A human exposure-based traffic assignment model for minimizing fine particulate matter (PM$_{2.5}$) intake from on-road vehicle emissions

Ahmad Bin Thaneya\textsuperscript{1,}\textsuperscript{*}, Joshua S Apte\textsuperscript{1,2} and Arpad Horvath\textsuperscript{1}

\textsuperscript{1} Department of Civil and Environmental Engineering, University of California, Berkeley, CA 94720, United States of America
\textsuperscript{2} School of Public Health, University of California, Berkeley, CA 94720, United States of America

* Author to whom any correspondence should be addressed.
E-mail: ahmad_binthaneya@berkeley.edu

Keywords: transportation, air quality, human health, Chicago

Abstract

An exposure-based traffic assignment (TA) model and accompanying analysis framework have been developed to quantify primary and secondary fine particulate matter (PM$_{2.5}$) exposure due to modeled on-road vehicle flow on a regional network at a high spatial resolution. The Chicago Metropolitan Area transportation network is used to demonstrate the model’s decision-informing power. The study compares the spatially distributed exposure impacts due to traffic emissions of two TA optimization scenarios: a baseline user equilibrium with respect to travel time (UET) and a novel system optimal with respect to pollutant intake (SOI). The UET and SOI scenarios are developed through the use of (a) the TA model used for obtaining vehicle flow patterns and characteristics including emissions, (b) a source-receptor matrix for PM$_{2.5}$ developed through a reduced-complexity air quality model to quantify primary and secondary PM$_{2.5}$ concentrations across the exposure domain, (c) spatial analysis for assessing exposure profiles at the census tract level, and (d) a health impact model to quantify exposure damages. The SOI scenario yields a 9% – 10% total reduction in exposure damages, with the most impacted census tracts benefiting from up to 20% – 30% of reductions, but leads to a 16% increase in travel time costs. Further reduction to PM$_{2.5}$ exposure by the SOI is hindered by network constraints, where travel demand in populous areas around the network must still be satisfied. The model can be used to systematically quantify the mitigation potential of different transportation exposure reduction strategies, to assess the exposure impacts of newly developed transportation infrastructure, and to address the equity implications of PM$_{2.5}$ exposure from traffic, all under realistic system behavior and bounded by actual system constraints.

1. Introduction

Exposure to transportation-attributable pollutants can lead to significant local and regional health impacts, including cardiovascular disease, respiratory disease, and stroke (Krewski et al 2009). The model developed in this study assesses exposure to primary (i.e. emitted directly from the vehicle tailpipe or due to tire and brake wear) and secondary (i.e. formed in the atmosphere from vehicle tailpipe precursor emissions) fine particulate matter (PM$_{2.5}$) due to on-road vehicle emissions.

The global health impacts associated with long-term exposure to PM$_{2.5}$ have been well documented in the literature. Approximately 95% of annual deaths from ambient air pollution are caused by PM$_{2.5}$ exposure (Tessum et al 2017). PM$_{2.5}$ was the highest-ranking environmental risk factor in 2019, leading to 4.1 million deaths, 7.3% of global deaths that year (Murray et al 2020). The transportation sector is the second most significant sector contributing to PM$_{2.5}$ exposure-related deaths in the United States (29 thousand deaths annually) (Thakrar et al 2020). Engineering and policy measures are urgently
needed to control and minimize transportation-sourced emissions and their associated PM$_{2.5}$ exposures.

Detailed modeling of emission rates, dynamics, and exposure is essential for identifying and testing effective exposure reduction strategies. Intra-urban variation in pollutant concentrations due to traffic flow and its proximity to populated areas, as well as meteorological and atmospheric conditions driving secondary pollutant formation, are essential factors to include, especially given that pollutant concentrations and exposure profiles can vary at the city block level (Chambliss et al 2021). Inhalation intake is a valuable exposure metric that represents the mass of pollutant cumulatively inhaled over a time period by the exposed human population. It is a more accurate proxy for estimating air pollution health impacts than emissions or ambient pollutant concentrations (Marshall et al 2005). Designing effective air pollution intervention strategies for public health must account for population distribution with respect to high pollution areas, which further suggests that minimizing pollutant intake, as opposed to targeting emissions or general pollutant concentrations, should be prioritized for achieving public health goals (Marshall et al 2005, Thakar et al 2020). Another useful metric for exposure mitigation is the intake fraction (iF) of an emission source that quantifies the total intake that would take place per unit of emissions from a source. Sources with higher iFs will lead to higher exposure and intake than sources with lower iFs per unit of emissions, meaning that high iF sources should be targeted when implementing emission control strategies for human health (Bennett et al 2002, Smith 2002). When considering outdoor emission sources, urban vehicles have a relatively high iF range that can vary between 1 and 100 parts per million [ppm] depending on the urban makeup of the exposure domain as well as the chemical and physical behavior of the pollutants (Lai et al 2000). This further motivates the need to target and control urban vehicle emissions for achieving exposure reduction goals.

The implementation of emission and exposure mitigation strategies requires understanding their effects on infrastructure systems as the feasibility and mitigation potential of such strategies must be rooted in actual infrastructure system behavior and bounded by system constraints. Modeling unintended impacts or co-benefits of such strategies on other transportation system metrics such as travel time may be the basis for the rejection or adoption of proposed strategies by policy-makers. Traffic assignment (TA) models are useful tools that historically have been used by transportation planners to assess the performance of transportation systems and evaluate the effects of potential enhancement measures on different transportation networks (Verhoef 1994). TA models are generally used to estimate traffic flow distribution on a transportation network based on some cost measure to be optimized given the representation of the road network, the travel demand across this network distributed by space and time, and the desired objective function (Patriksson 2015). Traditionally, TA models have minimized individual travel time to represent travel behavior and network flow conditions in a realistic manner. This has allowed planners to systematically determine network characteristics such as congestion, delay, vehicle emissions, and accessibility that resemble real network conditions (Verhoef 1994). TA models can be useful for exposure assessment and mitigation as modeled vehicle flow characteristics on a roadway network can allow one to estimate intraurban variation in air pollutant concentrations caused by traffic at a high spatial resolution. A TA can also allow one to explore mitigation options through scenario modeling, where potential reductions in air pollutant concentrations and exposures due to transportation system intervention strategies can be readily and systematically quantified. Furthermore, there is a growing literature of TA models used for optimizing environmental objectives including fuel consumption, greenhouse gas and other pollutant emissions, and urban pollutant concentrations (Szeto et al 2012). Trade-offs between travel time and environmental objectives may exist depending on the network setup and the particular environmental objective being optimized, which necessitates the use of such models to determine the extent of this trade-off and/or how it can be reduced. To our knowledge, no current TA model minimizes primary and secondary PM$_{2.5}$ exposure.

