U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

SMART Mobility

Urban Science Capstone Report

July 2020

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Foreword

The U.S. Department of Energy's Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium is a multiyear, multi-laboratory collaborative, managed by the Energy Efficient Mobility Systems Program of the Office of Energy Efficiency and Renewable Energy, Vehicle Technologies Office, dedicated to further understanding the energy implications and opportunities of advanced mobility technologies and services. The first three-year research phase of SMART Mobility occurred from 2017 through 2019, and included five research pillars: Connected and Automated Vehicles, Mobility Decision Science, Multi-Modal Freight, Urban Science, and Advanced Fueling Infrastructure. A sixth research thrust integrated aspects of all five pillars to develop a SMART Mobility Modeling Workflow to evaluate new transportation technologies and services at scale.

This report summarizes the work of the Urban Science Pillar. The Urban Science Pillar focuses on maximum-mobility and minimum-energy opportunities associated with emerging transportation and transportation-related technologies specifically within the urban context. Such technologies, often referred to as automated, connected, efficient (or electrified), and shared (ACES), have the potential to greatly improve mobility and related quality of life in urban areas. For information about the other Pillars and about the SMART Mobility Modeling Workflow, please refer to the relevant pillar's Capstone Report.

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List of Acronyms

ABM	agent (or activity)-based model
ACES	automated, connected, efficient (or electrified), and shared
AMD	Automated Mobility District
ASCE	American Society of Civil Engineers
AV	automated vehicle
CAR	privately owned automobile (mode)
CAV	connected and automated vehicle
CV	connected vehicle
DOE	U.S. Department of Energy
DOT	U.S. Department of Transportation
DTD	on-demand door-to-door ridesharing (mode)
EEMS	energy-efficient mobility systems
EPM	employer-provided mobility
EV	electric vehicle
FASTSim	Future Automotive Systems Technology Simulator
FXR	on-demand fixed-route ridesharing (mode)
GDP	gross domestic product
GGE	gasoline gallon equivalent
ISS	infrastructure spatial sensing
LiDAR	light detection and ranging
MDS	Mobility Decision Science
MEP	Mobility Energy Productivity
MOVES	MOtor Vehicle Emission Simulator
MPO	metropolitan planning organization
PUDO	pick-up and drop-off
PWT	passenger waiting time
RL	reinforcement learning

SAV	shared automated vehicle
SMART	Systems and Modeling for Accelerated Research in Transportation
SUMO	Simulation of Urban MObility
TNC	transportation network company
US	Urban Science
VDF	vehicle detour factor
VDH	vehicle deadheading distance
VLR	vehicle loading rate
VMT	vehicle miles traveled
VTT	vehicle travel time
WAK	walk (mode)
WKT	passenger walking time

Executive Summary

The Urban Science (US) Pillar focuses on maximum-mobility and minimum-energy opportunities associated with emerging transportation and transportation-related technologies specifically within the urban context. Such technologies, often referred to as automated, connected, efficient (or electrified), and shared (ACES), have the potential to greatly improve mobility and related quality of life in urban areas. Although all the SMART Mobility research pillars share some commonalities, Urban Science strives to model, analyze, and gain insights from the perspective of human settlements (the "city") as a living organism. This is especially critical as the United States is one of the most urbanized countries, and as more and more of the global population migrates to urban areas.[1] The urban mobility system consists of a complex network that reaches well beyond roads and vehicles and includes significant investments in public transit, private mobility services (such as taxis and transportation network companies, or TNCs), significant parking reserves, and curb management practices, not to mention the abundance of emerging on-demand micromobility services for the movement of people and goods such as e-bikes and scooters, which make the urban space a dynamic laboratory for mobility. Urban spaces also concentrate employment, markets, services, and attractions, which are the destinations for most trips. The concentration of human activities and ensuing density also creates the need and emphasis for space efficiency in urban environments, which is often less of a constraint in suburban or rural contexts. This mixture of transportation and mobility infrastructure and practice, combined with global urbanization trends, make urban spaces a critical focus of research for developing energy-efficient mobility systems (EEMS).

For the purpose of this report, the insights of the Urban Science research are organized into the following four thematic areas:

- Changes and Impacts on the Urban Traveler
- Development of the Mobility Energy Productivity Metric
- Urban Infrastructure & Built Environment Synergy with Mobility
- The Signal Control Network as the Urban Mobility Nerve Center.

Changes and Impacts on the Urban Traveler:

US Pillar research sought to identify the key issues, gaps, and opportunities related to emerging mobility systems in the urban space. The effort was anchored by a stakeholder engagement with the seven Smart City finalists from the U.S. Department of Transportation (DOT) Smart Cities competition in 2017. Interviews were conducted with representatives from Columbus, Ohio (Smart City grant awardee[2]); Portland, Oregon; Denver, Colorado; Kansas City, Missouri; Austin, Texas; San Francisco, California; and Pittsburg, Pennsylvania. These discussions emphasized the models, tools, data, and analytics that enable a Smart City and exposed common challenges, gaps, and research opportunities that informed the Urban Science portfolio. Indeed, the insights from these interviews directly led to much of the research and their corresponding findings shared in this summary. The US team interviewed the actors and institutions within the urban areas involved in Smart City initiatives, specifically querying them about the data infrastructure, metrics, and modeling capacity. The most significant commonalities, gaps, and opportunities from this research are outlined below[3]:

- All Smart Cities interviewed prioritized a robust, modern, and flexible data-sharing and exchange platform; however, resources to accomplish this goal are lacking. As a result, most cities are locked in outdated and siloed data architectures, making seamless data sharing challenging.
- Data sensing and collection technologies are maturing at a rapid pace, and many urban data stores are being supplanted by industry-available data collection rooted in the internet of things. Nowhere is this more evident than in the area of mobility, in which vehicle and humans routinely report their location

and speed via digital networks, providing rich transportation data sets that leapfrog existing sensor-based systems.

- Mobility models within the Smart Cities, typically managed by the metropolitan planning organization (MPO), are primarily road-vehicle based for the purposes of roadway infrastructure capital improvement programming and have little value in evaluating emerging modes in their existing state. New mobility technologies are being deployed in cities with minimal central planning or coordination—mainly reacting to market forces rather than proactively managing opportunities.
- Understanding the impacts of TNCs such as Uber and Lyft is fundamental for the cities. This includes assessing the long-term impacts, funding, equity, and sustainability issues. The city's airport, the "front door" to any medium- to large-sized city and its primary transportation hub connecting it to the world, is at the front line of the observed mobility shifts, with TNCs significantly displacing private-vehicle trips (and associated parking), car rentals, and transit.
- Cities are lacking appropriate metrics for smart city mobility analysis and transportation system effectiveness. Existing metrics are typically infrastructure focused and modal specific, and do not reflect the effectiveness of the system as a whole to provide mobility to citizens.

Figure 1. U.S. DOT Smart City Challenge finalists

New mobility options, prominently led by TNCs, have descended on urban areas within the last decade, creating a new norm for smartphone app-based mobility that many competitors, even public transit, are attempting to replicate. However, the extent of use of TNCs and their impacts on urban mobility (both positive and negative) are challenging to benchmark and assess as data from these companies are proprietary and business-sensitive. Even though some TNC data sets are beginning to emerge (most notably from Chicago[4] and New York[5]), systematic monitoring of the extent of TNC use and adoption remains problematic. Airports, generally a sub-jurisdiction to the city and a primary mobility hub, typically charge access fees to any commercial operations accessing the airport curb front that generate significant revenue and provide a data trail to quantify the impact of TNCs. Open records requests revealed revenue patterns that reflected rapid shifts away from other forms of transportation toward TNC use. This is unique in that it not only revealed growth patterns in TNC operations, but also impacts to parking, rental car, and sometimes transit and taxis. ***Data from multiple airports revealed that within 24 months of the introduction of TNC service at an airport, parking revenue on a per-passenger basis peaked and then began to decline (see Figure 2).*** Revenue records also indicated a similar pattern of reduced demand for car rentals. Data obtained from the San Francisco airport, which has had TNC service at the airport longer than any U.S. city, clearly show the uptake in TNC use at a growth rate that has grabbed the attention of airport finance as well as airport curbside management (see Figure 3). As a result of TNCs, airport revenues from ground access (such as parking and rental car surcharges) are failing to meet projected revenue forecasts. Gaps in revenue are only partially offset from fees charged for TNC access. However, airports that are currently at or near capacity with respect to parking can continue to grow without substantial capital investment in additional parking. Analysis of mode replacement indicates that during the period from 2014 to 2018, for every 100 new TNC transactions for ground transportation to and from the Denver airport, 35 replaced transit, 39 replaced parking (someone driving their personal vehicle to the airport), 16 replaced car rental, and 10 replaced taxi. These data suggest that for every three ride-hailing trips, roughly one parking space may no longer be needed at airports. Although airport trips represent a small fraction of overall travel in the city (in the Puget Sound Regional Council and Denver Regional Council of Governments regions, for example, travel to and from the airport represents just over 2% of all vehicle miles traveled generated by the region[6,7]) and analysis and results from airports are not directly transferable to other areas of the city due to the unique nature of airport trips, the impacts at airports inform trends in mode replacement and parking disruption in other parts of the city as a result of TNC adoption.

