Chapter 17
Intelligent Transportation System Solutions in Disadvantaged Communities

Matthew J. Barth, Kanok Boriboonsomsin, Guoyuan Wu, and Peng Hao

Abstract Many cities across the world are looking to use technology and innovation to improve the overall efficiency and safety for their residents. At the heart of these smart-city plans, a variety of intelligent transportation system technologies can be used to improve safety, enhance mobility measures (e.g., traffic flow), and minimize environmental impacts of a city's mobility ecosystem. Early implementations of these ITS technologies often take place in affluent cities, where there are many funding opportunities and suitable areas for deployment. However, it is critical that we also develop smart city solutions that are focused on improving conditions of disadvantaged and environmental justice communities, whose residents have suffered the most from unmitigated urban sprawl and its environmental and health impacts. As a leading example, Inland Southern California has grown to be one of the largest hubs of goods movement in the world. Numerous logistics facilities such as warehouses, rail facilities, and truck depots have rapidly spread throughout these communities, with the local residents bearing a disproportionate burden of truck traffic, poor air quality, and adverse health effects. Further, the majority of residents have lower-wage jobs and very few mobility options, other than low-end personal car ownership. To improve this situation, UC Riverside researchers have focused their smart city research on these impacted communities, finding innovative solutions to eco-friendly traffic management, developing better-shared (electric) mobility solutions for the community, improving freight movements, and enhancing the transition to vehicle electrification. Numerous research and development projects are currently underway in Inland Southern California, spanning advanced smart city modeling and impact analysis, community outreach events, and real-world technology demonstrations. This chapter describes several of these ITS solutions and their potential for improving many cities around the world.

M. J. Barth (✉) · K. Boriboonsomsin · G. Wu · P. Hao
Bourns College of Engineering-Center for Environmental Research and Technology, University of California-Riverside, Riverside, CA, USA
e-mail: matthew.barth@ucr.edu

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17.1 Introduction

One of the key goals of any "Smart City" is to improve a city's operational efficiency and promote economic growth while also improving the quality of life for its citizens. This is typically accomplished by using a variety of smart technologies and data analyses. Smart city characteristics include having effective and highly functional public transportation, progressive city planning, better infrastructure based around technology, and a variety of environmental initiatives that are focused on the public health. This leads to local citizens being able to live and work within the city, effectively uses a number of city resources.[1]

Every city that has goals of becoming "smarter" will have different characteristics based on their current conditions and future plans. Some cities will have clear pathways for improvement, while other cities will have greater challenges due to inherent burdens such as poor air quality, chronic public health problems, lack of affordable housing, and increased levels of poverty. These "disadvantaged" communities desperately want to improve their conditions; one of the key questions is how to take advantage of smart-city technology, infrastructure, and techniques to make these improvements happen.

In this chapter, we examine a variety of Intelligent Transportation System (ITS) solutions that are focused on disadvantaged communities. The general goal of ITS technology is to improve safety, enhance mobility measures (e.g., traffic flow), and minimize environmental impacts of a city's mobility ecosystem. To date, most of the early implementations of these ITS technologies often take place in affluent cities, where there are many funding opportunities and suitable areas for deployment. However, it is critical that we also examine smart city solutions that are focused on improving conditions of disadvantaged and environmental justice communi- ties, whose residents have suffered the most from unmitigated urban sprawl and its environmental and health impacts.

As a case study, we focus on Inland Southern California, including projects in the cities of Riverside and San Bernardino, California. Much of Inland Southern California is designated as "disadvantaged" based on California's CalEnviroScreen modeling tool [1]. Our research addresses a number of ITS topics for this region, including improved traffic flow along major arterial roadways, smart intersections, shared mobility solutions, and improved routing of heavy-duty trucks. This chapter draws on a number of recent publications on these topics, listed in the reference section.

17.1.1 Riverside's Smart City Partnership

The City of Riverside, California, and the University of California-Riverside (UCR) have joined together in the last several years to pursue a number of activities focused on making Riverside a "Smart City." Riverside is one of the largest cities in Inland

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Southern California and a key component of Southern California's economy. Riverside has a population of approximately 320,000 residents, medium densification of housing, four expanding universities, and steady growth in local and regional industrial development. A significant amount of rail freight passes through Riverside, coming to and from the ports of Los Angeles and Long Beach, which import over 40% of the goods coming in to the United States. Riverside has over 400 signalized intersections and experiences a number of transportation issues on a daily basis including traffic congestion and related air pollution. Riverside is part of Southern California's "Inland Empire," which has had a long history of dealing with air quality issues, suffering from some of the worst air pollution in the country dating back to the 1960s. However, with aggressive air quality regulations primarily aimed at the transportation sector, criteria pollutant emissions have been reduced by as much as 90% over the last half century.

More recently, greenhouse gas (GHG) emissions are now being aggressively targeted in the region to deal with climate change issues. The State of California has already taken steps to restructure environmental guidelines to de-emphasize the addition of roadway capacity as a congestion and environmental mitigation measure—an effort in which Riverside has been an active participant. Local leadership is now re-envisioning Riverside and embracing smart-city technology in order to bring relief to congested roadways, reduce emissions, encourage mode-shifts, improve safety, update parking requirements and zoning, and significantly enhance the quality of life of the City's residents and patrons. At the heart of this effort is the recent launching of Riverside's Transformative Climate Communities Program.

17.1.2 Transformative Climate Communities (TCC) Program

Funded by the State of California's Strategic Growth Council, the City and its partners received \$31.2 M in 2020 to pursue a broad community-based effort to empower Riverside's Eastside area, with the goal of creating new economic opportunities, and improving the health and well-being of Riverside residents. The project area centers around the City's 7th and Chicago housing project, known as Entrada, and contains most of the Eastside from the City's downtown Metrolink station all the way to UCR, as shown in Fig. 17.1. There are a number of projects that are being developed with this TCC funding, including providing high-quality multimodal transportation, affordable housing, urban greening, solar energy, and workforce development training in the targeted region. UCR researchers are working closely with the City, project leaders, and community stakeholders to identify and track specific indicators of project quality and assess public health, economic development, greenhouse gas reductions, and other outcomes for the entire program. This TCC Program is progressing well, more details can be found at https://storymaps.arcgis.com/stories/b5fffd6ae7744b8ab82bb8a725c25c36.

Since UCR is part of the Eastside community, UCR has ongoing efforts to improve local economic opportunities and health. This includes efforts at improving mobility

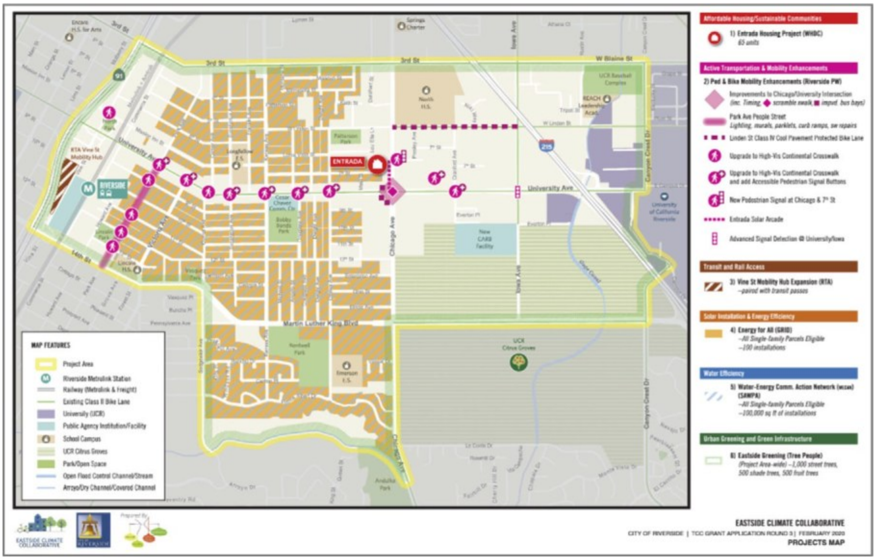

Fig. 17.1 City of Riverside's Eastside community, with various projects being developed as part of the Transformative Climate Communities Program. (permission for reusing this figure granted from the City of Riverside; original source: https://storymaps.arcgis.com/stories/b5fffd6ae7744b8ab82bb8a725c25c36. Base map accessed from ArcGIS Online, see https://www.esri.com/en-us/legal/copyright-proprietary-rights; Map image is the intellectual property of Esri and is used herein under license. Copyright © 2020 Esri and its licensors. All rights reserved)[2]

between the UCR campus and downtown Riverside, centered around a designation of an "Innovation Corridor," described below. In addition, UCR has been researching ways to reduce the impacts of goods movement, warehousing, and supply chain logistics in the region. This includes developing and assessing new technology and techniques to reduce the impacts heavy trucks have on local neighborhoods and working closely with the Center for Community Action and Environmental Justice on community outreach.

17.1.3 Riverside's Innovation Corridor and Smart Intersection

As part of Riverside's Transformative Climate Communities Program, the City and UCR have set out to create an "Innovation Corridor," a 6-mile section of University Avenue between the UCR campus and downtown (see Fig. 17.2 and [2]). This area

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was selected due to its proximity to an expanding transit and alternative transportation network, research institutions associated with UCR, and the ever-expanding entertainment destinations in the downtown region. Along this corridor, the traffic signal controllers were updated to be compatible with SAE connectivity standards. Further, several key intersections along this corridor have been set up with short-range communication roadside units. With this communications capability, Signal Phase and Timing (SPaT) messages from the traffic signal controllers can be directly transmitted to vehicles equipped with similar communication technology, traveling along the corridor. In addition to the SPaT messages, other information can be broadcast, such as positioning correction information and map information on the intersection configuration.