Our objective has been to develop an exposure-based TA model and accompanying analysis framework to quantify primary and secondary PM$_{2.5}$ exposure due to modeled on-road vehicle flow on a regional network at a high spatial resolution. Specifically, the model accounts for emissions from each individual link (i.e. roadway) and quantifies exposure concentrations at the census tract level. One of the uses of the model includes identifying transportation system design and management strategies that reduce human population exposure to PM$_{2.5}$. The major factors considered are those that facilitate human exposure to PM$_{2.5}$: emission source attributes of primary PM$_{2.5}$ and secondary PM$_{2.5}$ emission precursors (nitrogen oxides (NO$_x$), sulfur oxides (SO$_x$), volatile organic compounds (VOCs), and ammonia (NH$_3$)), pollutant physical transport and chemical transformations, and population exposure attributes (e.g. population distribution and breathing rates).

The main contributions of this work lie within (a) developing a human exposure-based framework that efficiently quantifies baseline health impacts of PM$_{2.5}$ exposure from the emissions of realistically modeled vehicle flow in transportation system networks, (b) creating an exposure-based quantitative model that can be readily integrated into existing transportation systems planning and management frameworks to be...
used for environmental health impact assessments of existing or newly proposed roadway infrastructure, and (c) developing a novel human exposure-based TA optimization model capable of routing traffic flow of a regional network in a manner that minimizes PM$_{2.5}$ intake across a large-scale exposure domain.

2. Methods

2.1. Exposure-based TA model framework and inputs

A case study of the Chicago Metropolitan Area (CMA) transportation network is used to demonstrate the exposure-based TA model’s development and decision-making power. The spatially distributed exposure impacts due to traffic flow emissions from the CMA are estimated using results from two TA optimization scenarios: (a) the user equilibrium with respect to travel time (UET) and (b) system optimal with respect to pollutant intake (SOI). A TA optimized for the travel time user equilibrium (UE) is regarded as a close approximation of realistic traffic conditions since this assignment principle assumes that drivers on the network choose minimum travel time paths to reach their destination. A system optimal (SO) assignment arranges traffic flow in a manner that minimizes a specific objective function across the whole system (Wardrop 1952), which in the case of the SOI assignment is PM$_{2.5}$ intake. Since exposure to both primary and secondary PM$_{2.5}$ is considered, the exposure domain is extended to include the entire state of Illinois as well as its four neighboring states: Wisconsin, Indiana, Ohio, and Michigan. PM$_{2.5}$ has regional impacts that may extend beyond the local emission source area, as Goodkind et al (2019a) showed that one quarter of total health damages may occur 256 km downwind of the source. Figure 1 shows the entire exposure domain considered and the CMA transportation network used in this study.

The framework incorporated (a) a TA model used for obtaining vehicle flow patterns and characteristics, including emissions, (b) a source-receptor matrix for PM$_{2.5}$ developed through a reduced complexity air quality model to quantify primary and secondary PM$_{2.5}$ concentrations across the exposure domain, (c) spatial analysis for assessing exposure profiles, and (d) a human health impact model to quantify exposure damages. The study developed baseline PM$_{2.5}$ exposures from daily traffic flow assumed to represent average traffic conditions in the CMA. Attaining daily traffic flows through the TA model required several inputs, the first being a representation of the temporal and geospatial distribution of travel demand across the network in the form of an Origin-Demand (O-D) travel demand matrix. The O-D matrix used for the CMA case study represents 1.4 million daily vehicle trips within the region. Another required input for the TA is the network topography. The Chicago regional transportation network for the case study represents a large-scale, detailed representation of the CMA network with 13 000 nodes and 40 000 links. Network data are sourced from a transportation network repository (Transportation Networks for Research Core Team 2021). The TA model is first populated with travel demand model O-D pairs along with the road network graph, including link characteristics (e.g. link capacities, free-flow travel times, and lengths) and link performance functions (i.e. individual link travel time or contribution to total system pollutant intake). The TA model then optimizes traffic flow on the network based on an objective function (i.e. cost function) of choice, which is the third required input for a TA. While several different TA models exist in the literature, the static fixed-demand TA formulation is adopted for this study. A static TA satisfies the goal of studying the effects of average (as opposed to instantaneous) traffic conditions on annually averaged chronic exposures to PM$_{2.5}$, which is the timeframe typically used to quantify PM$_{2.5}$ exposure health effects.

2.2. Transportation network mathematical representation

General TA formulations and models have been well described in the literature (Patriksson 2015). An overview of network and TA notation as well as their mathematical conditions are presented in the supplementary information (SI). The mathematical notation and descriptions used here are based on Boyles et al (2020). Table 1 shows a summary of the transportation network-related notation and additional variables/parameters used in the analysis.