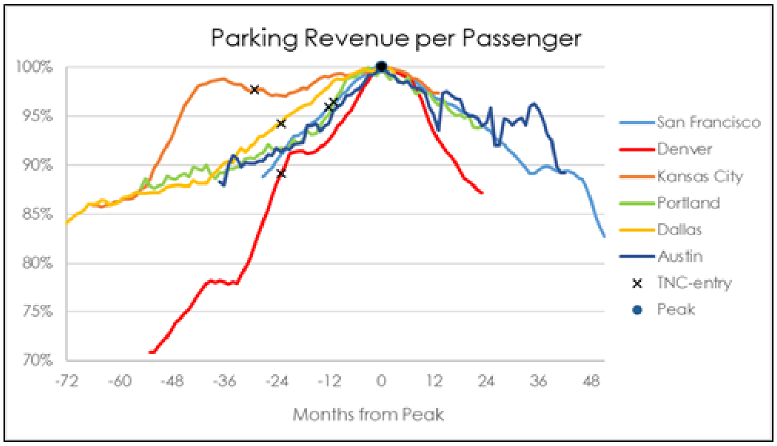

Figure 2. Impact of TNCs on parking revenue – trends from six major airports

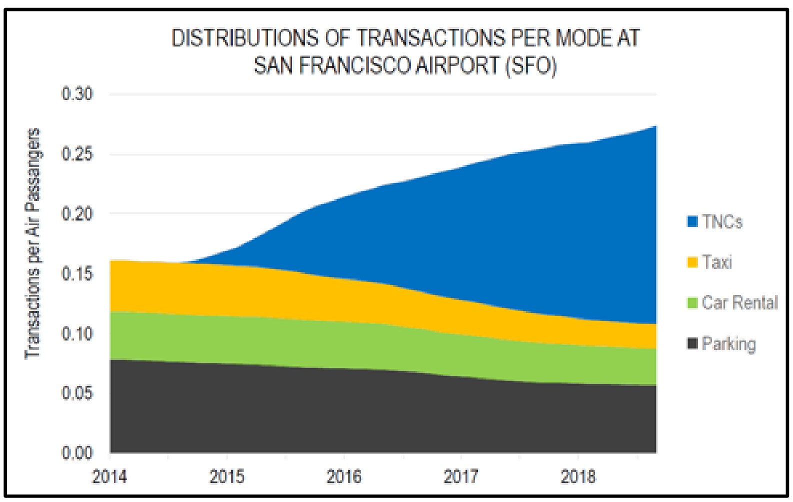

Figure 3. Distribution of San Francisco Airport revenue transactions per air passenger from 2014–2018

The extent to which emerging technologies impact different cities, or different parts of a city, is a primary research question. The US Pillar commenced a city typology effort that sought to establish linkages between adoption and impacts of new mobility technology with measurable urban characteristics such as sociodemographics, governance, education, income, and mobility infrastructure. Initial methodological approaches were applied to the State of New York, analyzing various mobility attributes such as propensity for alternative commuting behavior, vehicles per household, average vehicle fuel economy, and the number of registered electric vehicles (EVs) (Figure 4). The statistical clustering procedures identified four distinct regions, which the researchers labeled *Suburban, Urban, Rural,* and *Core Urban* due to their visual correlation with these geographic areas. Note that these labels are not a result of predefined geographic groupings but are simply labels for the four typologies identified by the algorithm. ***The urban typology revealed that the leading adopters of EVs were core urban and suburban residents who have relatively higher levels of income and education than the urban working class residents (Figure 17). This suggests that EV adoption is more closely correlated to socioeconomic than geographical traits.*** EV adoption rate for working class urban dwellers was even less than for the rural typology.

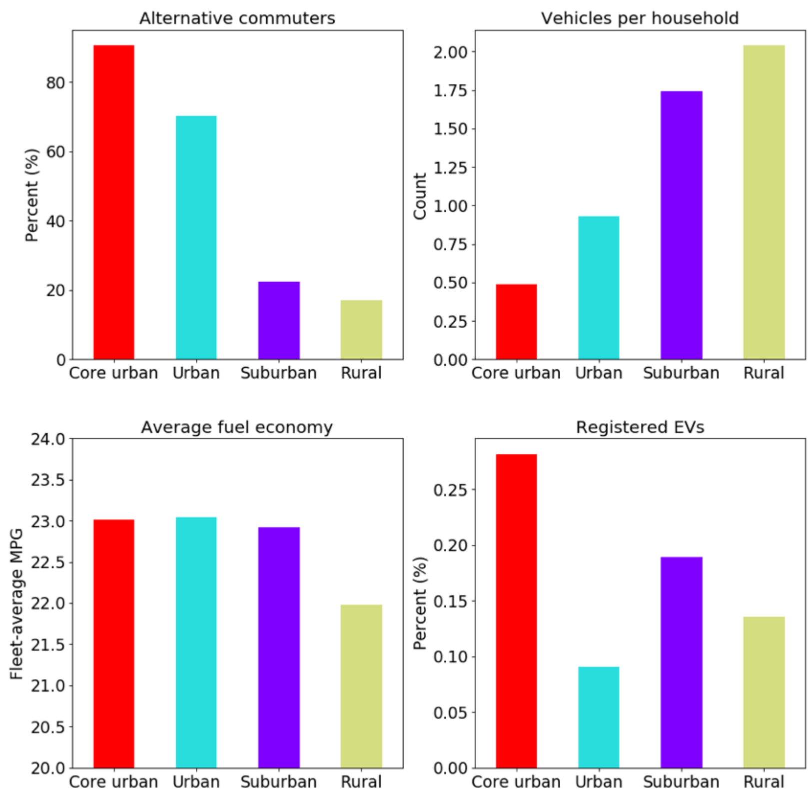

Figure 4. Mobility and energy outcomes by typology

Employer-provided mobility (EPM) refers to increased responsibility and involvement on the part of the employer to provide sustainable, efficient, and timely alternative commute solutions. Transportation Demand Management at an urban planning scale has long stressed carpooling and transit as means to reduce congestion and conserve fuel. However, the sprawling urban landscape and evolution from blue-collar shift work to a white-collar knowledge economy has resulted in continuous declines in both carpooling[8] and transit ridership.[9] EPM has emerged (or re-emerged) not as an outgrowth of a public Transportation Demand Management initiative, but rather as a requisite employee benefit, funded and managed by the employer similar to health and retirement benefits, in order for employers to compete in the current labor market. Data indicate that young people are delaying acquisition of a driver's license[10] and purchase of an automobile,[11] though debate continues on whether this is primarily a byproduct of the economy or a general behavioral shift. In either case, the shift is causing employers to provide alternatives to attract a growing and desirable source of labor. Combined with the fiscal incentive to avoid the sunk cost of parking infrastructure, which is particularly expensive in urban areas, employers are becoming motivated partners. Commuting represents approximately 15% of all household trips and 30% of household vehicle miles traveled in the latest 2017 National Household Travel Survey.[12] As commute trips are concentrated in the morning and evening peak hours (35% to 45% of vehicles in the morning and evening peak hours are commute trips), impacting commuting trip behavior has the greatest leverage of decreasing congestion and increasing fuel efficiency.

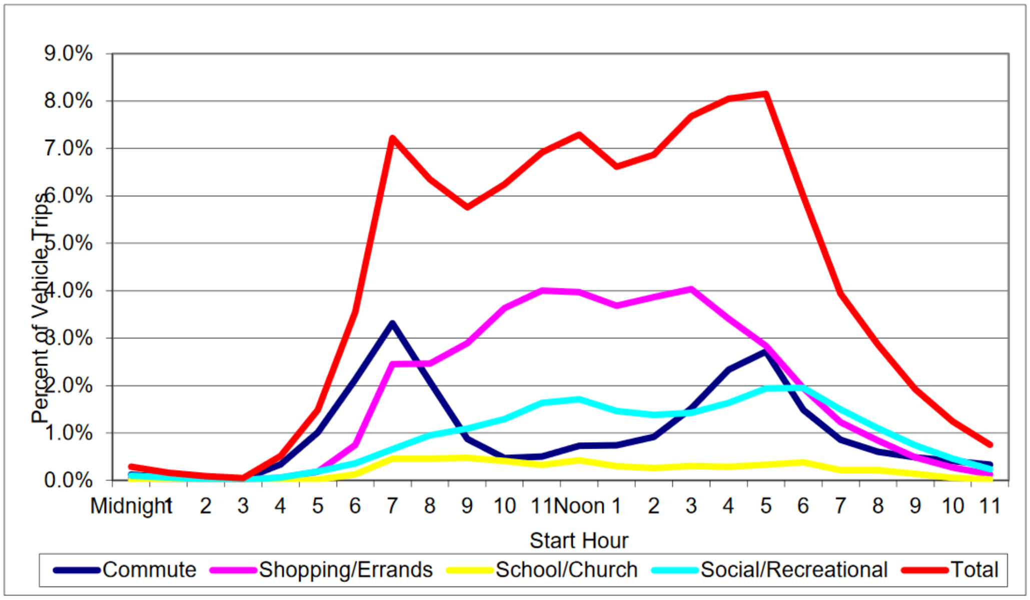

Figure 5. Distribution of vehicle trips by trip purpose and start time of trip

Source: 2017 National Household Travel Survey

A case study of four employment centers in metro Denver assumed a modest 2% uptake of EPM (as observed in EPM case studies from other cities). Based on extrapolating impacts at these four sites of focus to the regional level, the study estimated potential annual savings of 1.9 million gallons of gasoline for the Denver region. EPM is a significant development in that it directly impacts the most congested periods of the day and addresses a substantial motivating factor for vehicle ownership—that of getting to work. Results of discussions with stakeholders during workshops in Denver and Boulder indicated that telecommuting did not appear to be a viable option for many workers. Typical workplace policies at the time limited remote working to special circumstances and approval, and evaluation suggested that engagement in remote work was most likely to be for those who were self-employed and thus had no commute to replace, resulting in no energy impact. Thus, commuting solutions enabled by the employer may thus open up additional opportunities for car-free or car-light lifestyles.[13]