In addition to the communication capability between the traffic signals and the equipped vehicles, the Innovation Corridor also has several air quality monitors located along the roadway.

The overarching goal of this Innovative Corridor is to serve as a key testbed for connected and automated vehicles applications, for improving safety, traffic flow, and reducing pollutant emissions. Since this arterial corridor cuts directly through local neighborhoods, impacts from these applications should bring direct benefits to the community. One of the key connected vehicle applications that has been tested along the Innovation Corridor is described in Sect. 17.2.

Another key part of Riverside's Innovation Corridor, is a smart-intersection located at University Avenue and Iowa Street. This smart-intersection has been equipped with various surveillance systems, including a GridSmart fisheye camera system, as well as stationary LiDAR sensors that provide a detailed 3D view of the intersection and various road users, including cars, trucks, bicyclists, and pedestrians. This intersection is illustrated in Fig. 17.3, showing the location of the sensors at the intersection. This smart-intersection also serves as a key research testbed, where

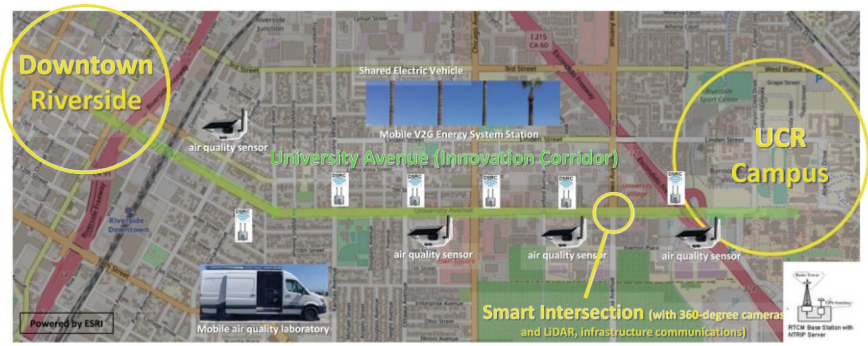


Fig. 17.2 City of Riverside's Innovation Corridor (i.e., a section of University Avenue between UCR and downtown), adapted from [11], permission for reusing this figure granted from UC Davis Institute of Transportation Studies; Base map from OpenStreetMap (https://www.openstreetmap.org/copyright); available under the Open Database License (https://www.opendatacommons.org)

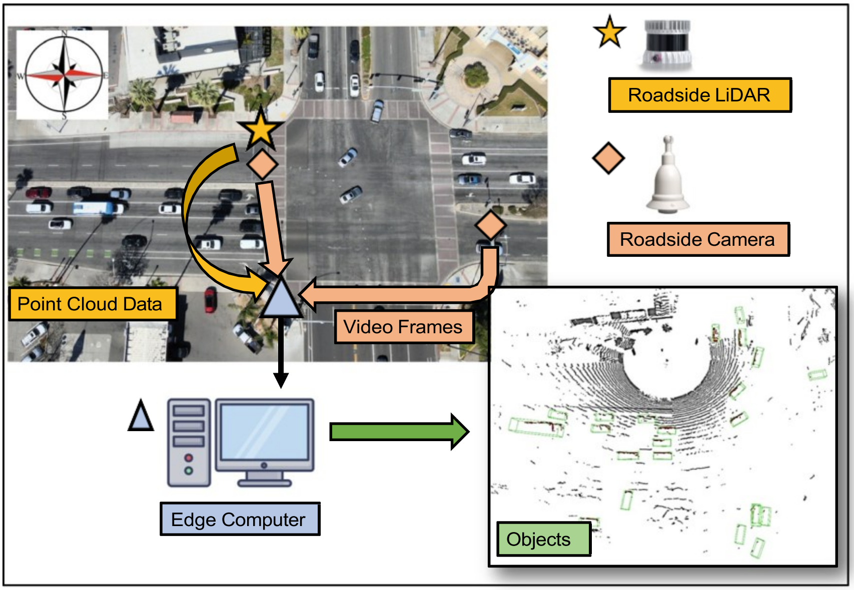


Fig. 17.3 City of Riverside's smart intersection (i.e., intersection of University Avenue and Iowa Street, along the Innovation Corridor)

we can conduct experiments in improving road user safety, mobility, and minimize emissions.

17.2 Eco-Friendly Cooperative Traffic Optimization

It is well known that roadway congestion is detrimental from many perspectives: it negatively impacts our mobility, leading to longer travel times, increased emissions, and increasing the total amount of fuel consumption. There are a number of congestion mitigation measures that can be deployed, many of which take advantage of ITS technology. For example, traffic signal optimization on our arterial roadways has long been recognized as a critical component in improving transportation efficiency and mitigating congestion at signalized intersections [3]. Traffic signal timing optimization aims to determine the ideal allocation of green, yellow, and red signal phases to minimize delays, reduce travel times, enhance traffic flow, and maximize intersection capacity [4]. With advances in sensors, communications, and computing, traffic-adaptive signal controllers can now utilize real-time vehicle detector data to measure traffic flow, which can in turn be used to optimize traffic passing through an intersection. Further, in a connected vehicle environment, vehicles can directly communicate with the infrastructure to provide information on vehicle status (e.g., location, speed, lane position, etc.) to traffic signal controllers, allowing for better signal timing optimization.

17.2.1 Vehicle Trajectory Planning

In addition to optimizing traffic signal timing, it is also possible to have vehicles adjust their speed trajectories based on information from the traffic signals. This trajectory planning optimization can be done in an eco-friendly way, to where energy consumption and emissions are minimized. Over the years, extensive research has been conducted on this type of vehicle trajectory optimization, resulting in the development of various models, algorithms, and optimization techniques. Commonly referred to as “Eco-Approach and Departure at Signalized Intersections” (EAD) in North America and “Green Light Optimized Speed Advisory” (GLOSA) in Europe, various pilot deployments have taken place around the world, including in Riverside California, along the Innovation Corridor.

We have carried out a variety of EAD experiments both in simulation as well as in the real-world, utilizing the enhanced infrastructure along the Innovation Corridor (more details can be found in [5]. The goals of this research are to demonstrate how connected vehicles can improve both mobility and environmental factors along a signalized arterial roadway. Like other CAV applications that involve determining optimal speed profiles for vehicles traveling within an urban transportation network, the EAD application utilizes:

- the SPaT data from the upcoming traffic signals;
- map and route information (e.g., stop-bar location, road grade, road speed limit, turning movement);
- downstream traffic conditions such as queue length; and
- the vehicle’s state and powertrain limitations (e.g., vehicle position, instantaneous speed, acceleration/deceleration limit), to determine the optimal recommended speed profile that can minimize the target vehicle’s energy consumption and tailpipe emissions when approaching to and departing from signalized intersections.

The EAD application inherently smooths traffic flow, thereby improving mobility, reducing energy consumption, and lowering tailpipe emissions. The advisory speed profile and other relevant information produced from the EAD algorithm can be conveyed to the driver typically through a human–machine interface (HMI or driver–vehicle interface, DVI), or through partial automation (e.g., a form of adaptive cruise control). In our research, we primarily utilize an HMI to provide the drivers with an advisory speed. Figure 17.4 illustrates a generalized system architecture for the EAD application. Technical detail on the application can be found in [2] and related publications.

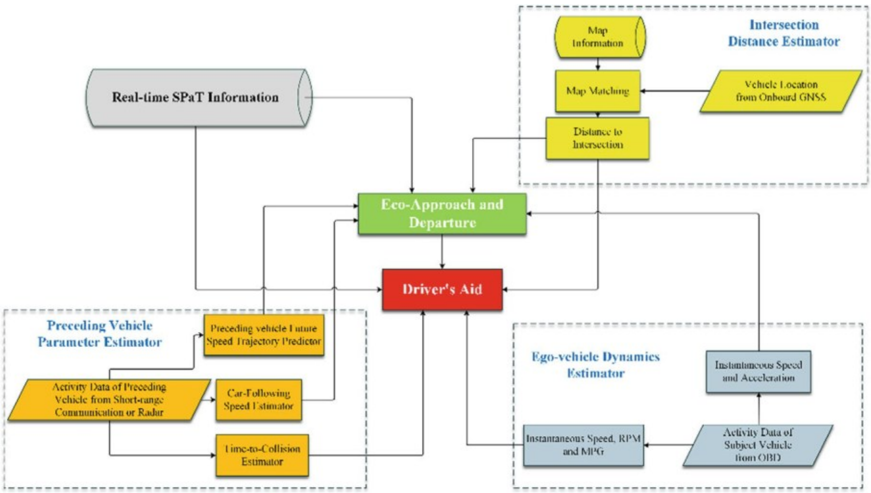


Fig. 17.4 The generalized system architecture of the EAD application that was implemented

We have carried out extensive testing of the EAD connected vehicle algorithm, both in simulation and the real world, with the goal to reduce the idling time at intersections, and avoid unnecessary accelerations, while also allowing for safe driving. The EAD algorithm calculates an optimal velocity to minimize fuel consumption as described in [6]. For our experiments, the signal controllers along the Innovation Corridor were set up to transmit SPaT information, providing a timestamp for the minimum time remaining and maximum time remaining to the connected vehicles in the experiment. Two instrumented vehicles are generally utilized in the experiments, where one test vehicle is utilized that fully implemented the connected vehicle EAD application, while the other vehicle is used as a comparison vehicle, driven normally with traffic without the EAD application. The experiments were conducted at various times throughout a typical weekday (e.g., between 10:00AM and noon, and 1:30PM–3:30PM). During the experiments, the actual fuel consumption from the vehicles were recorded in real time, along with detailed trajectory information (i.e., vehicle speed and position at 1 Hz). Once the vehicle trajectories were collected, they were used as input to well-calibrated vehicle emissions models to also estimate emission reductions.