2.2.1. UET assignment

The TA problem for the UET can be formulated as an optimization problem. The Beckmann Function (Beckmann et al 1956) is used for the UE optimization problem formulation where the link cost vector $x$ and the demand flow vector $h$ contain the optimization variables. The UET optimization objective function is shown in (1). $t_{ij}$ represents the total travel time on link $(i, j)$ in units of hours and is a function of link vehicle flow. The full optimization problem and associated constraints can be found in the SI.

\[
\min_{x, h} \sum_{(i,j) \in A} x_{ij} \int_0^h t_{ij}(x) \, dx
\]  

(1)

2.2.2. SOI assignment

2.2.2.1. SOI model and objective function formulation

An exposure-based TA can be formulated in a similar manner to traditional TAs. Like the travel time TA, the link cost vector $x$ and the demand flow vector $h$ contain the optimization variables. The constraints are also identical to the UET. However, it
A Bin Thaneya et al

Figure 1. (Left) Study area exposure domain disaggregated at the census tract level. The exposure domain extends through the ∼12 000 census tracts of the states of Illinois, Wisconsin, Indiana, Ohio, and Michigan. (Right) The Chicago Metropolitan Area (CMA) transportation network containing ∼13 000 nodes and ∼40 000 links. High free-flow speed (FFS) links (i.e. freeways) in [mph] are shown in bolded black, whereas low FFS links (i.e. roadways) are shown in grey.

Table 1. Summary of transportation network notation used and analysis variables and parameters.

| Symbol | Description | Units |
|--------|-------------|-------|
| A      | Set of links (i.e. edges) | (—) |
| P      | Set of pollutants considered (Primary PM_{2.5}/Secondary PM_{2.5} from Emission Precursors). | (—) |
| M      | Set of exposure zones within the study area. | (—) |
| h      | Vector containing all demand flows | (vehicles h\(^{-1}\)) |
| x      | Vector containing vehicle flow on all links | (vehicles h\(^{-1}\)) |
| \(l_{ij}\) | Length of link \((i, j)\) | (mile) |
| \(x_{ij}\) | Vehicle flow on link \((i, j)\) | (vehicles h\(^{-1}\)) |
| \(t_{ij}\) | Travel time on link \((i, j)\) | (h) |
| \(c_{pm-ij}\) | Exposure cost function | (grams of PM_{2.5} inhaled yr\(^{-1}\)) |
| \(E_{p-ij}\) | Pollutant emission rate function for pollutant \(p\) on link \((i, j)\) | (grams mile\(^{-1}\) h\(^{-1}\) per vehicle) |
| \(\Lambda_{pm-ij}\) | InMAP-generated population augmented source-receptor (intake fraction) matrix element for primary (secondary) PM_{2.5} (precursors) | (grams d\(^{-1}\) inhaled per grams h\(^{-1}\) emitted) |

Table 1 requires a different objective function. As mentioned, an SO intake model’s routing principle should aim to minimize system-wide pollutant intake for the study area. The SOI objective function is formulated in (2). \(M\) represents the set of exposure zones (i.e. census tracts) within the study area, \(P\) represents the pollutant pathways considered (primary PM_{2.5}/secondary PM_{2.5} from emission precursors), and \(c_{pm-ij}(x_{ij})\) is the exposure-based cost function that will be derived. \(c_{pm-ij}(x_{ij})\) represents the intake induced in exposure zone \(m\) due to the emissions from link \((i, j)\) of pollutant \(p\). A summation over all links is required to get the induced intake contribution of all network links, and an extra summation is required to sum over the intake induced in all exposure zones. A final summation enumerates over all five PM_{2.5} pathways. The development of the SOI exposure-based cost function for mobile sources will be presented next. It requires two modeling components: (a) emissions modeling and (b) exposure modeling.

\[
\min_{x, h} \sum_{p \in P} \sum_{m \in M} \sum_{(i, j) \in A} c_{pm-ij}(x_{ij})
\]  

2.2.2.2 Emissions modeling

PM_{2.5} is both a primary and secondary pollutant given that it is either emitted directly from an emission source or it is formed in the atmosphere from precursor emissions, respectively. The modeling framework accounts for both primary and secondary PM_{2.5} sourced from vehicle flow within network. Secondary PM_{2.5} precursor emissions that
are accounted for include NO$_2$, SO$_2$, VOCs, and NH$_3$. Vehicle emission rates are estimated using the California Air Resources Board Emission FACTor (EMFAC) average-speed, static-emissions model. EMFAC provides on-road vehicle emission factors disaggregated by various vehicle characteristics and average traveling speed (ARB 2021). The TA simulation output provides average vehicle flows and speeds per road segment throughout a 24 h period, which for the purposes of this study is assumed to represent an average day of traffic flow on the network. Using the link flows and average speeds, an average emissions inventory of primary PM$_{2.5}$ and secondary PM$_{2.5}$ precursor emissions is estimated for the network. The functional form of the emissions functions used in the TA (represented by $E_{p-ij}(x_{ij})$ as the per-vehicle per-mile emissions of pollutant $p$ from link $(i,j)$ with respect to optimization variable is presented in the SI.

Plotted emission rate curves and EMFAC data points for primary PM$_{2.5}$, NO$_2$, VOCs, SO$_2$, and NH$_3$ are shown in figure 2. All pollutants follow a similar trend of decreasing emissions with higher speed. To understand how network parameters, road types, and congestion conditions affect emissions, an approach similar to Patil (2016) was adopted where the emission rates were plotted as functions of the link flow-to-capacity ratio for varying link free-flow speeds (FFSs) in figure 2. Generally, traveling on high FFS links leads to lower overall emissions per unit distance. Higher congestion conditions, signified by higher flow-to-capacity ratios, lead to more emissions for all pollutants. To ensure convexity conditions of the TA are satisfied, the convex adjusted functions are plotted in figure 2 using dashed lines. This is discussed further in the SI. The convex adjusted functions are only used to run the SOI optimization, while the original emission functions are used to generate the final concentration and exposure profiles.