Development of the Mobility Energy Productivity Metric

Mobility Energy Productivity addresses the need for a holistic measure of the effectiveness of an urban mobility system; it provides an overall target metric within the DOE's SMART Mobility Lab Consortium to measure progress toward a maximum-mobility, minimum-energy future. This metric, termed the Mobility Energy Productivity (MEP) metric is fundamentally a location-based accessibility metric that scores access to employment, goods, and services with respect to travel time, affordability, and energy. ***Mobility, with respect to the MEP metric, is defined as the effectiveness of a transportation system to connect citizens to a wide variety of goods, services, and employment that define a high quality of life.*** The metric, which can be computed for any mode, encompasses a spectrum of trip purposes informed by established literature and produces a quantitative measure of the potential mobility at a location. The MEP metric enables the measurement of the potential of emerging mobility systems to more efficiently (with respect to travel time, affordability, and energy)

Mobility: The effectiveness of a network or system to connect people to goods, services, and employment that define a high quality of life.

connect people to opportunities such as employment, health care, groceries, retail, entertainment, education, and recreation.

The MEP metric addresses the lack of open and practical metrics to quantify the productivity of an urban transportation system comprised of multiple modes, both existing and emerging. The MEP metric is a scalable, open-source metric that takes into account infrastructure and land use in addition to the properties of various available modes of transport when quantifying and comparing the energy productivity of mobility options. The MEP metric serves as a unifying lens through which research under the SMART Mobility Laboratory Consortium's portfolio of workflow modeling results is assessed, both in a quantitative and a visual sense. The metric was also developed to be scalable and open source so that any city can adopt it to track the impact of emerging transportation technologies on the effectiveness of mobility in a region, either through direct measure or through integration into prevailing metropolitan travel-demand forecasting models.

The generalized MEP formulation weights access to a spectrum of employment, goods, and service opportunities with respect to travel time, affordability, and energy. The MEP metric expands upon familiar and popular metrics such as walk,[14] bike,[15] and transit score,[16] which are proprietary and mode specific, creating an open framework and standard method to assess the efficiency of the mobility provided by any mode of transport. At its base as an accessiblity metric, the MEP metric enumerates opportunties (such as employement, health care, grocery stores, restauraunts, etc.) appropriately weighted based on the travel time, cost, and energy intensity of the mode. The numeric score generated by the MEP methodology provides a robust assessment of the quality of mobility provided to a traveler at any given location, through any mode, to a variety of opportunities. A conceptual formulation of the MEP metric (as shown in Figure 6) uses travel time, land-use data, modal energy efficiency, affordability data, and travel-demand data to assess the ability of the transportation system to connect citizens at any point in the city to a spectrum of opportunities that define quality of life.

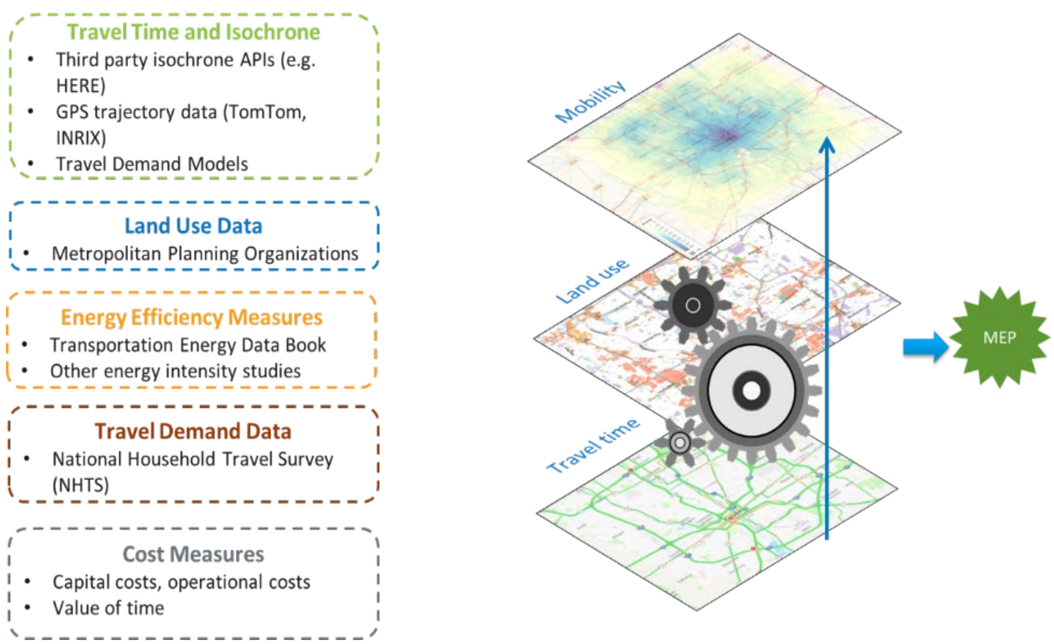

Figure 6. Computation framework and data input for the MEP metric

A toolkit has been developed to efficiently implement the MEP metric at the city level. This toolkit has been applied to establish baseline MEP measures for over 60 U.S. cities. Through a partnership with the American Society of Civil Engineers (ASCE), the MEP metric is being advanced as a foundational metric for the ASCE Transportation and Development Institute ES-X series of standards for Smart Cities.[17]

The MEP metric, integrated into the SMART Modeling Workflow process, has served as the top-level assessment of changes in mobility scenarios, allowing for visuals of future scenarios (as shown for San Francisco in Figure 7), quickly comparing before and after future adoption scenarios of ACES technologies, as well as their policy, land-use, and infrastructure ramifications. The visualizations are all within the lens of the effectiveness of connecting people to a spectrum of opportunities to enhance quality of life relative to travel time, affordability, and energy.

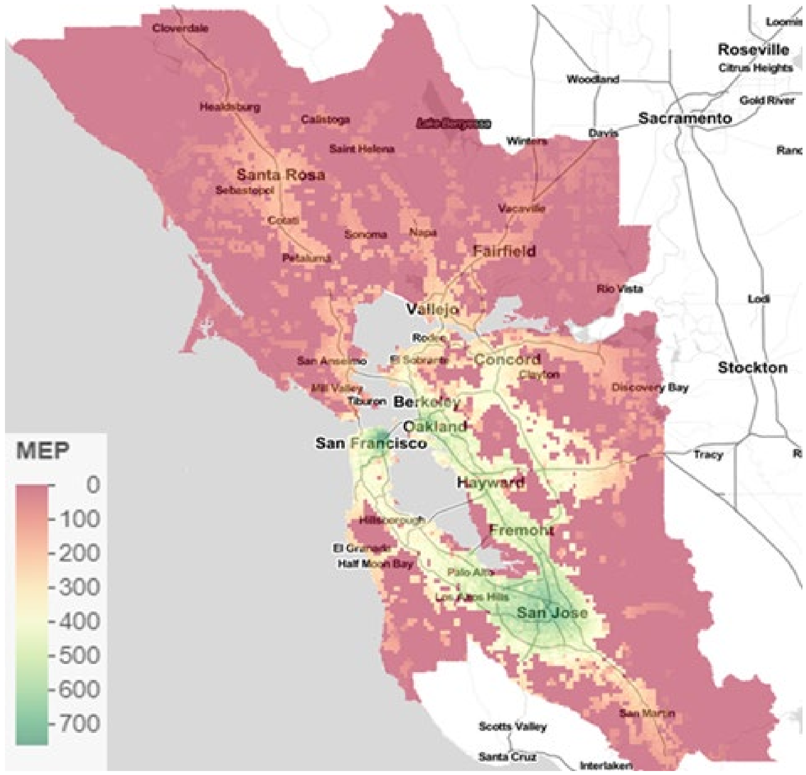

Figure 7. A representative MEP visualization for the San Francisco metropolitan region

Urban Infrastructure & Built Environment Synergy with Mobility

Our transportation system connects us with the physical environment—that is, the end destinations that provide the goods, services, and employment we seek. As transportation systems evolve, so do the physical structures that accommodate the mobility systems (such as roads and curbside) and the destinations themselves. The famous line from the popular movie *Field of Dreams*, "If you build it, they will come," is often cited within transportation planning circles with respect to transportation improvements, referring to how road improvements tend to spark housing and retail development.