As an example of our results, Table 17.1 shows the CO_2 and fuel consumption for scenarios carried out both in simulation as well as the real world. In general, the simulation results tended to provide slightly greater reductions compared to the real-world results. But, in general, the EAD application generally provides reductions in the range of 5–15%.

Table 17.1 EAD experimental results

Results		No EAD	EAD	Improvement (%)
Simulation	CO_2 (g/mi)	541.04	479.02	11.46
	Fuel (g/mi)	163.62	144.86	11.5
Real-World	CO_2 (g/mi)	430.7	402.3	6.6
	Fuel (g/mi)	137.63	128.5	6.63

17.2.2 Vehicle Trajectory and Traffic Signal Timing Co-optimization

In recent years, there has been growing interest in developing methods for the co-optimization of traffic signal timing and adjusting vehicle trajectories at signalized intersections [5]. This is motivated by the fact that traditional traffic signal control methods, which typically focus on optimizing traffic flow, can lead to inefficient vehicle movements and increased fuel consumption [5]. By also making adjustments to vehicle speed trajectories, it would be possible to improve both on traffic flow as well as achieving lower energy consumption and emissions. Again, this co-optimization leverages advances in connected and automated vehicle technologies, enabling vehicles to communicate with each other and with the traffic signal system in real time, and to adjust their speed under the prevailing traffic conditions.

As part of our research, we have developed a co-optimization technique referred to as “Eco-friendly Cooperative Traffic Optimization” or ECoTOp, described in detail in [5, 8]. The ECoTOp framework combines vehicle eco-trajectory planning optimization and traffic signal optimization to achieve enhanced transportation performance at individual signalized intersections. The goal of the ECoTOp framework is not to just find a single optimized solution for traffic throughput and lower emissions but to provide a system that can be dynamically adjusted to select the most suit- able optimization strategy based on real-time traffic conditions and environmental considerations.

The ECoTOp system is comprised of two major modules: a traffic signal optimization module and the eco-trajectory planning module (from [5]). These modules are designed to interact with each other but often have inherent conflicts when pursuing their own optimization goals. The traffic signal optimization module seeks reliable information from incoming vehicles, including current dynamic state and future movement, as early as possible. It also requires the flexibility to adjust the signal timing plan at any time to adapt to the dynamic traffic conditions. On the other hand, the eco-trajectory planning module requires reliable signal timing informa- tion ahead of time to plan trajectories that can reduce energy consumption and emissions. However, vehicles operating under the eco-trajectory plan still require some flexibility in operation to improve safety, mobility, and energy performance in certain situations, such as emergency braking and lane changing.

In general, it is not feasible to create an ideal co-optimized system in an isolated intersection with mixed traffic due to two main reasons. Firstly, unconnected vehicles with human drivers typically have diverse driving styles, which can sometimes be unpredictable. Secondly, the limitations in sensing, communication, and control sometimes make it impossible to predict the time and state when each vehicle enters the system, even for connected and autonomous vehicles. In a mixed traffic environment, each module must make trade-offs to achieve an integrated optimization. This section presents the method for interaction between the two modules.

The ECoTOp system achieves the co-optimization of signal control and vehicle trajectory by following the flowchart depicted in Fig. 17.5. The ECoTOp system works as follows for the co-optimization of signal control and vehicle trajectory [5]:

(1) The number of vehicles is determined for each lane in the network within the communication range.
(2) The number of vehicles is calculated that can be served within the current green time for each lane.
(3) Based on these values, two things are determined: the time required for the delayed vehicles controlled by the phase for that lane to pass through the intersection, and also the time required for maximum throughput.
(4) This information is then used as input to a Sequential Least Squares Programming (SLSQP) optimizer in order to obtain the new phase times.

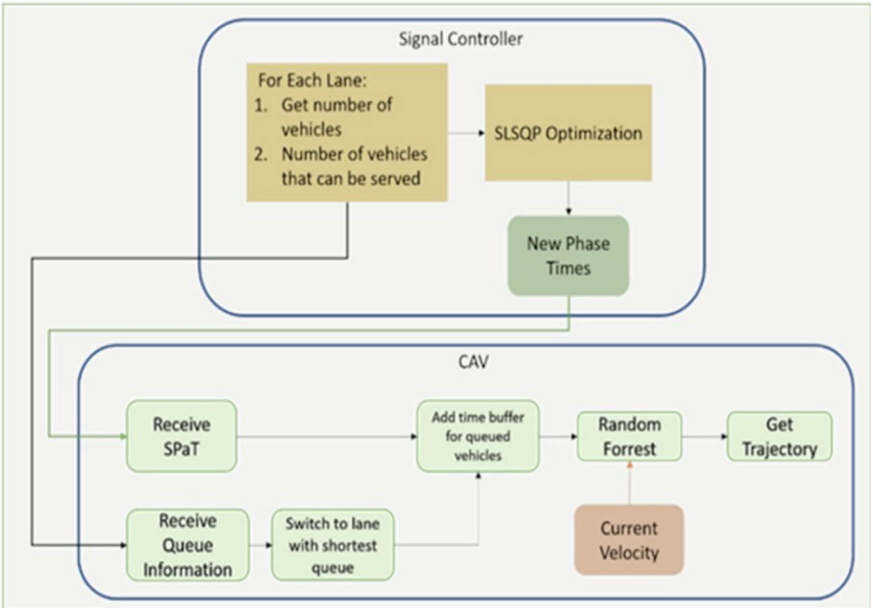


Fig. 17.5 ECoTOp algorithm flowchart (from [5], permission for reusing this figure granted by author David Oswald)

(5) Simultaneously, each connected vehicle receives the Signal Phase and Timing (SPaT) information and queue information.
(6) As in the standard EAD algorithm, the queue information is used to possibly change lanes and to calculate timing for the trajectory planning.
(7) Given this timing and the current vehicle velocity, a Random Forest-based trajectory optimizer is used to obtain each individual vehicle trajectory.
(8) Finally, the signal controller is updated with the optimal phase timing obtained from the SLSQP optimizer.

In order to evaluate the effectiveness of our ECoTOp system, we carried out a high-fidelity simulation of Riverside's smart intersection along the Innovation Corridor (University and Iowa Avenues). This simulation was carefully calibrated with measured traffic volumes and turning movements, along with the current phase and timing information. Different levels of the connected vehicle penetration rate were used and compared to three other scenarios: (1) a baseline scenario where the intersection timing is setup as it is today, with no vehicles performing EAD; (2) an optimized traffic signal timing algorithm (without vehicles performing EAD); and (3) a pure EAD scenario, with current standard signal timing. The results of this are depicted in Fig. 17.6, where we show CO_2 emissions (proportional to energy consumption) and traffic throughput as a measure of mobility. Figure 17.6 thereby consists of four quadrants: the upper left shows the results of the baseline scenario (no EAD, no signal optimization); the upper right shows the results for only optimizing signal timing; the lower left shows EAD trajectory planning only; and the lower right shows the results of the co-optimized ECoTOp system (from [5]). Figure 17.6 illustrates the results for 100% connected vehicle penetration rate and a volume to capacity ratio (V/C) of 0.82.

There are several takeaways from these results: As shown in the lower left quadrant, the EAD trajectory planning algorithm results in a CO_2 savings of approximately 11.7%, as expected; however, the EAD-only scenario has a small negative impact on mobility (i.e., throughput is decreased by 7%). For the upper right quadrant, the signal optimization algorithm improves throughput by approximately 17.5%, with negligible impacts on CO_2 emissions ($\pm$1%). When the full ECoTOp system is in place, there is both a CO_2 benefit (~7%) and a throughput increase (~9%). Again, this is a snapshot of a typical result, a more expansive sensitivity analysis is carried out and reported in [5].

It is clear that there are trade-offs between the environmental benefits and mobility (i.e., throughput) in our co-optimization scenarios. Another important feature of the ECoTOp system is that it can be made adaptable based on dynamically changing traffic conditions. Essentially, the parameters of the ECoTOp system can be changed depending on the traffic conditions (e.g., traffic volume), changes in the vehicle mix, as well as the desire of the City to either emphasize environmental improvements or mobility, or some mixture. For example, if a bad air quality day is forecasted, it may make sense to minimize emissions for that day (note that criteria air pollutants track closely with CO_2) at the expense of slightly lower traffic throughput. Conversely, the City may choose to maximize throughput after a major public event when it is in the

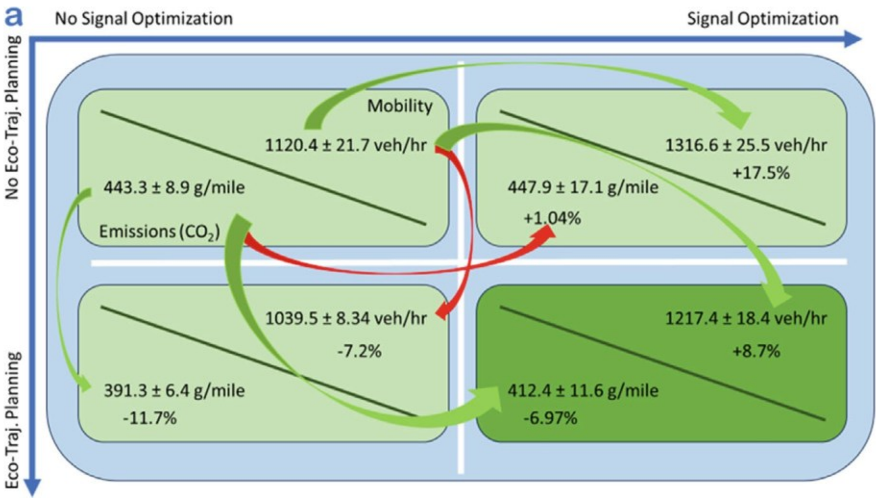


Fig. 17.6 ECoTOp experimental results (lower right), compared to baseline (upper left), EAD-only trajectory planning (lower left), and signal optimization only (upper right) (from [5], permission for reusing this figure granted by author David Oswald)

interest to clear traffic quickly. By simply dialing in the appropriate parameters to the ECoTOp system, the overall system can be made adaptable and versatile, as part of the overall smart city design.