2.2.2.3. Exposure modeling
The next step in developing the SOI objective function is transforming the emissions from the links into exposure concentrations at the exposure zones. This requires accounting for the physical transport and chemical transformation of pollutants as they travel from the vehicles to the receptor points where intake takes place. In addition to primary PM$_{2.5}$ concentrations, the secondary PM$_{2.5}$ species that result from primary NO$_2$, SO$_2$, VOCs, and NH$_3$ emissions include particulate nitrate ($p$NO$_3$), particulate sulfate ($p$SO$_4$), secondary organic aerosols (SOA), and particulate ammonium ($p$NH$_4$), respectively. Annual-average changes in outdoor PM$_{2.5}$ concentrations are estimated using the intervention model of air pollution (InMAP) model, a reduced-complexity air quality model (Tessum et al 2017). Due to the large number of simulations required and the high computational costs of running both an optimization model and an air quality model, the InMAP Source-Receptor Matrix (ISRM) is adopted. The ISRM is a series of matrices that holds linear relationships between marginal changes in primary PM$_{2.5}$ and secondary PM$_{2.5}$ precursor emissions and marginal changes in annual average PM$_{2.5}$ concentrations between all source and receptor locations (Goodkind et al 2019b). The performance of the ISRM has been evaluated in Goodkind et al (2019a) and has been shown to have average bias and error values that are well within published air quality model performance criteria. The InMAP ISRM data for the study area are extracted from Goodkind et al (2019b), and the obtained ISRM grid for the study area is shown in figure 3.

The InMAP ISRM is integrated into the SOI optimization model by augmenting it with population (United States Census Bureau 2019) and breathing rate data (Marty et al 2002) before spatially joining it to the transportation network. This results in an $i$,$j$ matrix represented by $\{A_{p} \in \mathbb{R}^{M \times A}\}$ for each pollutant $p$. The rows correspond to the study area census tracts, while the columns correspond to the network links. Figure 3 shows the resulting form of the $i$,$j$ matrices and illustrative maps of $i$,$j$ values in ppm for the census tracts and network links for the CMA. Details regarding the development of the $i$,$j$ matrices can be found in the SI.

2.2.2.4. SOI exposure cost function
Combining the derived emissions and exposure components results in the SOI objective function used in the exposure-based TA. The exposure cost function $c_{pm-ij}(x_{ij})$ is displayed in (3) and is a product of four scalar quantities. The components dependent on the optimization variable can be grouped as a combined second term $(x_{ij}E_{p-ij}(x_{ij})l_{ij})$, which is the product of the vehicle flow $x_{ij}$, the per-vehicle per-mile emission rate function $E_{p-ij}(x_{ij})$, and the link length $l_{ij}$. This product represents the total emissions of pollutant $p$ from link $(i,j)$. The first term is composed of an element $(A_{pm-ij})$ from the group of $i$,$j$ matrices derived in the previous subsection and is independent of the optimization variable. It represents the intake induced in exposure zone $m$ due to a unit of emissions of pollutant $p$ from link $(i,j)$. The element $A_{pm-ij}$ is multiplied by $(x_{ij}E_{p-ij}(x_{ij})l_{ij})$ to get the total intake induced in exposure zone $m$. The total intake within the exposure domain is quantified by summing over all links, exposure zones, and PM$_{2.5}$ species as per (2). The numerical implementation of the TA follows the Franke–Wolfe algorithm, which solves the optimization problem through a combined series of iterative linear minimization problems and a shortest path algorithm. The detailed solution algorithm is extensively documented in the literature (Boyles et al 2020).

$$c_{pm-ij}(x_{ij}) = A_{pm-ij}x_{ij}E_{p-ij}(x_{ij})l_{ij} \quad (3)$$
Figure 2. PM$_{2.5}$, NO$_x$, VOC, SO$_x$, and NH$_3$ vehicle emission rates calculated in [g/mi per vehicle] as a function of vehicle speed. Original emission data points are shown as black dots and are derived from the California Air Resources Board (ARB) EMission FACtor (EMFAC) average-speed, static-emissions model. Emission function curves and convex-adjusted curves are generated for each pollutant and are shown in solid red and dashed red, respectively. $R^2$ goodness-of-fit values relative to the original EMFAC emission data points are also displayed for both the regular and convex-adjusted fits. Differences between the EMFAC functions and the convex-adjusted functions are small given the similar $R^2$ values. Emission rates are also plotted as a function of the optimization objective function in the form of flow-to-capacity ratio for six different free-flow speeds (FFS). Solid lines show the original emission curves while the dashed lines show the convex-adjusted emission curves.
Figure 3. (Left) InMAP Source-Receptor Matrix (ISRM) grid cells for the exposure domain. The ISRM holds linear relationships between marginal changes in primary PM$_{2.5}$ and secondary PM$_{2.5}$ precursor emissions and marginal changes in annual average PM$_{2.5}$ concentrations between all source and receptor locations on the InMAP grid. (Right) ISRM relationships are extracted from the original ISRM grid and spatially joined to the exposure domain census tracts and Chicago Metropolitan Area (CMA) links, yielding five intake fraction (iF) matrices (Primary PM$_{2.5}$; NO$_x$; VOCs-SOA; SO$_x$-pSO$_4$; NH$_3$-pNH$_4$) to be used in the exposure-based traffic assignment (TA) optimization. The rows of the matrices represent the domain census tracts, while the columns represent the CMA network links. The two sets of maps visualize iF intensity in ppm for the census tracts (outer maps) and the links (inner maps) for each of the PM$_{2.5}$ pollutant relationships. The scales represent the sum of the rows or columns within each matrix: the link iF scale (in this case the sum of each column) represents the total intake induced in all the census tracts per unit of emission from that link. The census tract iF scale (in this case the sum of each row) represents how much intake is induced in each tract if there were a unit of emissions from each link in the network. Darker colors represent high iF values, whereas lighter colors represent low iF values. The census tract iF maps show that census tracts closer in proximity to the CMA network have higher iF values which decrease in magnitude the farther the census tracts are from the network. The link iF maps show that links located in the high-density Chicago urban center have high iF values, which decrease in magnitude for links located in the low-density CMA outskirts.