Identifying how cities and systems within cities respond to the rapidly changing mobility environment is crucial to understanding how cities may develop over time, and whether they will deviate from long-held patterns from the automotive age. To respond to this, ***the UrbanSim land development model[18] was extended to include a lightweight dynamic traffic assignment feedback loop so that the impact of ACES technologies on future land-use scenarios could be assessed.*** This enhanced land-use model was then integrated into the SMART Mobility Workflow process to inform how development patterns will evolve with mobility technology. Integration of UrbanSim land-use planning into the SMART Workflow was significant in that it:

- Built on existing the UrbanSim software, already prevalent in many cities, so that these enhancements would derive benefits beyond SMART

- Dictated performance enhancement to run in reasonable time, which benefitted both DOE and other downstream applications
- Integrated into the POLARIS and the modeling framework for Behavior, Energy, Autonomy, and Mobility (BEAM) SMART Mobility Workflow process, paving the way for similar integration in other long-term planning frameworks
- Most importantly, created a full feedback loop, revealing how mobility enhancement would impact land-use development patterns.

Like land use, the parking and curbside infrastructure supporting mobility is also quickly evolving. Emerging mobility modes such as TNCs and bike, scooter, and vehicle sharing are causing a rapid evolution of the curbside space once dominated by vehicle parking. Competition for curbside space has expanded beyond traditional on-street parking, pedestrian and bicycle activities, and freight delivery to include on-demand mobility activities (ride-hailing, car share, bike share, e-scooter, and other dockless micromobility) and increased "microfreight" arising from the rapid adoption of e-commerce (e.g., parcel and food deliveries). This new competition is causing cities to respond with new organizational approaches, management practices, and allocation policies to keep the curbside safe and maximally productive.[19]

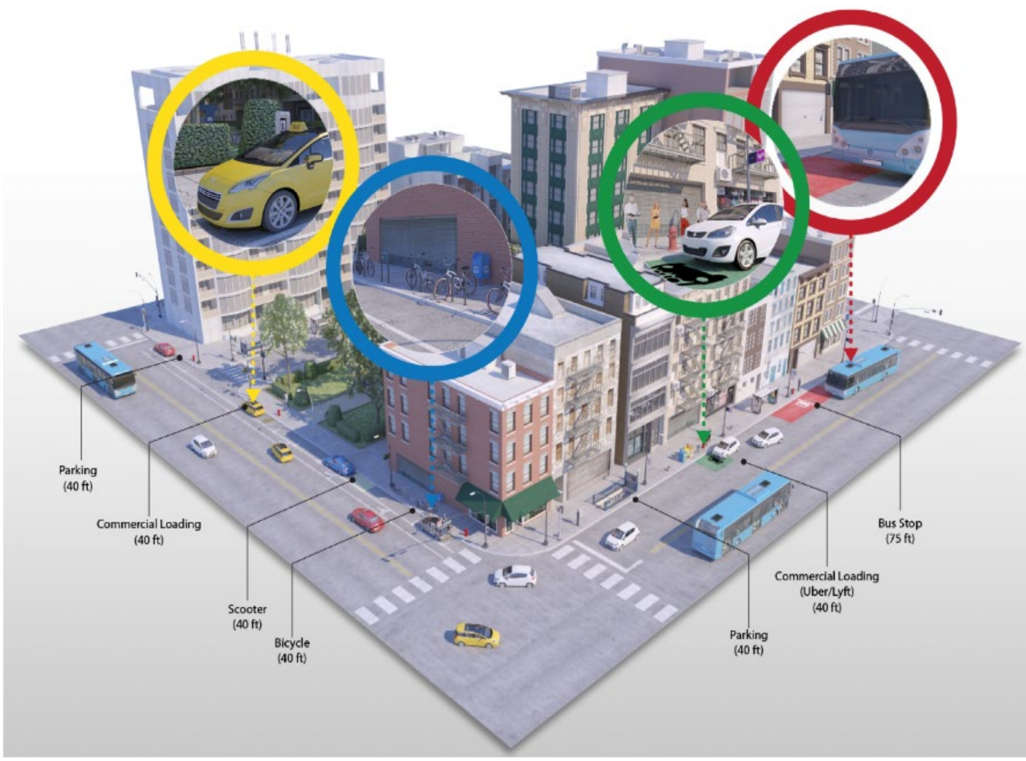

Figure 8. Curbside topology diagram showing competing uses for curb space

This US curbside topology research team convened a variety of cities, airports, and MPOs to examine how cities are responding to these changing pressures on their curbside space. The interviews identified how curbside management is rapidly evolving:

- Reorganization has occurred in many cities, transforming "parking management" to "curbside management," restructuring and increasing staff to respond to curbside pressures.

- Data availability related to pick-up and drop-off (PUDO) activity is challenging and inconsistent. Some cities receive data from TNCs and some do not. Real-time data collection on curb activity is a current gap; analysis of this gap will enable proactive and dynamic curbside management when addressed.
- Operational failures at the curbside spill over into travel lanes, creating public-safety hazards that are particularly acute in situations such as at closing times of bars in nightlife districts. ***Although there exist revenue and mobility efficiency concerns, safety of the public is critical and was the primary stimulus prompting action within cities.***

The Urban Science pillar developed a curbside allocation model to support rational reallocation of curbside space, balancing outcomes such as economic welfare, traffic throughput, safety, and sustainability. Based on the bid-rent model of urban real estate, this framework allows road network operators to optimally manage their curbside allocations. The framework assists in reallocating curbside space to the appropriate mixture of ride-hailing PUDO zones, traditional parking, freight delivery, micromobility corrals, and the like. This research and optimization framework is important as cities quickly respond and evolve to accommodate safe and efficient mobility services at activity-intense districts.

The US Pillar also created the ***Automated Mobility District (AMD) toolkit***, which addresses the application of automated vehicle (AV) technology, enabling fleets of shuttles to serve geographically confined areas such as campuses or confined districts. Shared and automated public mobility resulting from the hybridization of AVs with on-demand mobility service has the potential for significant economic, system, and energy efficiencies within dense activity districts. ***AMD is an emerging term describing a campus-sized implementation of automated-shared mobility services within a confined geographic region or district***. In such a district, automated fleets of shuttles serve a majority of mobility needs, dissuading the use of personal vehicles in places like central business districts, mixed-use developments, and university campuses. The research effort continues to track the demonstration and deployment projects of automated electric shuttles in the United States and throughout the world, documenting lessons learned as projects are migrating quickly from small-scale demonstrations to larger-scale operational public mobility systems.

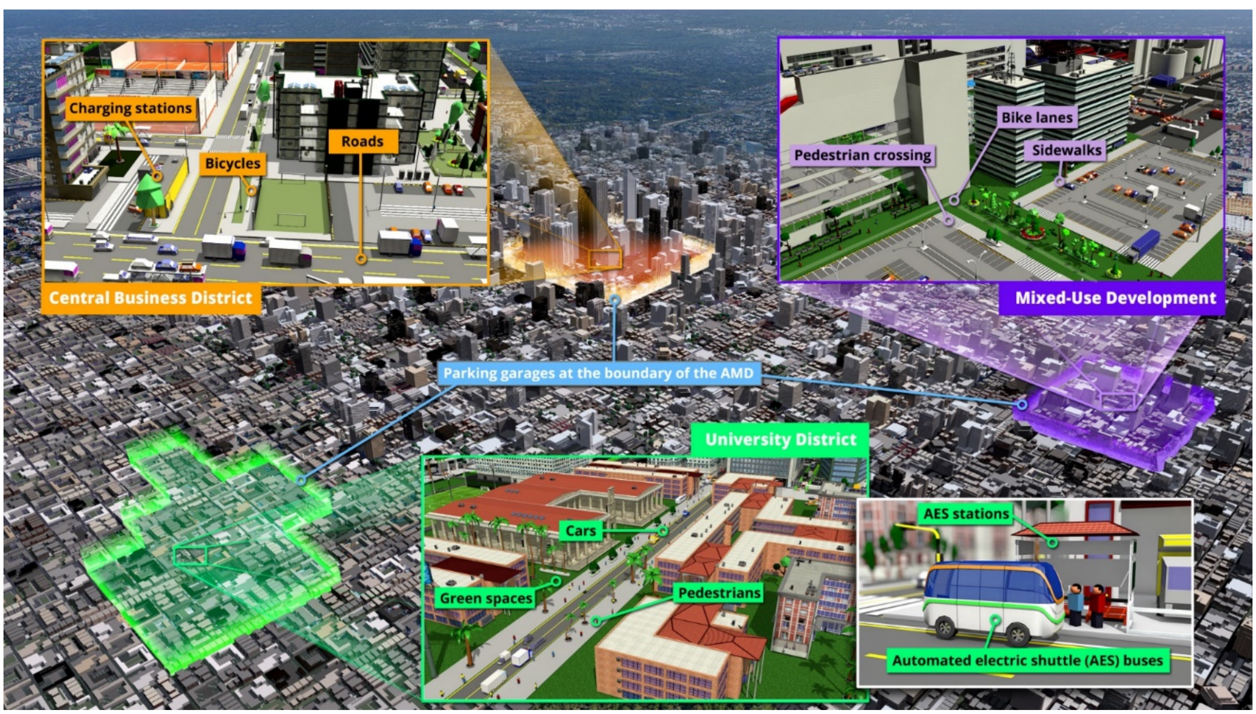

Figure 9. Graphical depiction of Automated Mobility Districts[20]