17.3 Riverside Shared Mobility

Like many cities in California, the City of Riverside is moving forward with multiple options and strategies for personal mobility, with the idea of reducing our dependency on a personal-automobile ownership model that is very common today, particularly in Southern California. As part of Riverside's Transformative Climate Communities Program (described in Sect. 17.1), the City is exploring future deployment of shared mobility. Many forms of shared mobility have been discussed, following the general shared mobility definition of shared-use of a vehicle, bicycle, or other mode that enables users to have short-term access to transportation modes on an "as-needed" basis [9]. This included examining carsharing, personal vehicle sharing (PVS, including peer-to-peer (P2P) carsharing and fractional ownership), scooter sharing, bike-sharing, transportation network companies (TNCs, also known as ridesourcing or ridehailing such as Uber and Lyft), ridesharing (i.e., carpooling, vanpooling), microtransit, and courier network services as defined in [9].

17.3.1 Shared Mobility Planning

As part of our research program, we have engaged with the City of Riverside to help develop a shared mobility plan. Our research activities include assisting with community outreach in evaluating what types of shared mobility might work in the city, and conducting extensive modeling of zero-carbon carsharing options within the City. We are also working closely with a local carsharing company called StratosShare [10]. This local company is an on-demand carsharing operator that exclusively rents low-carbon vehicles (e.g., EVs, hydrogen fuel cell electric vehicles) by the hour or day to the public, throughout Inland Southern California. Drivers download the StratosShare app, create accounts, select time of use as well as pickup/drop-off locations, and push to start. StratosShare was founded under the vision to provide a low-cost zero-emission shared-use transportation to Inland Southern California. StratosShare is already up and running, working with the California Energy Commission and Toyota in deploying 15 vehicles in disadvantaged communities throughout Riverside and San Bernardino Counties. These vehicles are strategically located at train stations, universities, airports, and downtown locations to provide a first/last-mile transportation solution. StratosShare is planning to expand their system with additional vehicles and additional locations, so they played a strong role in Riverside's shared mobility planning.

To better understand the mobility needs of the community, we worked with the City of Riverside and StratosShare to develop and carry out a targeted community survey, consisting of a number of questions that were directed at establishing existing travel patterns and needs. In addition, several questions were aimed directly at the potential of a zero-emission carsharing system. The results and analysis of these surveys can be found in [11] and have informed the team on how to best deploy shared mobility, and also served as input to a comprehensive travel demand model, described in further detail below. In summary, the survey indicated that City residents utilize private vehicles for most of their travel, but the community in general was very much in favor of improving other modes such as walking, public transit, biking, and shared mobility. Most survey respondents agreed that it is important to create a sustainable community, by making it easier and safer to use active and public transportation. The majority of respondents were in favor of zero-emission carsharing.

17.3.2 Shared Mobility Modeling

A critical part of our research was to develop extensive shared mobility modeling tools, working with StratosShare and the City of Riverside. Specifically, the focus was on evaluating different scenarios for a carsharing system utilizing a zero-emission fleet. From the literature, it is clear that carsharing systems show great potential in reducing vehicle ownership, achieving VMT and GHG reductions, encouraging alternative transportation modes, and increasing access and mobility of disadvantaged communities (e.g., see [9, 12–15]). Further, it has been shown that vehicle electrification and increased automation have the potential to reduce carsharing GHG emissions, along with reducing private vehicle ownership (see, e.g., [16–18]). For all of these reasons, Riverside wants to increase zero-emission carsharing operations within the community.

It is important to note that many of the existing carsharing studies focus on analyzing the impact of the carsharing program *after* their real-world deployment. It is more challenging to predict the impact of carsharing *before* implementation due to the lack of behavioral data from the participants. To overcome this issue, two methodologies have been applied in existing research. The first method is primarily survey-based and has been applied in many cases (see, e.g., [19–21]). Another mechanism for predicting carsharing success is based on discrete-choice modeling. For example, in a carsharing study for London, a Perceived Activity Set (PAS) model was created to build a conceptual framework of shared mobility, referring to a set of out-of-home activities that encompass their potential travel needs when making decisions that structurally affect their accessibility [22]. This modeling method focused on the long-term impact of carsharing, including the decision to purchase or sell a car or a bike, and the decision to subscribe the transit/carsharing membership. Another study in Rotterdam, Netherland, developed a method in modeling the short-term impact of carsharing using discrete choice model, choosing between five conventional modes: car driver, car passenger, public transport, cycling, and walking. Carsharing was considered as a new mode that was introduced within the mode choice, meaning that a new utility function was required for the carsharing alternative, consisting of variables that are likely to explain carsharing demand.

In our research, the goal was to predict the impact of the potential deployment of zero-emission carsharing in the City of Riverside. A hybrid model was developed with three key components: survey data, discrete-choice model, and agent-based simulation. In our modeling effort, we first derived travel demand data and travelers' activity schedules, and then applied this to the BEAM model (Behavior, Energy, Autonomy, and Mobility), developed by Lawrence Berkeley National Laboratory [23]. BEAM is a mesoscopic simulation model for urban transportation systems with particular support on shared mobility modeling, energy estimation, and computation over large-scale networks. With proper travel demand and travelers' activity schedules, BEAM can evaluate traffic condition, energy consumption and air quality for the entire network, and predict the mode choice and routing decision for each individual agent.

The trips in BEAM are associated with the travelers' demographic information synthesized by *PopGen* and *CEMDAP*, other modeling components of the BEAM framework [23]. A discrete choice model was applied to describe the model choice behavior with existing means of transportation, e.g., car driving, car passenger, public transit, cycling, and walking. The parameters for this model were adopted from literature, and then calibrated using data from our Eastside Climate Collaborative Survey (see Sect. 17.3.1) and other localized data. We then introduced carsharing service into this discrete choice model to study its impact on travel behavior and its benefit on fossil fuel savings and greenhouse gas reduction considering the mode shift from private cars to zero-emission carsharing vehicles.

17.3.2.1 BEAM Model Development and Calibration

In a discrete-choice model, typically there are three types of variables: (1) vari- ables that represent the level-of-service data of a certain mode (e.g., travel time and cost); (2) dummy variables that represent the characteristics of a person (e.g., age, gender, and income) or a household (e.g., number of cars and income); and (3) an alternative specific constant to represent variables that are not present in the utility function but still affect the mode choice. The traveler's daily trip activity data and the corresponding person/household attributes are critical to estimate the mode share for transportation. In our modeling efforts, we introduced a simulation-based data collection method using the BEAM tools which provided calibrated level-of-service data and person/household data to support the discrete choice model, as illustrated in Fig. 17.7.

To acquire personal and household information, we generated raw data using *PopGen*, and calibrated them using latest survey data, including information on population, age, and income for each zone in the City. Next in the calibration process, we utilized data from the Southern California Association of Governments (SCAG) [24]. The SCAG region encompasses 6 counties (Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura) and 191 cities in an area covering more than 38,000 square miles. SCAG develops long-range regional transportation plans including sustainable communities' strategies and growth forecast components, regional transportation improvement programs, regional housing needs allocations and a portion of the South Coast Air Quality management plans [24]. Zone-based

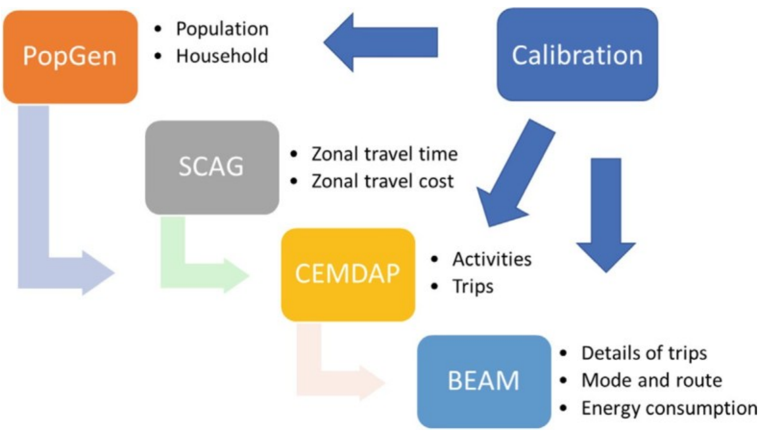


Fig. 17.7 System diagram for data collection (from [11], permission for reusing this figure granted from UC Davis Institute of Transportation Studies)

level-of-service travel data (LOS-data) from SCAG is necessary to analyze carsharing alternatives, identifying travel time, travel cost, along access/egress time for public transit.