2.2.2.5. Exposure damages modeling
Monetized social costs of travel time and monetary damages due to incidence of premature mortality attributable to exposure to PM$_{2.5}$ are also quantified to understand the total social costs associated with the UET and SOI as well as their differences. Social costs associated with travel time are estimated using a value of travel time savings as suggested by U.S. federal government guidance on appraisal of transportation time savings (USDOT 2016). Incidence of premature mortality due to chronic PM$_{2.5}$ exposure are quantified based on the different PM$_{2.5}$ exposure damages models referenced in Tessum et al (2019).

3. Results

3.1. Network congestion and flow
The two TA optimizations utilize different routing principles, which yield different congestion levels within the network. Higher delay is present for the SOI assignment relative to the UET assignment, with most of the congestion increase arising in the CMA outskirts. The SOI assignment, however, does relieve some of the congestion within the Chicago urban center and on some major freeways. In terms of system-wide delay, the UET leads to a total of 3.96 thousand vehicle delay hours per day, while the SOI assignment leads to 4.83 thousand vehicle delay hours per day (+22%).

The difference in network congestion and delay can be attributed to the difference in network vehicle flows observed in both scenarios. The UET assigns traffic in a manner that minimizes individual travel time for all trips, meaning that it will choose minimum travel time routes between all O-Ds. This is translated into assigning higher vehicle flow on high FFS links (i.e. freeways) and local roadways in the Chicago urban center, where a higher concentration of O-Ds are present. The SOI, on the other hand, seeks to assign traffic in a manner that minimizes PM$_{2.5}$ intake across the network, meaning that it will assign high vehicle flow onto low iF links. Link iFs are closely correlated to census tract population density distribution, where links located near high population density pockets will have high iF values. The difference in vehicle flow between the UET and SOI is shown in...
4, where it illustrates the links with increased vehicle flow in each of the UET (figure 4(a)) and SOI (figure 4(b)) relative to the other assignment. Generally, the SOI moves flow away from links located within and near the Chicago urban center, which have high iFs, and reroutes trips around the high population density areas onto low iF links in the CMA outskirts. While the SOI’s assignment principle does lead to lower intake by utilizing the low iF links, the act of rerouting onto the CMA outskirts increases overall network travel time. The total travel time for the UET assignment is 14.6 million vehicle hours traveled per day, while the SOI leads to 17.0 million vehicle hours traveled per day (+16%).

Figure 5 shows how link iF values relate to vehicle flow and emissions for both the UET and SOI assignments. The scatter plots in the 1st and 3rd rows show the difference in flow and emissions, respectively, between the two assignments as a function of link iF by subtracting UET values from SOI ones. The differences in flows and emissions on links with similar iFs from are then grouped and summed (shown in the 2nd and 4th rows) to better capture the general aggregate relationship between those metrics and link iFs in the two assignments. The high positive peaks showcase the large amount of flow and emissions the SOI shifts onto low iF links. The smaller negative peaks signify the SOI scenario’s attempt to move flow and emissions away from higher iF links whenever possible. The difference in magnitude between the positive and negative peaks is due to large amounts of flow and emissions in the SOI scenario being shifted onto low iF roadways in the CMA outskirts that are essentially unused in the UET scenario, whereas some high iF roadways in SOI scenario must still be utilized to ensure that travel demand between all O-D pairs is met by paths available on the network.

### 3.2. Exposure results

Differences in PM$_{2.5}$ intake in the CMA census tracts between the UET and SOI assignments are shown in figure 6. Results are only shown for the CMA census tracts since approximately 95% of total PM$_{2.5}$ intake takes place in the 2200 census tracts in the CMA, which represent 20% of all census tracts considered in the optimization program. This could be due to Chicago’s location, where Lake Michigan lies to the east followed by a large stretch of land before the next largest urban center (Detroit). No nearby large urban centers can be found to the west either. Therefore, in this instance, most of the exposure ended up taking place within the CMA. If one were to analyze a different system with more secondary pollutant emission precursors (e.g. electric power systems), or run a case study on an urban area such as California’s South Coast where large pockets of urban centers are within closer proximity, then including a smaller exposure domain within the optimization might outsource exposure to populations unaccounted for. A regional domain is still used here to encourage researchers using infrastructure system optimization models to incorporate a large enough exposure domain that ensures that ‘optimal’ solutions does not minimize local exposure at the expense of populations not within the domain.

Elevated levels of PM$_{2.5}$ intake are found in the Chicago urban center due to a combination of high population numbers and PM$_{2.5}$ concentrations. Intake levels decrease gradually towards the CMA outskirts where there is less traffic flow. Regarding the differences between both scenarios, the UET leads to higher intake in the high population density Chicago urban center relative to the SOI. The SOI does also lead to higher intake in some census tracts in the CMA outskirts; however, the increase in those tracts is much smaller in magnitude than the increases observed in the UET assignment. The difference in intake rates follows the previously discussed trends in vehicle flow due to the routing principles of the UET and SOI assignments. The scatter plot in figure 6 also shows the change in PM$_{2.5}$ intake resulting from each assignment in relation to the population density in the tracts. The SOI assignment generally attempts to reduce intake in high population density tracts with higher iF. Conversely, the SOI only slightly increases intake rates for a few low population density tracts.

