and temporal variation of personal street-level PM2.5 exposure, and allow the identification of trends that could facilitate heuristic optimisation alongside that based on historic data. By gathering heart rate data and power output alongside the sensor module, a framework for learning and updating physiological parameters for the RDD model could be developed, with each commute improving the model’s prediction until prediction of route RDD can occur in real-time. There is also scope for application of our findings to optimise the level of assistance provided by electric bicycles.

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**Appendix**

Given a power requirement for a given road segment calculated using Equation 1, Equation 3 can then be then used to calculate the individual’s steady-state HR at this power output.

\[
VR = \begin{cases} 
\text{IF } s_{sex} = M & e^{0.021 \cdot HR + 1.03} \\
\text{ELSE} & e^{0.023 \cdot HR + 0.57}
\end{cases}
\]

The individual’s HR can then be used to estimate their ventilation rate, \( VR \), under the given conditions [15].

\[
IF = 1 - 0.5 \left(1 - \frac{1}{1 + 0.00076 \cdot \text{MMD}^2}\right)
\]

\[
DF = IF \left(0.0587 + \frac{0.911}{1 + e^{4.77 + 1.485 \ln(\text{MMD})}} + \frac{0.943}{1 + e^{0.508 - 2.58 \ln(\text{MMD})}}\right)
\]

The above equations can then be used to calculate the deposition fraction, where \( IF \) is the proportion of pollution which is inhaled (the inhalation fraction), and \( DF \) the proportion that is deposited in the individual’s lungs (the deposition fraction). MMD represents the mass-median diameter of the particulates the individual is exposed to in \( \mu m \).

\[
\text{RDD} = VR \cdot DF \cdot t \cdot e
\]

Finally, RDD can be calculated using the above equation, where \( RDD \) is the individualised recieved deposition dose, \( t \) is the duration of the exposure in minutes and \( e \) is the level of exposure in \( \mu g m^{-3} \).