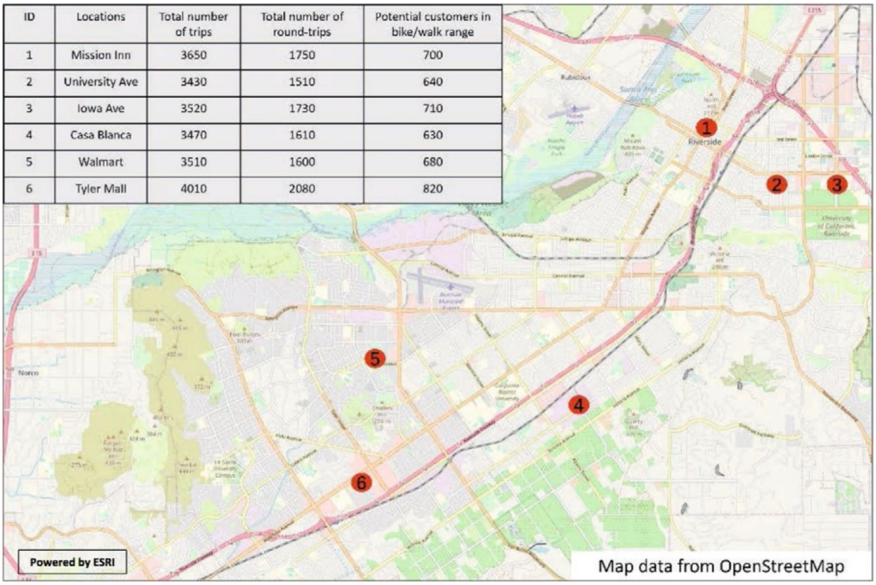
Next, we utilized Comprehensive Econometric Micro-simulator for Daily Activity-travel Patterns (*CEMDAP*) software, representing a system of econometric models that represent the decision-making behavior of individuals [25]. It is one of the first systems to comprehensively simulate the activity–travel patterns of workers as well as non-workers in a continuous time domain. Given various land-use, socio-demographic, activity system, and transportation level-of-service attributes as input, the system provides as output the complete daily activity–travel patterns for each individual in the household [25]. With the data from *PopGen* and SCAG, *CEMDAP* creates daily activities for each person in the region of study (i.e., Riverside).

The personal/household data from *PopGen* and trip data from *CEMDAP* were then loaded into BEAM to derive the mode-specific level-of-service data for all the travelers. The BEAM model implementation for the City of Riverside was coded and calibrated using multiple data sources. This Riverside BEAM model was then able to serve as a powerful platform to evaluate the performance of the current shared mobility systems and predict the results of the future deployment, including link-by-link trajectories, mode and routing decisions, and energy consumption and CO_2 production. Further details of the Riverside BEAM model development and calibration are provided in [11].

17.3.2.2 BEAM Modeling Results

To evaluate the potential impact of zero-emission carsharing in the City of Riverside, we first identified potential locations of carsharing stations and the demand around the station, based on community input data. Figure 17.8 shows six potential locations suggested by the community and the city. Station 1 is in Eastside neighborhood near Mission Inn. Stations 2 and 3 are in University neighborhood near UCR campus. These three stations will be deployed along the Innovative Corridor (see Sect. 17.1), and the other three will be in the southern part of Riverside, one in Casa Blanca neighborhood, one in Airport neighborhood, and one in La Sierra neighborhood close to the shopping mall named Galleria at Tyler. Using the BEAM model, we identified the potential customers of the carsharing service at each station as the travelers who live, work or have other activities within walk/bike range of the station and plan to make roundtrips from that station. The table at the left-top corner of Fig. 17.8 shows the number of potential customers and trips at each station.

Next, we applied the discrete choice model to estimate the mode share of those potential customers around each station. Figure 17.9 shows the mode share before and after introducing carsharing for the trips with a work-commute purpose. For the "before carsharing" scenario, the mode shares for all conventional modes are very close to the survey results, showing good performance in coefficient calibration. For the "after carsharing" scenario, the mode share for carsharing for work trips was



ID	Locations	Total number of trips	Total number of round-trips	Potential customers in bike/walk range
1	Mission Inn	3650	1750	700
2	University Ave	3430	1510	640
3	Iowa Ave	3520	1730	710
4	Casa Blanca	3470	1610	630
5	Walmart	3510	1600	680
6	Tyler Mall	4010	2080	820

Fig. 17.8 Potential locations and travel demand of carsharing stations, from [11], permission for reusing this figure granted from UC Davis Institute of Trans-portation Studies; Base map from OpenStreetMap (https://www.openstreetmap.org/copyright); available under the Open Database License (http://www.opendatacommons.org)

between 8 and 13%. About two thirds of the carsharing trips are shifted from car driving trips, and the rest are shifted from other modes including car passenger, public transit, cycling, and walking. Due to the introduction of carsharing services, it was predicted that trips from single driver cars would be reduced by 8–12%, trips as car passenger (including carpool and taxi) would be reduced by 10–26%, and trips as transit passenger would be reduced by 4–16%. Walking and bicycle trips were less impacted by carsharing, with 6 and 3% reduction, respectively.

For non-work trips, we evaluated trips associated with education, as well as trips "for other purposes" (e.g., shopping, etc.). It was found that for education-based trips, the carsharing mode share shift is less than 1%, having little impact on conventional modes. For trips with other purposes, the carsharing mode share shift was predicted to be between 15 and 23%, as shown in Fig. 17.10. Among all the new carsharing trips, 39% of them are shifted from car driving trips.

It is clear that the potential for carsharing services can enhance the accessibility of the local residents near the stations, especially for the household that do not own a private car. According to the numerical results, for the people without cars in their households, the mode share of carsharing for work trip increases by 17–40%. Considering the high correlation between income and car ownership, the carsharing program would significantly improve the accessibility of the disadvantaged communities.

When considering that the carsharing fleet would be zero-emissions (electric or fuel cell), the mode shift from gasoline private vehicles to electric carsharing vehicles

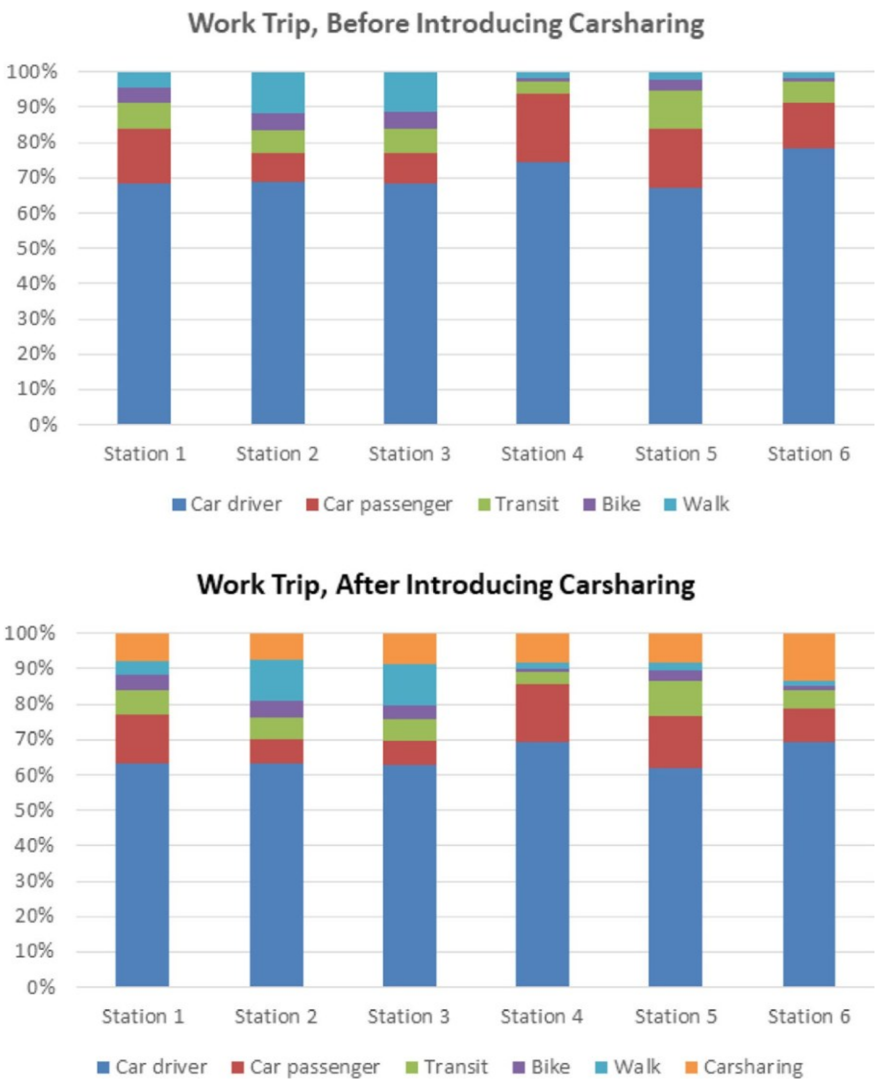


Fig. 17.9 Mode shares for work trips before (top) and after (bottom) introducing carsharing (from [11], permission for reusing this figure granted from UC Davis Institute of Transportation Studies)

would significantly reduce fuel consumption and greenhouse gas emissions. Based on our modeling results, it is expected that greenhouse gas emissions would go down by 10%, simply by reducing the use of the private gasoline-powered cars after introducing carsharing in the neighborhood. Besides the direct mode-shift impact shown in the proposed model, carsharing would also serve as the last-mile solution for public transit and further reduce private car trips from this carsharing-transit synergy. In the long term, the reduction of car ownership will further decrease the