Addressing the lack of available, practical, and efficient planning and modeling tools, the AMD modeling and simulation toolkit provides a planning tool for communities seeking to implement automated shuttle services within a district or campus. The AMD toolkit was designed to serve as a sub-model that can be integrated and exercised within existing transportation demand models. ***The toolkit, based on the Simulation of Urban MObility (SUMO)[21] open-source traffic simulation package, assists in determining the number, size, and operational parameters of the shuttle system to meet expected demand, as well as calculating mobility and energy benefits on a before/after basis.*** Based on existing or projected demand, the toolkit simulates automated shuttle service either using on-demand or fixed-route operation, performs mode-choice modeling based on travel time and convenience, calculates travel time and delay, and assesses energy use through integration of DOE vehicle energy models—specifically the Future Automotive Systems Technology Simulator (FASTSim[22]). The developed toolkit was applied in the proposed automated shuttle deployments in Greenville, South Carolina, to optimize fleet size, vehicle size, and route selection for shuttles. In one simulation study, it was found that for a given demand, the travel cost decreases with increasing battery range for the shuttles. In another simulation carried out using the mode-choice module, it was observed that reducing seat capacity of low-speed automated shuttles has lesser (and more gradual) impact on mode share of automated shuttles compared to reducing fleet size. The AMD toolkit can help examine the tradeoffs between fleet size, vehicle capacity, and vehicle range (of EVs) with respect to demand and can guide deployments in rightsizing the fleet for their context.

The Signal Control Network as the Urban Mobility Nerve Center

The signalized intersection is the hallmark of the urban roadway network, where sensing and control allow for the safe deconfliction of vehicle and pedestrian movements. In recent years, signal control has also allowed for safe and efficient transit priority as well as accommodating cycling and scooter throughput. In 2007, approximately 2.4 million intersection-related crashes occurred, representing 40% of all reported crashes and 21.5% of traffic fatalities,[23] underscoring the importance of safety and designing redundant, fault-tolerant architectures at signal-controlled intersections. With the onset of connected and automated vehicles and the proliferation of advanced sensing as an outcome of AV research and development, the US Pillar's research in this sector investigated the potential to reduce delay, conserve energy, and enhance safety that may result from enhanced sensing (either by vehicles or at the intersection) and control at signalized intersections.

Signal optimization routines based on modern machine-learning techniques – specifically, reinforcement learning (RL) – were tested to examine the tradeoff between minimization of delay and minimization of energy consumption in signal control. The research investigated RL-based control strategies at various levels of connected vehicle (CV) penetration. Utilizing the DOT-provided real-world NG-SIM[24] data to build and calibrate a signalized arterial within a traffic microsimulation tool, an RL-based control algorithm was implemented with three different strategies or goals: (1) minimize only delay, (2) minimize only energy/fuel, and (3) minimize energy/fuel with a penalty for number of stops at the signalized intersections. In the first two strategies the objective was met, but at the expense of significant penalties for energy and delay, respectively. The third strategy, that of minimizing energy with a penalty for stops, was implemented to balance competing concerns (delay versus energy). The third strategy was implemented with different penalty values for stopping vehicles, and *the results show that with the appropriate weighting for stops, it was possible to have more than an 8% reduction in both average travel time and energy consumption on the arterial corridor compared with the base (non-optimized) case.* These results were based on the assumption of 100% CV penetration. Further experimentation revealed that benefits from RL-based signal optimization begin to appear at 40% CV penetration.

In another US study, modern stochastic control theory was applied to a grid of signal controllers (whereas the first RL example was a corridor-based control and progression) to examine the envelope of benefits under the assumption of 100% CV penetration (that is, the signal was aware of the position and velocity of every vehicle on the network, providing full observability). A stochastic control algorithm was developed that balanced traffic queue lengths across the roadway grid and thus minimized delay across the network. These algorithms were applied to a network of intersections in the city of Bellevue, Washington (see Figure 10), and it was shown that the control approach reduced the average travel delays by up to 40% compared to the existing pretimed controls.

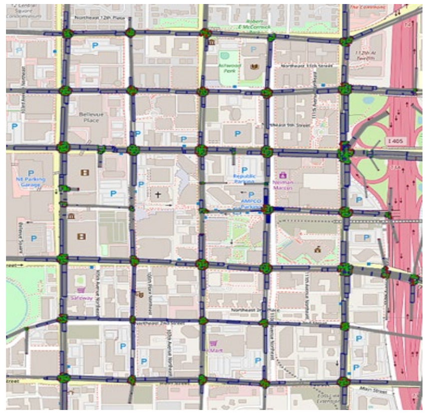

Figure 10. Signalized grid test network in Bellevue, WA

Advances in spatial sensing such as light detection and ranging (LiDAR), radar, and artificial-intelligence-enhanced video analysis, fueled by the race to deploy fully automated vehicles, are beginning to be considered and deployed at intersections. Previously, control examples assumed that the controller had full observability (that is, full knowledge of the location and velocity of all vehicles) in order to minimize delay and energy. Spatial sensors deployed at intersections could provide position and speed of vehicles, cyclists, scooters, and pedestrians within the range of view of the sensor, theoretically accelerating the benefits anticipated from 100% CV-based traffic signal control but with no minimum CV penetration requirement. Furthermore, infrastructure-based sensing could extend benefits beyond just vehicles, to include cyclists and pedestrians for example. ***The US team assessed the extent of benefits that infrastructure-based sensing could capture in comparison with 100% CV penetration, specifically determining the sensing range required to produce equivalent CV control benefits.*** Two published traffic control algorithms designed to leverage CV data were tested using simulated infrastructure-based data. To mimic infrastructure-based data, the position data typically available from the CV Basic Safety Messages were presented to the algorithms only within the sensor-range threshold. Results obtained from a single-intersection test network show that the benefits of full CV-based intersection control are obtained from either algorithm if vehicles are detected and tracked 20 seconds prior to arrival, equating to a distance of approximately 250 meters.

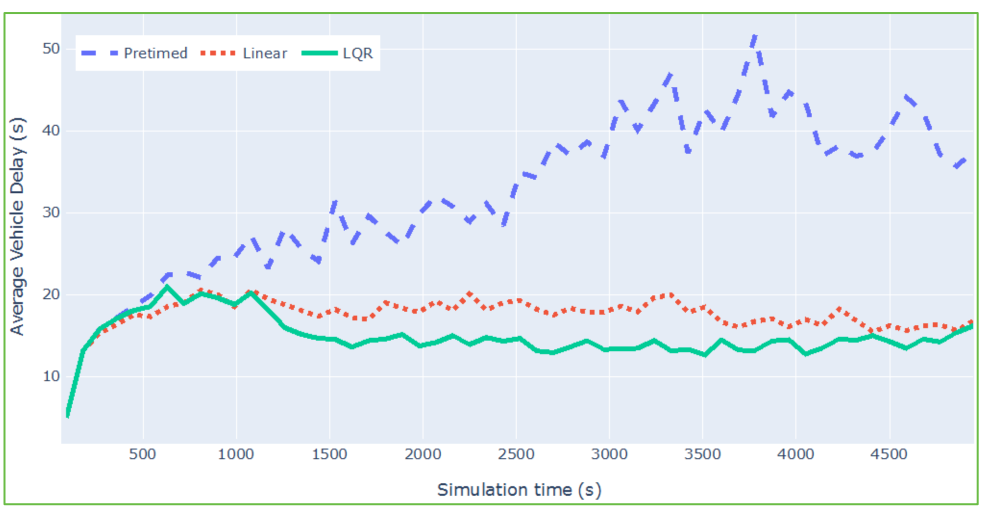

Figure 11. Result of Modern Stochastic Control (LQR) compared with pretimed and linear control algorithms

Because intersections are critical to safety, as evidenced by 40% of crashes occurring at intersections, the US team also addressed safety implications and their relationship to energy and intersection performance. Quality signal timing has long been acknowledged to not only decrease delay, but also to increase safety (reduction of crashes).[25] Although demonstrated in longitudinal time studies at specific signal intersections using crash statistics before and after signal retiming, generalized safety parameters as a function of modern signal performance measures have not be realized until now. The US team accomplished this as a result of work in the city of Columbus, Ohio, in which big data sets consisting of individual trajectory (latitude and longitude) traces were analyzed from 2018 along ten critical corridors to assess advanced traffic signal performance measures.[26] The intersection performance metrics, specifically the percent of arrivals on green, were analyzed with respect to historical crash data. The resulting regression analysis (see Figure 12), reveals that for every 10% increase in arrivals on green, four accidents per year are avoided. Therefore, along with the energy benefits of improved vehicle progression related to avoided stops, energy benefits also accrue from avoided accidents.