The UET and SOI assignments result in a population-weighted PM$_{2.5}$ concentration of 1.13 µg m$^{-3}$ and 1.02 µg m$^{-3}$ (−10%), respectively. In terms of intake, the UET and SOI assignments lead to a total PM$_{2.5}$ intake of 60.5 and 55.2 kgPM$_{2.5}$ yr$^{-1}$ (−9%), respectively. The relative increase in intake caused by the SOI assignment due to the rerouted flow to the CMA outskirts is small. Overall, the SOI leads to an intake increase of 0.94 kgPM$_{2.5}$ yr$^{-1}$ relative to an intake reduction of 6.02 kgPM$_{2.5}$ yr$^{-1}$. Regarding the PM$_{2.5}$ intake attributable to each of the five PM$_{2.5}$ species, primary PM$_{2.5}$ and NO$_x$ yield the highest contributions at approximately 40% each, while NH$_3$, VOCs, and SO$_x$ contribute about 17%, 2%, and 1%, respectively. The high proportion of intake due to primary PM$_{2.5}$ is expected given that this form of PM$_{2.5}$ leads to exposures soon after it is emitted from vehicles in addition to the proximity of roadways to people (i.e. high iF). High exposures of PM$_{2.5}$ due to NO$_x$ emissions can be attributed to the large amount of NO$_x$ emitted from on-road vehicles despite NO$_2$-pNO$_x$ having lower iFs given its secondary pollutant status.

The benefits of the SOI become even more pronounced upon looking at the exposure reductions for the most impacted populations (i.e. ones that experience the highest exposure impacts) as well as populations that benefit from the largest reductions in exposure impacts. The SOI reduces PM$_{2.5}$ intake by...
Figure 4. (a) Network map showing links that have increased vehicle flow in the user equilibrium for time (UET) assignment relative to the system optimal for intake (SOI) assignment, whereas the opposite is shown in (b). The general trend is that the SOI assignment routes vehicles away from the links in the high population density Chicago urban center, which have high PM$_{2.5}$ intake fractions (iFs), and towards links in the low population density Chicago Metropolitan Area (CMA) outskirts, which have lower PM$_{2.5}$ iFs.
Figure 5. (1st row) Scatter plots showing the difference in vehicle flow on every network link and the intake fraction (iF) of the link between the user equilibrium for time (UET) assignment and the system optimal for intake (SOI) assignments. Each column represents one of the five PM$_{2.5}$ pollutant species considered: Primary PM$_{2.5}$, pNO$_x$, SOA, pSO$_4$, and pNH$_4$. The difference is taken by subtracting UET flows from SOI flows (positive points show the increased flows in the SOI while the negative points show the reduced flows in the UET). (2nd row) The difference in flows on links with similar iFs from the 1st row are aggregated and summed to show the general relationship between the flow differences and the link iFs. (3rd & 4th rows) Scatter and aggregated line plots that are similar to the top two rows, but they plot the difference in emissions between the five pollutants considered and iF for each link. Trends here are in alignment with the observed vehicle rerouting trends seen in figures 4(a) and (b), where the SOI reroutes traffic away from high iF links located in the Chicago urban center towards the lower iF links in the Chicago Metropolitan Area (CMA) outskirts.
Figure 6. (Left) Difference in intake in [grams yr$^{-1}$] per census tract due to vehicle emissions between the user equilibrium for time (UET) and system optimal for intake (SOI) assignments. The difference is taken by subtracting the UET intake values from the SOI intake values. Higher intake rates can be seen near the high population density census tracts closer to the Chicago urban center for the UET assignment relative to the SOI assignment. The SOI assignment increases intake in some low population density tracts within the Chicago Metropolitan Area (CMA) outskirts (shown in red); however, the magnitude in increase is much smaller relative to the obtained reductions (shown in blue). (Right) Scatter plot comparing the change in PM$_{2.5}$ intake resulting from each assignment in relation to the population density in the tracts.

Table 2. Monetized social costs of travel time and monetary damages due to incidence of premature mortality attributable to exposure to PM$_{2.5}$ for the user equilibrium for time (UET) and system optimal for intake (SOI) assignments.

| Scenario (Strategy) | Travel time costs | Monetized PM$_{2.5}$ exposure damage costs | Combined travel time and exposure costs |
|---------------------|-------------------|-------------------------------------------|--------------------------------------|
| UET                 | $\$54$ B yr$^{-1}$ | $4.0 – 4.7$ B yr$^{-1}$                   | $58 – 59$ B yr$^{-1}$                |
| SOI                 | +16%               | $-9% – -10%$                              | +14% – +15%                           |

3.3. System cost and exposure damages results

Table 2 shows aggregated system level travel time costs and monetized exposure damage costs. Values for the UET scenario are displayed, whereas the values for the SOI are given as percent differences relative to the UET scenario, which represents the baseline. The SOI leads to a 9% – 10% reduction in exposure damages but leads to a 16% increase in travel time costs. Overall, the combined social costs for the SOI are higher than the UET due to travel time costs being generally larger in magnitude than exposure damage costs.

4. Discussion

Results show that the SOI does yield reasonable exposure reductions relative to baseline conditions by shifting traffic flow away from high iF links and high population density areas. The 9% – 10% reduction achieved is in line with performances of...
other TA optimization models that minimize environmental objectives such as fuel consumption or emissions (Szeto et al. 2012). Further reduction to PM$_{2.5}$ exposure by the SOI is hindered by network constraints where travel demand throughout the network must still be satisfied. This means that although travel through high iF roadways is minimized, some travel through them is inevitable when alternatives are not present, especially given that there is high travel demand to the Chicago Urban Center, where the cluster of high iF roadways is located. However, the SOI effectively reduces exposure for the most impacted populations, where PM$_{2.5}$ exposure reductions can be as high as 20% – 30%. While the SOI does reduce exposure damages, it does lead to a net increase in combined social costs when accounting for the added travel time under the assumption that monetized travel time costs and exposure damages are comparable.