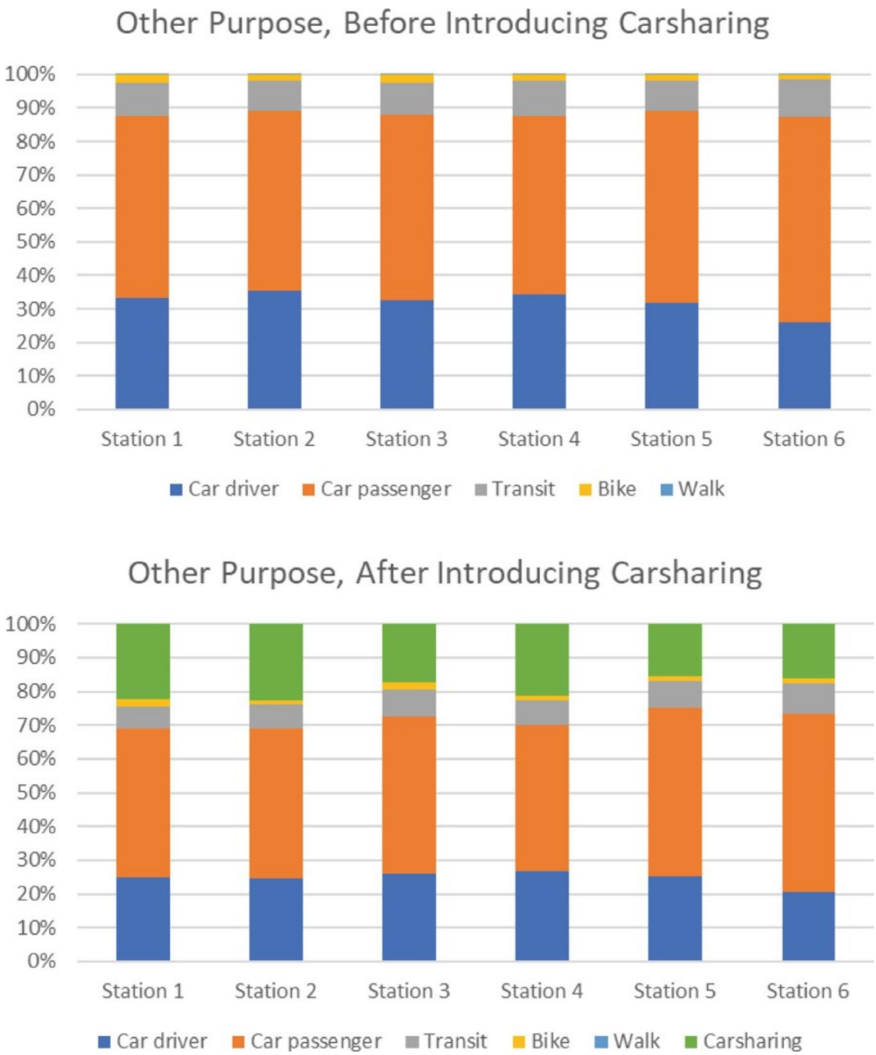


Fig. 17.10 Mode shares for non-work trips before (top) and after (bottom) introducing carsharing (from [11], permission for reusing this figure granted from UC Davis Institute of Transportation Studies)

travel demand and therefore reduce fuel consumption and greenhouse gas emissions. These benefits are being explored in future research.

17.3.3 Shared Mobility in Riverside: Key Conclusions and Recommendations

As shown by our survey and modeling results, a zero-emission carsharing service can be a promising approach to improving the accessibility and environmental sustainability of communities. To successfully implement the carsharing services, the following recommendations can be made:

- The preferable locations of the carsharing stations should be in a community with high population density, where the residents of that community can quickly access to the station conveniently by walking or cycling.
- Since people who don't have cars in the household will likely have higher use rates of carsharing services for their travel, car ownership is a critical index in identifying the best locations for carsharing stations. As such, a disadvantaged area with lower car ownership will receive larger benefits from introducing zero-emission carsharing.
- Age is another key factor impacting the acceptance of carsharing. Carsharing receives higher interest in a community with higher percentage of people aged 45 or below.
- Reducing access/egress time can increase the popularity of carsharing. This can be achieved by easier parking and simple check-out/check-in transactions.
- Based on our Riverside community survey, it was found that 40% of the respondents are not that interested in zero-emission carsharing services. As such, outreach activities will play a critical role to further increase the acceptance of carsharing in the community.

17.4 Goods Movement and Innovative Truck Routing

Due to a variety of factors, Inland Southern California has grown to become one of the largest hubs of goods movement activity in the nation, with considerable infrastructure, employment, and economics connected to the logistics industry. This logistics industry will continue to grow as an important part of the economy, but it is critical that it be managed in a way that the quality of life in the communities is preserved, negative environmental impacts are minimized, and good-paying jobs are prevalent. Imports throughout the nation continue to increase, placing increased stress on the current logistics supply chain. Currently, more than 44% of the nation's goods pass through Inland Southern California on their way to their final destinations—as such, the nation greatly depends on a properly functioning goods movement system in Inland Southern California.

It is clear that goods movement activities in the region have grown substantially over the last few decades and there are many underlying positive elements, including a rich flow of goods and wealth, as well as substantial employment opportunities. But, in addition to these positive elements, there are also a number of negative elements, including:

- Air quality in the region is poor, notably due to the huge flow of diesel-fueled heavy vehicles (both trucks and locomotives), generating nitrogen oxides (NOx), particulate matter, and greenhouse gas emissions; this has adversely affected the public health and quality of life in the region.
- Traffic congestion in the region is severe across all roadway types (freeways, arterial roadways), negatively affecting the quality of life in the region. This leads to not only increased emissions but also an economic loss due to time spent in traffic.
- The employment situation in the region is quite volatile, with many of the logistics related employment opportunities being part-time, temporary, low-paying, and lacking upward career mobility. Employment is also under the threat of replacement by automation, and subject to pandemic-related and other negative health considerations.
- Land use has been negatively affected, where greenery is being replaced by densely packed warehouses, storage facilities, truck and trailer parking, and massive railyards; this has decreased the social and environmental attractiveness, and precluded the implementation of facilities from higher value sectors such as high-tech, manufacturing, and R&D parks.
- Social equity has suffered, where the impacts of air pollution, congestion, and other measures are significantly higher on disadvantaged communities in the region.

It is important to note that the poor air quality associated with goods movement is not due to warehouse operations itself, but instead is mostly due to its associated transportation activities. The internal operation of warehouses typically has a high degree of automation and are highly electrified that can be accomplished cleanly with renewable electricity. Indeed, several warehouses have been awarded a high level of green building certificates. The majority of the poor air quality is associated with the heavy-duty freight transportation sector, which includes diesel trucks and locomotives. This accounts for well over 90% of the emissions associated with warehouse operations. We currently rely on heavy-duty vehicles in high volume that travel significant distances in the region. This flow of heavy-duty vehicles to/from logistics facilities in Inland Southern California is also a major cause of congestion and road infrastructure deterioration on roadways all over the region. While the majority of these heavy vehicles are diesel-powered, there is currently a big push to transition these vehicles to zero emissions, based on battery or fuel cell technology.

The proliferation of freight facilities and heavy-duty vehicles is also caused by the fact that most of the companies operating in the Inland Southern California logistic ecosystem are in many ways operating in silos. Warehouses are typically built in areas that have low land prices; this usually drives where warehouses are located. It is often the case that commercial zoning is adjacent to disadvantaged communities and freeways. There are many documented cases of these communities unsuccessfully opposing the locations of proposed warehouses in recent years. However, there is a large incentive for the cities and counties to acquire revenue from these transactions. In the absence of other offers for commercial development, and potentially due to the lack of resources of the communities opposing to the development, it has become common that logistics warehouses constitute a major portion of these neighborhoods. This places the negative impacts of air pollution, noise, and congestion from truck traffic on these areas in comparison to a zoning pattern that would space the warehouses out throughout the region. Planning and zoning requirements among cities and counties also can vary greatly, often times leading to inefficiencies in the overall arrangement of the broader logistic operations.

17.4.1 Innovative Truck Routing in Inland Southern California

Over the last several years, we have been developing a number of intelligent transportation system technologies, such as advanced fleet management tools, to mitigate the negative impacts of goods movement. These tools include, for instance, intelligent fleet scheduling software tailored for electric trucks, dynamic time-of-day fleet scheduling software, geofencing strategies, and low pollutant exposure truck routing. These tools are coupled with our research in connected and automated vehicles, with a focus on heavy-duty vehicles, leading to more efficient truck operations and smoother traffic flow.

As an example of our recent efforts, we have carried out a case study where we have employed our low pollutant exposure routing technique around the San Bernardino Airport, which is being built out as a major air cargo hub for Amazon, UPS, and FedEx here in Inland Southern California. This airport mainly supports air cargo operations and it has recently been approved to undergo a major expansion [26]. The surrounding community is largely classified as a disadvantaged community (under California SB 535, see [1]). Local residents, communities, and organizations have been expressing concerns about future employment opportunities and environmental impacts [27].