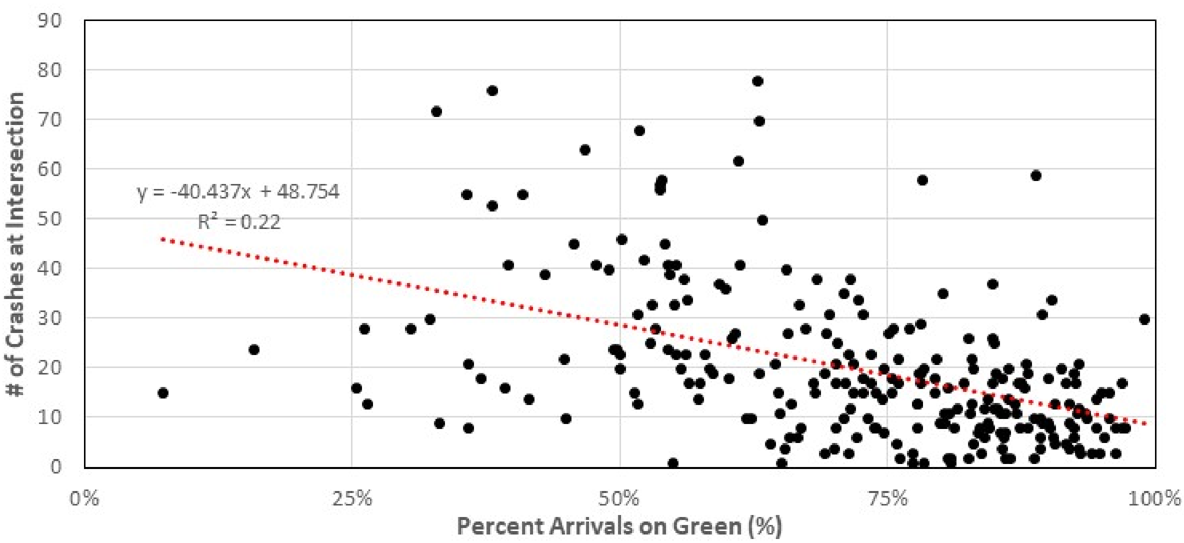

Figure 12. Number of crashes versus percent arrivals on green across ten signalized corridors in Columbus, Ohio

Whereas most energy benefits of signal control in prevailing literature are derived from more efficient vehicle flow, another US effort performed a holistic assessment of the equivalent energy consequences from improved safety—including avoidance of fatal, injury, and property-damage-only (PDO) incidents. Benefits accrue not only from avoidance of traffic congestion, but also from avoidance of loss of human life and loss of human productivity resulting from either fatal or debilitating injuries. Using an extensive economic impact analysis of crashes from 2010[27] in which the impacts of fatal, injury, and PDO crashes were assessed, and using the ratio of the United States gross domestic product (GDP) to total energy consumed, this study estimated the GDP-weighted equivalent energy impact for each fatal, injury, and PDO crash. The analysis separated economic impacts into three categories: direct, indirect–loss of human capital, and indirect–willingness to pay to avoid the crashes. Even if only direct impacts are considered, the GDP-weighted energy impact resulting for a fatal, injury, and PDO crash are 10,987, 1,710, and 382 gasoline gallon equivalent (GGE), respectively, whereas the energy impact from induced congestion are 358, 153, and 108 GGE, respectively. ***Total GDP-weighted direct energy impacts for PDO crashes (which do not include indirect impacts with respect to lost human productivity or willingness to pay) are over three times larger than the energy impact from induced congestion alone, further underscoring the need for a more holistic approach with respect to energy and safety.***[28]

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1 Introduction

1.1 Overview of the Urban Science Pillar

The U.S. Department of Energy's (DOE's) Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium is a multiyear, multi-laboratory collaborative dedicated to further understanding the energy implications and opportunities of advanced mobility technologies and services. The SMART Mobility Consortium consists of five pillars of research:

- Connected and Automated Vehicles (CAVs): Identifying the energy, technology, and use implications of connectivity and automation and identifying efficient CAV solutions
- Mobility Decision Science: Understanding the human role in the mobility system, including travel decision making and technology adoption in the context of future mobility
- Multi-Modal Freight: Evaluating the evolution of freight movement and understanding the impacts of new modes for long-distance goods transport and last-mile package delivery
- Urban Science (US): Understanding the linkages between transportation networks and the built environment and identifying the potential to enhance access to economic opportunity
- Advanced Fueling Infrastructure: Understanding the costs, benefits, and requirements for fueling/charging infrastructure to support energy efficient future mobility systems.

The SMART Mobility Consortium creates tools and generates knowledge about how future mobility systems may evolve and identifies ways to improve their mobility energy productivity. The consortium also identifies research and development gaps that the Energy Efficient Mobility Systems (EEMS) Program may address through its advanced research portfolio and generates insights that will be shared with mobility stakeholders.

The US Pillar focuses on maximum-mobility and minimum-energy opportunities associated with emerging transportation and transportation-related technologies specifically within the urban context. Such transportation technologies, often referred to as automated, connected, efficient (or electrified), and shared (ACES), have the potential to greatly improve mobility and related quality of life in urban areas. The US Pillar targets mobility enhancements combined with associated energy efficiencies of new urban mobility strategies, informed from Smart City stakeholder engagement where knowledge generated and coupled mobility-energy assessments can advance efforts across all 498 U.S. urban areas. Smart Cities is used in the context of the U.S. DOT Smart City Challenge,[29] referring to the application of data, communications, and automation technologies by the city for the improvement of the lives of the citizens, particularly mobility. Although the SMART Mobility pillars share many things in common, as all are attempting to gain insight into future sustainable mobility, US always strove to model, analyze, and gain insights from the perspective of human settlements (the "city") as a living organism.

The research undertaken by the US Pillar leverages the SMART Mobility Consortium's key capabilities to produce data, tools, models, and analysis for integrated insights, visualizations, and knowledge that can guide efforts towards affordable, reliable, adaptable, and efficient urban mobility systems. Transforming urban energy and mobility futures requires the participation of transportation authorities, utilities, city governments, MPOs, private sector, employers, and service users, all of whom are key stakeholders in urban mobility and are involved in diverse city planning and operations. US emphasizes local engagement with government decision makers, researchers, the business community, and data/technical personnel to identify site-specific and replicable solutions. This engagement brings to the forefront many critical perspectives that influence the quality of urban life and the choice and utilization of new and existing mobility systems. Cities are places where new practices, data resources, and investments in transportation systems, infrastructure, and its governing policies are quickly evolving, and cities are acting in both ad hoc ways (such as when technologies emerge overnight, as the case with shared e-scooters) as well as proactivity to these stimuli. The overarching goal of the U.S. research framework is ultimately to develop a layered toolkit to support and enhance sustainable mobility for any city as it navigates and manages the many emerging ACES mobility technologies.

1.2 Recent Trends in Transportation and Urban Mobility

Within the past decade, but most intensively in just the past few years, the transportation system has experienced what is commonly referred to as a disruptive period. The advent of multiple new transportation technologies and practices has begun to dramatically transform the urban mobility landscape. The concept of shared mobility at a large scale began to emerge with the appearance of car-share, bike-share, and eventually various ride-hailing operations in the early years of the 21st century and proliferated to numerous cities, reaching most urban areas in the United States. These initial shared mobility options were enabled by nearly ubiquitous digital communication, computation, and wireless technologies (the core elements of "smartphone" technologies) to process access requests and payments and to manage responses to demand in real time. In a short period, innovators capitalized on the possibilities afforded by these tools through guided evolution of communication and mobility to devise new forms of mobility.

Most visibly, the introduction of transportation network companies (TNCs) has quickly and broadly spread the concept of on-demand mobility, enabled by shared economics and made possible through an ever-expanding communication network of smartphone technologies and enhanced wireless network capacity. The popularity of TNCs has empowered development of subsequent on-demand mobility, including currently emerging and quickly evolving micromobility options such as shared e-scooters and docked and dockless bikes and e-bikes. Each of these new mobility options has begun to exert impacts on the existing mobility environment, resulting in changes to parking demand, transit use, and the way people think about getting to the places they want to go, especially in the urban domain with dense spacing of various destinations, and where driving is not always the most convenient and cost-effective option due to parking and congestion issues. In addition, "microfreight" deliveries as a result of rapid adoption of e-commerce add to the curb-front pressure and competition for space once dominated by vehicle parking.

In addition to the transformative changes catalyzed by on-demand and shared services, other emergent technologies are poised to induce substantial effects on urban mobility. EVs and their charging infrastructure have a growing presence in cities and are showing signs of increasing adoption. Not only do EVs have greater energy efficiency than internal combustion engine vehicles, but they improve air quality through reduced point source emissions within the city, which is highly attractive to urban areas striving to improve air quality.