Several limitations and sources of uncertainty exist within the modeling framework. The TA modeled average daily traffic conditions, which may not capture irregular and extreme traffic congestion that could affect total emissions. Figure 2 shows that there is a steep increase in emissions after a certain congestion point, which may be the case during peak hours. Thus, the emissions inventory used may be underestimated. Given that the framework uses modeled flows rooted in assumptions regarding daily trips and travel behavior, the obtained traffic flows and proceeding analysis are driven by the validity of these assumptions. Imprecision may also be introduced in the emissions and concentrations modeling since average vehicle emission functions and linearized emissions-concentration relationships are used. The use of California-based fleet as a proxy for the CMA is another limitation. Lower ambient temperatures often lead to higher vehicle emissions (Nam et al. 2010), and the colder temperatures in the CMA relative to California could have a noticeable impact on the emissions profile. California also imposes some of the strictest emission limits in the United States, which is an aspect that may not be reflected by the actual CMA vehicle fleet. Therefore, the model could be underestimating the emissions inventory and subsequent induced exposures.

Overall, since the study analyzes long-term exposure to PM$_{2.5}$ and chronic health impacts, obtaining average exposure trends may be sufficient for the study goals. Despite the uncertainty in the methodology, the results are in line with similar findings in the literature to a reasonable degree. The population-weighted PM$_{2.5}$ concentration for the UET scenario is 1.13 $\mu$g m$^{-3}$, which is close to the population-weighted PM$_{2.5}$ concentration due to all California on-road mobile sources ($\sim$1.6 $\mu$g m$^{-3}$) found in (Apte et al. 2019). The discrepancy between the findings may arise due to the differences in the study domain, the number and types of trips accounted for, and the considered transportation emission sources. Furthermore, normalizing the UET scenario’s mortality rate on a per-capita basis results in a value of $\sim$6 deaths per 10$^5$ people per year, which is within the same order of magnitude as both the $\sim$33 deaths per 10$^5$ people per year value reported in Apte et al. (2015) and the $\sim$10 deaths per 10$^5$ people per year reported in Thakrar et al. (2020), attributable to all-source- and transportation-related PM$_{2.5}$ exposure, respectively, in the United States.

Using the analysis framework developed, several insights regarding transportation systems management and PM$_{2.5}$ exposure mitigation can be described. For one, this study demonstrated the importance of employing a systematic quantification of exposure profiles derived from realistic system behavior and bounded by actual system constraints (Nahlik et al. 2016, Helmrich et al. 2021). Being able to generate realistic traffic flows and model their changes under different scenarios can help quantify the extent of possible exposure reductions and compute effects on other transportation metrics such as travel time. While it may not be expected in the near future for a system operator to use this modeling framework to reroute traffic for the sole purpose of minimizing exposure, the insights gained from this exercise can inform engineering design and policy decisions for offsetting baseline intake levels (e.g. through exposure-based pricing schemes). Furthermore, this framework can help in pursuing the individual and combined mitigation potentials of other strategies such as higher alternative fuel penetration (Taptich et al. 2018, Tong et al. 2021, Somers et al. 2022) (also accounting for their changes over time (Grubert et al. 2020)), exposure-based toll setting (de Palma and Lindsey 2011), particle building filtration enhancement (Riley et al. 2002), and population relocation from high-pollution areas. Another use for the model would be performing exposure impact studies of newly proposed roadway infrastructure, including local construction and supply chain characteristics (Cicas et al. 2007). The modeling framework can also aid in assessing the equity implications of the proposed strategies where careful consideration should be given to ensuring that the net decrease in total exposure yielded by any strategy does not come at the cost of widening the exposure gap of disadvantaged groups (e.g. by routing more vehicles towards roadways in proximity to low-income census tracts).

Future iterations of this work should include the consideration of diurnal pollutant dynamics and seasonal differences in pollutant emission trends and meteorology when the ability of modeling such behavior becomes efficient at scale, especially given the computational expense of running both a TA and air quality model for serial scenario modeling. Time-period-resolved travel demand data of different trip types should also be incorporated since it will allow for the modeling of on-peak and off-peak traffic
flow to obtain a more comprehensive representation of network congestion and the network emissions inventory. Validating the simulated traffic flow against measured traffic flow would be valuable. Future work should also consider using the model to assess the equity implications of PM$_{2.5}$ exposure from traffic and its infrastructure (Brinkman and Miller 2021) as well as developing an exposure-based TA aimed at reducing the exposure gap of disadvantaged groups.

**Data availability statement**

The data that support the findings of this study are available upon reasonable request from the authors.

**Acknowledgments**

A B T gratefully acknowledges the United Arab Emirates Ministry of Education Scholarship Program for supporting his graduate studies that led to this work.

**Conflict of interest**

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

**Funding**

The authors received no financial support for the research, authorship, and/or publication of this article.

**ORCID iDs**

Ahmad Bin Thaneya  [https://orcid.org/0000-0002-7604-6123](https://orcid.org/0000-0002-7604-6123)

Joshua S Apte  [https://orcid.org/0000-0002-2796-3478](https://orcid.org/0000-0002-2796-3478)

Arpad Horvath  [https://orcid.org/0000-0003-1340-7099](https://orcid.org/0000-0003-1340-7099)

**References**

Air Resources Board (ARB) 2021 Mobile source emission inventory—EMFAC2021 database (available at: [https://arb.ca.gov/emfac/](https://arb.ca.gov/emfac/) (Accessed 24 May 2021)

Apte J S, Chambliss S, Tessum C and Marshall J D 2019 A tool to prioritize sources for reducing high PM$_{2.5}$ exposures in environmental justice communities in California (California Air Resources Board) (available at: [https://ww3.arb.ca.gov/research/single-project_ajax.php?row_id=67021](https://ww3.arb.ca.gov/research/single-project_ajax.php?row_id=67021))

Apte J S, Marshall J D, Cohen A J and Brauer M 2015 Addressing Air Resources Board (ARB) 2021 Mobile source emission inventory—EMFAC2021 database (available at: [https://arb.ca.gov/emfac/](https://arb.ca.gov/emfac/) (Accessed 24 May 2021)