For this case study, we have applied our exposure-based routing technique, which guides heavy-duty diesel trucks (HDDTs) through a community in a way that lowers the total exposure of community members to the pollutant emissions from the truck without significantly increasing travel time [28]. The exposure-based routing technique was applied to the San Bernardino Airport area, as shown in Fig. 17.11. This area is bounded by Freeway I-215 in the west, I-10 in the south, and I-210 curving from south to north then connecting the east–west side. Corners one, two, three, and four correspond to the Northwest, Northeast, Southeast, and Southwest corners of the San Bernardino city area, respectively. The location of San Bernardino Airport west side is marked in the figure below, and we evaluated the potential HDDT trips from the four corners to and from the airport.

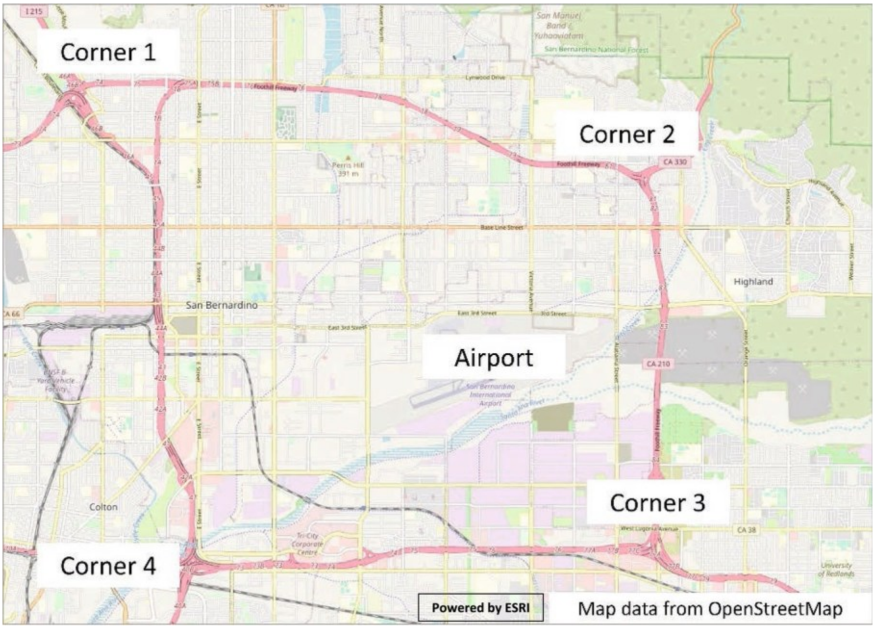


Fig. 17.11 Map of Study Area, from [11], permission for reusing this figure granted from UC Davis Institute of Trans-portation Studies; Base map from OpenStreetMap (https://www.openstreetmap.org/copyright); available under the Open Database License (http://www.opendatacommons.org)

Figure 17.12 presents the methodological framework of exposure-based routing. It involves a modeling chain that starts from vehicle emission modeling to air dispersion modeling, human exposure assessment, and finally vehicle route calculation where the output from one step is used as an input for the next step. In addition, each step also requires other inputs. The inputs and assumptions associated with each modeling step are described below.

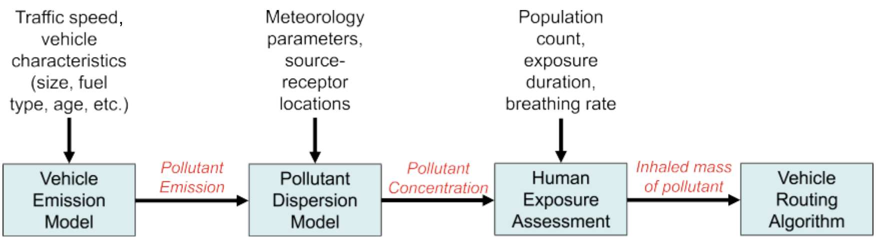


Fig. 17.12 Methodological framework of exposure-based routing (adapted from [11], permission for reusing this figure granted from UC Davis Institute of Transportation Studies)

17.4.1.1 Vehicle Emissions Modeling

The calculation of emissions was focused on fine Particulate Matter ($PM_{2.5}$), Nitrogen Oxide (NO_x), and Carbon Dioxide (CO_2) emissions from HDDTs. They were calculated using the following equation:

$$E_{i,j} = V_{i,k} \times L_i \times EF_{j,k},$$

where $E_{i,\ j}$ is the mass emission of pollutant j on link i; $V_{i,\ k}$ is the HDDT volume on link i with link speed k; L_i is the length of link i; and $EF_{j,\ k}$ is the emission factor of pollutant j at speed k. The calculation was done for a single heavy-duty diesel truck of model year 2012, but for all the roadway links in the modeling area. It was assumed that this truck would be traveling at the speed equal to the speed limit of each roadway link. The data regarding speed limit on roadway links was obtained from a commercial digital roadway map. Emission factors of the truck were obtained from CARB's EMFAC2017 model [29, 30], which is a regulatory model for estimating on-road mobile source emissions in California. Only running exhaust $PM_{2.5}$, NO_x and CO_2 emissions were calculated.

17.4.1.2 Air Dispersion Modeling

An atmospheric dispersion model was needed to estimate the concentration of air pollutants emitted from vehicular sources at specific receptor locations. In this study, R-LINE, a research grade dispersion model for near-roadway assessment was used [31]. Micro-meteorology data inputs for R-LINE such as temperature, wind speed, wind direction, surface friction velocity, and Monin–Obukhov length were obtained for Redlands Station from South Coast Air Quality Management District website [32]. Source height was assumed to be 2.5 m (~8.2 ft), which represents a typical height of exhaust stacks of heavy-duty diesel trucks. Receptor height was assumed to be 1 m (~3.3 ft), which represents an average height of 5-year-old children.

17.4.1.3 Human Exposure Assessment

In this research, pollutant exposure is referred to the amount of pollutant inhaled by a group of subjects. Therefore, inhaled mass (IM) was used to represent the pollutant exposure, which was calculated as

$$IM = C * Pop * t * BR,$$

where C is the pollutant concentration (μg/m^3) in a given microenvironment; Pop is the number of subjects in the microenvironment; t is the truck travel time on the road link (hour); and *BR* is the breathing rate (m^3/hour/capita) of the subjects exposed to the pollutant.

Breathing rates of population in different age groups were based on the U.S. EPA's Exposure Factors Handbook [33]. In addition, the California Office of Environmental Health Hazard Assessment's Technical Support Document of Exposure Assessment and Stochastic Analysis included detailed breathing rate scenarios [34]. It is desirable to reduce population exposure to traffic-related air pollutants because tailpipe emissions, such as $PM_{2.5}$ and NO_x, are associated with health risks in young children, older adults, patients, and even healthy adults [35–37]. Thus, in this research, both population-wide average breathing rate of 17 m^3/day and population-specific breathing rate were applied.

17.4.1.4 Vehicle Route Calculation

The Shortest Path Problem (SPP) is traditionally aimed at finding a travel route between a pair of origin–destination (OD) points that has the shortest distance or shortest travel time. However, in this research, the vehicle routing objective is to reduce inhaled mass of pollutant while limiting the increase in travel distance within a reasonable range for the trip. This is a multi-objective SPP studied by many researchers (e.g., [38]). Several methods for solving multi-objective SPP are summarized in [39]. In previous studies, we used a weighting method that transformed the multi-objective SPP into a single-objective SPP. The specific methods can be found in [40]. In this study, due to the limited number of OD pairs, we simply selected freeway routes and compared them with manually selected alternative routes that have similar travel time.

17.4.1.5 Network Characterization

Figure 17.13 shows four entry/exit points located at the four corners of the study area. The sensitive facilities or receptors considered in this study are primarily used by individuals that are most susceptible to the effects of air pollution. Daycares, schools (elementary to high schools), assisted living homes, and public parks were chosen as the sensitive facilities. The population data were projected to calendar year 2018 at census block level based on 2010 Census and 2018 American Community Survey. Population at sensitive facilities were projected based on school enrollment data and census population. Population at residential blocks are estimated based on several sources including population by age groups [41], employment data [42, 43], and school enrollment rate [44, 45].

To better understand how the R-LINE model parameters impact the output concentration values, a sensitivity analysis of road width and freeway sound barrier options in R-LINE was performed. The results showed that for the current modeling scenario, the road width and sound barrier options only have minor effects on the modeled concentration results. On the other hand, the most impactful factors are traffic

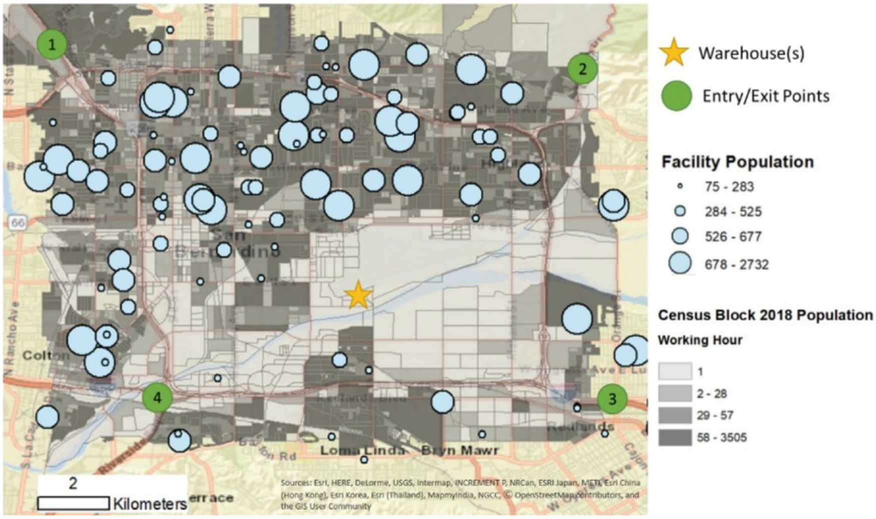


Fig. 17.13 Map of population, sensitive facilities, and truck trip attractions in San Bernardino (from [11], permission for reusing this figure granted from UC Davis Institute of Trans-portation Studies; base map accessed from ArcGIS Online, see https://www.esri.com/en-us/legal/copyright-proprietary-rights; Map image is the intellectual property of Esri and is used herein under license Copyright © 2020 Esri and its licensors. All rights reserved)

speeds, emission factors, meteorological conditions, and population distribution. The influence of varying breathing rates was also examined where three different breathing rate scenarios were applied: an averaged breathing rate of 15 m^3/day, an age-group specific breathing rates (in m^3/day), and age-group specific breathing rates normalized by average body mass (in m^3/day/kg).