Automated vehicles (AVs) are at a nascent stage but are likely to undergo initial rollout in the near future. AVs are currently emerging from the "trough of disillusionment"[30] and beginning to reveal their productivity potential. AVs are anticipated to further redefine perceptions of mobility, potentially freeing travelers from the task of piloting vehicles, accelerating mobility-on-demand and mobility-as-a-service business models, reducing vehicle ownership rates while more efficiently moving people through shared-use models and contributing to safer roads with reduced human error. However, it is also possible that outcomes may be less favorable if AVs are used only in a fashion similar to current privately owned vehicles.

Many of the same communication, sensing, and data processing technologies that have enabled on-demand mobility services are being applied to infrastructure management and traffic signalization processes. Systems of sensors and communication are being designed to improve the accuracy of navigation, enhance traffic management, and inform CAVs of obstacles beyond the line of sight as they begin to come into use. Such technology is beginning to be applied to the curb front to proactively monitor curb space as cities evolve from hourly parking to PUDO zones. Although these tools are somewhat less visible to individual users, smart traffic management tools have the capability to better manage traffic flows, coordinate demand, inform smart routing, and overall reduce congestion, contributing to improved system energy efficiency. Coupled with onboard vehicle sensors and communications, infrastructure sensors form an interconnected network necessary for large-scale connected and automated traffic management.

The current environment of urban transportation is sometimes described as disruptive, in that the rapid changes are forcing transportation planners and society in general to adapt in a compressed timeframe. Such substantial changes have not been encountered since the introduction of the automobile more than a century ago. It is critical to identify and attempt to understand the magnitude of the effects and develop methods to measure, analyze, and model the impacts of emergent modes in order to more effectively plan for and design the future. Meeting these critical needs is perhaps the greatest challenge in transportation today.

To address these challenges, the SMART Mobility US Pillar comprises research organized around mobility in urban settings, taking a systems approach to identifying, measuring, and analyzing a range of data streams critical to understanding urban mobility. Multiple emerging technologies and practices in this space are rapidly maturing. In fact, many of these technologies either appeared or greatly expanded since the onset of the SMART Mobility initiative. Considering the evolving factors and new technologies, the US team has taken an iterative approach to research work.

Researchers, industry, and communities are seeking to improve the quality of transportation while maximizing the energy efficiency, equity, and safety of transportation services by leveraging emerging data platforms, new mobility technologies, and results from extensive modeling and simulation. As transportation may soon reach over 30% of U.S. energy consumption, and with urban areas representing an increasing proportion of the U.S. population (>80% since 2010), a critical need exists to engage in approaches to enhancing mobility informed by urban data science.[31,32] This includes identifying, documenting, and comparing key attributes across diverse implementations of city mobility and energy data collection and modeling.

Cities themselves are critical partners and the primary stakeholders in efforts seeking to understand and respond to these changes, requiring ongoing engagement and relationship building to enable understanding of the specific context of deployment, demonstrations, and experimental environments, and to tap into their data streams. As a corollary, city leaders and their constituent stakeholders are also a primary audience for the research and insights from the SMART initiative.

1.3 Research Themes and Report Organization

Cities have witnessed an immense amount of change in the transportation system from just a decade ago. In many places, options from which citizens may choose to satisfy their mobility needs have greatly expanded with the emergence of shared and on-demand services. City agencies, transportation service operators, and urban planners have had to adjust to the rapid evolution of these mobility options, requiring alterations to existing transportation demand models, operations practice, and policy and regulation from an administrative approach to respond to emerging ACES mobility technologies and fully leverage their benefits. Cities and their surrounding urban areas are the focal point of the rapidly changing mobility landscape and are thus the key focus area in a set of research initiatives whose objective is to identify emerging technologies and practices, gain access to data streams, and develop or adapt analytical methods and models to be able to inform current and future city-scale strategies. The US Pillar Capstone Report is grouped into four thematic research areas to begin to address the issues and opportunities for advancing EEMS within the urban context:

- Changes and Impacts on the Urban Traveler
- Development of the Mobility Energy Productivity (MEP) Metric
- Urban Infrastructure and Built Environment Synergy with Mobility
- The Signal Control Network as the Urban Mobility Nerve Center.

1.3.1 Changes and Impacts on the Urban Traveler

The research initiatives in this theme emphasize stakeholder engagement, data collection, and fundamental analysis of mobility changes. The US team visited each of the seven Smart City finalists from the U.S. Department of Transportation (DOT) Smart City Challenge[33] to gain detailed characterization of each of the seven cities' transportation models and data environments with respect to managing emerging mobility technology. The foundational insight gained from these interactions contributed to identifying gaps and critical areas for further research.

Objectively measuring and modeling the impact of TNCs was a primary objective of US research in this theme, and a gap exposed by stakeholder engagement. The effects of TNC services are readily apparent at airports as well as other dense urban activity centers where parking is costly or not convenient. A US research initiative examined airport revenue records made available through open record requests to document in detail the rapid adoption of TNCs for airport access. Analysis of these data quantified TNC growth, as well as associated declines in parking, car rental, and mass transit. These findings are critical for airports because infrastructure investments in parking facilities and rental car facilities are being impacted (lower revenue growth in the short term and deferred capital investment in the long term). The TNC impacts at airports can also inform similar directional impacts in other parts of the city, though at different magnitudes.

Replicability of impacts, as well as replicability of mobility solutions between cities, were the objectives of another research effort in this theme. A city typology initiative began to characterize (or cluster) various urban environments with respect to experienced or anticipated impacts of various ACES mobility technologies based on measurable sociodemographic, environmental, land use, transportation infrastructure, and governance attributes.

Lastly as young adults are waiting longer to obtain a driver's license or own an automobile,[34,35] employers are experiencing pressure to adopt mobility strategies to recruit qualified candidates in a competitive job environment. As a result, employers are becoming more active in providing alternative commute solutions. Employer-provided mobility (EPM) research investigates these emerging dynamics and estimates the potential for increased commuting efficiency if adopted at scale.

1.3.2 Development of the Mobility Energy Productivity (MEP) Metric

An identified gap from Smart City finalist stakeholder engagement was the need for better metrics in the urban mobility domain. Concurrently, the DOE had an acute need to quantify mobility to inform research work across the SMART Mobility Laboratory Consortium and to set targets and goals with respect to the overall program. In response, the Urban Science team embarked on an initiative with the objective to quantify the effectiveness of the holistic urban transportation system relative to travel time, affordability, and energy. This resulted in the development of the Mobility Energy Productivity (MEP) metric, which has since been broadly integrated into the SMART Modeling Workflow initiative. At its core, the MEP metric measures the productivity of a mobility system in the generic sense, that is, a benefit–cost perspective, where the benefit is the ability to connect people to goods, services, and employment, and the costs are that of travel time, affordability, and energy.

The MEP metric has many potential uses beyond SMART research. For example, it can be used to predict the return on investment of new transportation infrastructure, new technology, land use, and changes in practice, policies, regulation, and management, all evaluated with respect to improving access to goods, services, and employment which define the quality of life of citizens. The tenets of the MEP metric and sample applications and insights are provided in this report.

1.3.3 Urban Infrastructure and Built Environment Synergy with Mobility

The city mobility environment cannot be adequately addressed without taking into account the buildings, sidewalks, parking garages, and other built infrastructure that link people to destinations such as housing, retail, services, and employment. The developed landscape is constantly evolving, being shaped by economic forces, available technologies, and urban planning, as well as the efficiency of the transportation system. This thematic area investigates changes in urban infrastructure at multiple scales.

Transportation modeling at the regional level has used existing land use maps, as well as forecasts of future development with respect to jobs, housing, industry, business, and retail. However, modeling major changes in development patterns as a result of new mobility technologies has not been accomplished within a full feedback loop of how mobility shifts impact future land use. The US team extended the open-source UrbanSim[36] model such that future land-use forecasts are predicated on the effectiveness of future mobility and the many possible future scenarios that ACES mobility technology can provide.

At the district scale, the automated mobility district (AMD) toolkit was developed both as a planning and an assessment tool. It allows for quantifying the mobility and energy impacts resulting from the use of shared, automated electric vehicles as campus or district circulators and last-mile solutions. As a planning tool, the AMD toolkit analyzes the number, size, service model (on demand vs. fixed route), and other operational parameters of an automated system with respect to the desired operational benchmarks, as well as quantifies the energy footprint of an AMD relative to traditional vehicle access.

Lastly, competition for curb space has intensified as a result of TNCs, e-commerce, and micromobility, requiring PUDO zones for TNCs and freight delivery as well as micromobility corrals for storage of scooters and bicycles. The Curb Topology research initiative documented the issues and responses from cities and industry in response to this evolving pressure on curbside use and introduces a curbside value model to appropriately allocate space for various competing purposes.