Chambliss S E et al 2021 Local- and regional-scale racial and ethnic disparities in air pollution determined by long-term mobile monitoring Proc. Natl Acad. Sci. 118 e2109249118

Cicas G, Hendrickson C T, Horvath A and Matthews H S 2007 A regional version of a U.S. economic input-output life-cycle assessment model Int. J. Life Cycle Assess. 12 365–72

De Palma A D and Lindsey R 2011 Traffic congestion pricing methodologies and technologies Transp. Res. C 19 1377–99

Goodkind A L, Tessum C W and Coggins J S 2019b. InMAP source-receptor matrix (ISRM) dataset (version 1.2.1) [data set] (Zenodo) (available at: [http://doi.org/10.5281/zenodo.2589760](http://doi.org/10.5281/zenodo.2589760)) (Accessed 24 May 2021)

Goodkind A L, Tessum C W, Coggins J S, Hill J D and Marshall J D 2019a Fine-scale damage estimates of particulate matter air pollution reveal opportunities for location-specific mitigation of emissions Proc. Natl Acad. Sci. 116 8775–80

Grubert E, Stokes-Draut J, Horvath A and Eisenstein W 2020 Utility-specific projections of electricity sector greenhouse gas emissions: a committed emissions model-based case study of California through 2050 Environ. Res. Lett. 15 104004

Helmrich A, Markolf S, Rui L, Carvalhaes T, Kim Y, Bondank E, Natarajan M, Ahmad N and Chester M 2021 Centralization and decentralization for resilient infrastructure and complexity Environ. Res.: Infrastruct. Sustain. 1 021001

Krewski D et al 2009 Extended follow-up and spatial analysis of the american cancer society study linking particulate air pollution and mortality Res. Rep. 115–36

Lai A C K, Thatcher T L and Nazaroff W W 2000 Inhalation transfer factors for air pollution health risk assessment J. Air Waste Manage. Assoc. 50 1688–99

Marshall J D, Teoh S-K and Nazaroff W W 2005 Intake fraction of nonreactive vehicle emissions in US urban areas Environ. Sci. Technol. 39 1363–71

Marty M A, Blaisdell R J, Broadwin R, Hill M, Shimer D and Jenkins M 2002 Distribution of daily breathing rates for use in California’s air toxics hot spots program risk assessments Hum. Ecol. Risk Assess. 8 1723–37

Murray C J L et al 2020 Global burden of 87 risk factors in 204 Countries and Territories, 1990–2019: a systematic analysis for the global burden of disease study 2019 Lancet 396 1223–49

Nalihk M J, Kaehr A T, Chester M V, Horvath A and Taptich M N 2016 Goods movement life cycle assessment for greenhouse gas reduction goals J. Ind. Ecol. 20 317–28

Nam E, Sundeep Kishan R W, Baldauf C R, Fulper M S and Warila J 2010 Temperature effects on particulate matter emissions from light-duty, gasoline-powered motor vehicles Environ. Sci. Technol. 44 4672–7

Patil G R 2016 Emission-based static traffic assignment models Environ. Model. Assess. 21 629–42

Patriksson M 2015 The Traffic Assignment Problem: Models and Methods (Minea, NY: Courier Dover Publications)

Riley W J, McKone T E, Lai A C K and Nazaroff W W 2002 Indoor particulate matter of outdoor origin: importance of size-dependent removal mechanisms Environ. Sci. Technol. 36 200–7

Smith K R 2002 Place makes the poison: Wesolowski Award lecture—1999 J. Expo. Sci. Environ. Epidemiol. 12 167–71

Somers M, Batan L, Al-Alawi B and Bradley T H 2022 A California-specific life cycle assessment model to support evaluation of low-carbon transportation fuels and policy Environ. Res.: Infrastruct. Sustain. 2 011001

Boyles S D, Lownes N E and Unnikrishnan A 2020 Transportation network analysis, volume i, version 0.85 (available at: [https://shoyles.github.io/blubook.html](https://shoyles.github.io/blubook.html)) (Accessed 24 May 2021)
Szeto W Y, Jaber X and Wong S C 2012 Road network equilibrium approaches to environmental sustainability Transp. Rev. 32 491–518

Taptich M N, Scown C D, Piscopo K and Horvath A 2018 Drop-in biofuels offer strategies for meeting California’s 2030 climate mandate Environ. Res. Lett. 13 094018

Tessum C W et al 2019 Inequity in consumption of goods and services adds to racial-ethnic disparities in air pollution exposure Proc. Natl Acad. Sci. 116 6001–6

Tessum C W, Hill J D and Marshall J D 2017 InMAP: a model for air pollution interventions PLoS One 12 e0176131

Thakrar S K et al 2020 Reducing mortality from air pollution in the united states by targeting specific emission sources Environ. Sci. Technol. Lett. 7 639–45

Tong F, Wolfson D, Jenn A, Scown C D and Auffhammer M 2021 Energy consumption and charging load profiles from long-haul truck electrification in the United States Environ. Res.: Infrastruct. Sustain. 1 025007

Transportation Networks for Research Core Team 2021 Transportation networks for research (available at: https://github.com/bstabler/TransportationNetworks) (Accessed 24 May 2021)

United States Census Bureau 2019 2019 American Community survey 5-Year estimates (Washington, DC: US Department of Commerce) (available at: www.census.gov/programs-surveys/acs/) (Accessed 24 May 2021)

United States Department of Transportation (USDOT) 2016 Revised departmental guidance on valuation of travel time in economic analysis Memorandum to Secretarial Officers Modal Administrators. Office of the Secretary of Transportation (available at: www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-valuation-travel-time-economic) (Accessed 24 May 2021)

Verhoef E 1994 External effects and social costs of road transport Transp. Res. A 28 273–87

Wardrop J G 1952 Some theoretical aspects of road traffic research Proc. Inst. Civ. Eng. 1 325–62