We first consider modeled $PM_{2.5}$ *IM* values at sensitive facilities and census blocks based on the meteorological conditions at 10 A.M. on May 9, 2016, assuming a population-averaged breathing rate of 15 m^3/day. For instance, a $PM_{2.5}$ *IM* value of 0.23 μg/link means that there would be 0.23 μg of $PM_{2.5}$ inhaled by the nearby population after the truck traversed this roadway link in the given scenario. As air pollutants from one roadway link can reach multiple facilities/blocks within 1,500 m, the *IM* values of roadway links are generally higher for those near large sensitive facilities and densely populated census blocks. We also consider the wind direction, and it can be observed that roadway links upwind of large sensitive facilities and densely populated census blocks generally have higher *IM* values than those downwind.

Figure 17.14 shows the aggregated $PM_{2.5}$ *IM* values from both sensitive facilities and census blocks based on the meteorological conditions at 10 A.M. and 3 P.M. on May 9, 2016, assuming a population-averaged breathing rate of 15 m^3/day. The aggregated $PM_{2.5}$ *IM* values are generally higher at 10 A.M., when compared to that at 3 P.M., due to the more turbulent condition in the afternoon contributing to

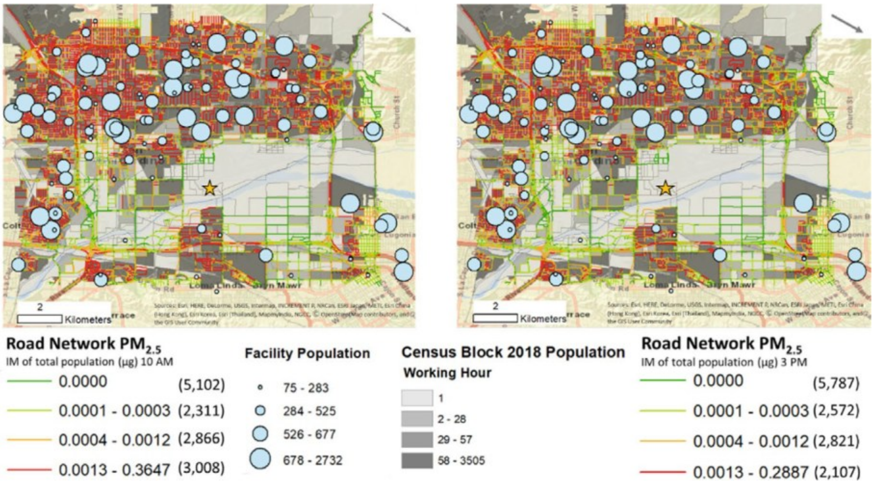


Fig. 17.14 Total inhaled mass of $PM_{2.5}$ (μg/link) at 10 A.M. (left) and 3 P.M. (right) assuming a population-averaged breathing rate of 15 m^3/day (from [11], permission for reusing this figure granted from UC Davis Institute of Transportation Studies; base map accessed from ArcGIS Online, see https://www.esri.com/en-us/legal/copyright-proprietary-rights; Map image is the intellectual property of Esri and is used herein under license Copyright © 2020 Esri and its licensors. All rights reserved)

faster dispersion of air pollutants. The comparison shows how the meteorological conditions can affect the *IM* values.

17.4.2 Low-Exposure Route Comparison

For trips that connect the four freeway corners and the air cargo hub, both a "baseline" route (typically the shortest-time route) and a low-exposure route (LER) were determined. We then weighted those truck routes based on the number of trucks coming from and going to those respective freeway corners. To estimate the number of trucks entering and exiting the four corners, we used truck flow data from the California Department of Transportation's Freeway Performance Measurement System [46].

As an example of our results, we calculated the total amount of IM of emissions for the weighted average of all four corners at 10 A.M., assuming a population-averaged breathing rate of 15 m^3/day. These results are shown in Fig. 17.15. In general, it can be seen that as compared to the baseline routes, the low-exposure routes reduce IM of PM2.5 by 46%, IM of NOx by 20%, and CO_2 emissions (and thus, vehicle fuel consumption) by 4%, on average. On the other hand, the low-exposure routes increase travel time by 29%, on average.

Has truck flow																
MY 2012 10am		Baseline Route (A)					Low Exposure Route (B)					Difference (v.s. baseline route)				
Corner #	No. of Trucks	Driving Distance (miles)	Driving duration (min)	$PM_{2.5}$ IM (ug)	NO_x IM (mg)	CO_2 (kg)	Driving Distance (miles)	Driving duration (min)	$PM_{2.5}$ IM (ug)	NO_x IM (mg)	CO_2 (kg)	Driving Distance (miles)	Driving duration (min)	$PM_{2.5}$ IM (ug)	NO_x IM (mg)	CO_2 (kg)
1	45	514.1	580.8	5390.1	485.5	836.3	418.9	685.4	2436.2	455.2	676.5	-95.2	104.6	-2953.8	-30.3	-159.8
2	11	107.6	151.0	794.6	72.8	164.6	99.2	201.0	102.5	45.0	175.9	-8.4	50.0	-692.1	-27.8	11.3
3	133	628.6	845.0	6985.4	647.0	1073.3	662.2	1155.5	4545.3	442.6	1117.2	33.6	310.5	-2440.0	-204.5	43.9
4	26	148.0	192.8	284.3	31.2	251.5	155.5	236.6	238.7	44.9	269.2	7.5	43.8	-45.6	13.7	17.7
Total	215	1398.3	1769.7	13454.4	1236.5	2325.7	1335.8	2278.6	7322.8	987.7	2238.8	-62.5	508.9	-6131.5	-248.8	-86.9
												-4%	29%	-46%	-20%	-4%

Fig. 17.15 Comparison of baseline routing to low-exposure routes at 10 A.M

These results will vary by time of day, and with other roadway networks (more details, analyses, and examples are provided in [11]). However, pro-active low-exposure routing strategies may result in a significantly lower inhaled mass of PM2.5 emissions by simply routing heavy-duty diesel trucks differently at different times of the day. From a policy perspective, it may be possible to encourage voluntary actions by truck companies to use these emerging routing technologies to divert heavy-duty truck traffic to low-impact routes, accepting a trade-off between slightly increased delivery time and reducing the exposure of PM2.5 and NOx to residents and sensitive receptors such as schools and hospitals. As an added incentive, there would be a slight reduction in their fleet average fuel consumption. Another policy approach would be to have local cities utilize their authority to designate truck routes through their communities, choosing routes that have the least air pollution impact on their residents.

As with the traffic signal management described in Sect. 17.2, these routing operations can be changed dynamically throughout the day. For example, when school children are walking to or from school, it would be best to have trucks maximally take advantage of low-exposure routing. In contrast, when there is less exposure risk (for example at night), it would be possible to switch the routing to "shortest-distance" or "shortest-time" routes so that trucks can make deliveries in the most efficient manner.

17.5 Conclusions and Future Work

In this chapter, we described a number of ITS solutions that are aimed at improving a city's mobility eco-system, with a focus on minimizing the negative impacts on disadvantaged and environmental justice communities, while enhancing the overall mobility and safety. These ITS solutions, along with many others, should be part of a Smart-City Playbook that cities across the world can use, learning about the synergies and trade-offs between different strategies.

Our research has primarily been focused on Inland Southern California, which suffers from high levels of traffic congestion, poor air quality that results from (in-part) vehicle emissions, and lack of alternative modes of transportation other than the ubiquitous personal vehicle. To better demonstrate and quantify the improvements that can be brought about by ITS solutions along a typical arterial roadway, we developed a real-world testbed in Riverside, California, called the Innovation

Corridor. This testbed runs squarely through disadvantaged neighborhoods, and ITS applications that can decrease congestion, lower emissions, and improve safety have a direct benefit on the local community. In addition, we are designing and deploying new carsharing options for these communities, so that they are not necessarily locked in to the inefficiencies of the personal car ownership model. Lastly, we are attempting to look for better solutions for the goods movement industry, where we can still enjoy the economic benefits of our goods movement system, but not necessarily suffer from all of their negative impacts.

Another key aspect of these strategies is that they can all be deployed in a way that is synergistic and dynamically adjustable to deal with changing conditions. There are often trade-offs between safety, mobility, and environmental considerations, and cities should recognize that they do not need to be locked into one solution all the time. The example applications described in this chapter can easily be adjusted by simply changing parameters within the algorithms. Any smart city should take advantage of this capability, essentially tuning their solutions to maximize benefits to their communities.

The UC Riverside team will continue to improve on the ITS solutions outlined in this chapter, deploy and test them in the real world, and develop new ideas that are squarely focused on improving the conditions of the local community.

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