1.3.4 The Signal Control Network as the Urban Mobility Nerve Center

Coordinated and optimized management of traffic flow in urban areas has long been an objective of traffic signal control. Recent advancements in sensing and communication technologies have opened doors to enhance observability of traffic and pedestrian flows. Previously, vehicle presence was sensed though inductive loops, and pedestrian presence (if sensed at all) though crosswalk call buttons. Technology is beginning to provide solutions to knowing the location and velocity of each vehicle and pedestrian at the intersection, opening up opportunities for enhanced control strategies.[37,38,39,40] In a broader sense, the signal control network in cities represents the active mobility management data system, which is evolving to include not only more effective vehicle coordination along arterials and collectors, but also the nerve center that actively optimizes transportation across modes (vehicles, CAVs, transit, micromobility), as well as infrastructure (curb space as well as signalized intersections).

Through a combination of vehicle- and infrastructure-based sensors and advanced communication technologies, transportation system managers can gain greatly enhanced observability into their local signal control roadway networks. US research in this thematic area explored the enhanced potential of both connected vehicle data and infrastructure spatial-sensing data (such as LiDAR, radar, and AI-processed video) at signalized intersections to improve efficiency, reduce delay, and improve safety (about half of all vehicle crashes occur at intersections[41,42,43]). CAVs provide their location and speed to the signal controller to optimize signal timing. Whereas significant CAV penetration is years away (perhaps decades), infrastructure spatial sensing has the potential to enable applications and benefits of CAV technologies in the near term by providing equivalent data for all objects (vehicles, cyclists, pedestrians, scooters, etc.) in the field of view of the sensor array. Such data (either communicated from vehicles or harvested from advanced sensors at intersections) can be leveraged to improve traffic flow and enhance safety and may also be communicated to vehicles for additional applications. Research initiatives in this area quantify the reduction in delay, energy, or both resulting from enhanced observability from either CAVs or infrastructure spatial sensing.

A special emphasis in this thematic area is the relationship between safety and energy. Although signal timing is traditionally optimized for throughput, avoidance of stops, and/or energy efficiency, safety remains the paramount objective in traffic operations. Using an industry big-data set comprising the location of vehicles reported every few seconds (latitude and longitude of the vehicle) of approximately 2% of vehicles in Columbus, Ohio, the US team research initiative first assessed the performance of ten signalized corridors and then indexed the measured signal performance to the crash history on those corridors. The results established a quantifiable link between well-timed signals and safety for the first time. In another initiative, the energy benefits resulting from avoided crashes—both direct (delays, congestion, slower speeds) and indirect (lost human capital and productivity)—are estimated.

1.4 Focus of Analysis for the Pillar

As much of the recent and emerging advances in mobility technology and practice have taken place in urban settings, the focus of analysis for the US Pillar is the mobility dynamic at the city level. Urban travelers, whether commuting, attending to errands, or just passing through, interact with the built environment and infrastructure of the urban setting, with their transportation behavior guided by physical cues and social norms. Together, these dynamics comprise a complex set of factors, including economics, convenience, safety, and accessibility, which make a travel mode more or less desirable or convenient for a specific trip, individual, and place. These elements are defined in part by the characteristics of the city in which the trip takes place and understanding how the urban setting influences mobility outcomes is of central interest within the US Pillar.

Table 1 provides an overview of the major initiatives in the pillar that will be presented and discussed in research findings, and their primary mapping onto the four themes. This is not an exhaustive listing of the research projects under the Urban Science umbrella, but merely reflects an overview of the major initiatives and subsequent findings. The authors took the liberty of combining projects under one heading, where appropriate, for the sake of brevity.

Table 1. Overview of Urban Science and Thematic Areas

Thematic Areas	Changes and Impacts on the Urban Traveler	Development of the Mobility Energy Productivity Metric	Urban Infrastructure & Built Environment Synergy with Mobility	The Signal Control Network as the Urban Mobility Nerve Center
Urban Science Pillar Tasks	Curation of Smart City Data and Models TNC Impacts on Mobility Choices at Airports Urban Typology Employer-Provided Mobility Benefits	The Development and Application of the MEP Metric	Extending Urban Land-Use Models with Dynamic Mobility Models AMD Toolkit Curbside Topology	Energy and Delay Minimization with Reinforcement Learning and Connected Vehicles Stochastic and Distributed Signal Control with Connected and Automated Vehicles Infrastructure Spatial Sensing at Intersections Energy Equivalence of Safety at Intersections Harnessing Vehicle Trajectory Data for Performance of Pretimed Signal Optimization

Research questions addressed in the US Pillar include:

- How has, or will, ACES mobility technologies impact diverse urban travelers, systems, and services?
- What are the long-term energy and travel impacts from changing urban environments?

- How is mobility quantified? Can we increase overall energy in the transportation sector if the corresponding benefits increase proportionally greater? How can this be measured?
- Can SMART Mobility research insights and findings be enhanced by making relevant outcomes transferable among cities with similar characteristics?
- Can coupling land use and transportation models quantify both the impact of urban growth on mobility patterns and the impact of evolving mobility on development patterns?
- How do curb space and parking management impact emerging mobility, including management of TNCs, shared bikes, e-scooters, buses (transit), and other mobility-as-a-service options, all competing for limited curb space?
- Can the net mobility gains and energy benefits of shared automated electric vehicles deployed for public mobility in a geofenced dense urban setting (defined as an automated mobility district) be quantified?
- What are the mobility and efficiency gains from implementation of CAVs and advanced sensing at intersections?
- Do safety enhancements at intersections resulting from CAVs and infrastructure sensing provide a greater energy impact than that of simply improved vehicle dynamics? Is there an energy benefit from increased safety?

These are the fundamental questions that shaped the US portfolio of research, resulting not only in published fundamental gains in knowledge and understanding, but also in resources for cities to use while pursuing program and infrastructure investment to enhance mobility for its citizens in a sustainable fashion.

2 Research Findings

2.1 Changes and Impacts on the Urban Traveler

This thematic portion of US focused on collecting and analyzing data for the swiftly changing mobility landscape, gaining insight, developing fundamental models, and testing the transferability of the insights and models from location to location, with particular emphasis on urban areas. Cities are at the forefront of emerging transportation developments. Cities are complex systems that respond to and affect input. Operators, travelers, and the infrastructure of the streetscape are forced to adapt as new mobility options are introduced. At present, innovation, application, and adaptation are in continual flux as new options appear, some growing and gaining popularity, and some not able to achieve sufficient adoption to achieve takeoff as a commonly accepted mobility option. Concurrently, established modes and practices are compelled to adjust to new practices and behaviors. The results from this first thematic area, "Changes and Impacts to the Urban Traveler," are presented in four sections: 2.1.1: Curation of Smart City Data and Models, 2.1.2:Transportation Network Company Impacts on Mobility Choices at Airports, 2.1.3:Urban Typology, and 2.1.4:Employer-Provided Mobility Benefits.

2.1.1 Curation of Smart City Data and Models

This foundational research and analysis, accomplished in year one of the SMART Mobility Consortium, explored aspiring Smart Cities'[44] evolving mobility data and modeling capacity as well as how new approaches are emerging to support data-driven Smart City mobility programs, projects, and policies. With respect to data, systems such as the "Smart Columbus Operating System" in Columbus, Ohio, or the "PORTAL" data archive in Portland, Oregon, are being developed to provide the foundational transactional data repository to support both operations and planning for mobility as well as other smart city functions and initiatives. Each Smart City finalist had some type of data initiative either native to the city or in close partnership with a stakeholder such as a local university or MPO. In all cases (with the exception of Smart Columbus, the U.S. DOT Smart City grant awardee) the data initiative was organic, building on existing resources and previous data initiatives, and struggled for both resources and traction as a central data hub for new mobility. The Smart Columbus Operating System[45,46], which was developed from scratch using modern tools and techniques and specifically to support the Smart Columbus initiative, came into operation in 2019 and represents the first of a new breed of city mobility data systems. However, it is too soon to determine its relative success in providing a central data repository and transactional engine in Columbus, although results to this point are encouraging.

Methodology: Direct stakeholder engagement, interviews, and data collection with the seven U.S. DOT Smart City finalists

Data: Data obtained directly through interviews, reviews of city-specific Smart City literature, and data sets directly obtain from cities and their partners

Analytical Methods: Review information collected from interviews, workshops, and synthesis and comparison across all seven Smart Cities and their stakeholders

With respect to large-scale transportation models, in some cities that were interviewed in 2016 and 2017, modeling support for new mobility systems was evolving from MPO regional travel demand models to take into account emerging mobility technologies such as AVs, ride hailing, and car sharing, while in other cities such efforts have not yet begun as of the time of stakeholder interviews. However, even for the few that were attempting to adapt existing models, such efforts are generally lagging with respect to demonstration and implementation of new mobility technologies. Data and modeling constructs generally lag deployment (instead of informing deployment). Exploration into new systems (or response to new mobility offerings thrust upon the city such as shared electric scooters) is, for the most part, pursued without the aid or insight of parallel modeling activities (at least not modeling activities in the traditional sense of regional travel-demand modeling). Across all cities, data systems and analysis are being pressured to evolve to understand the related energy, environmental, economic, and societal impacts of fundamental shifts in human behavior and new mobility choices. However, this evolution remains in its nascent state, even now.

The curation of SMART City data and models interfaced with the seven U.S. DOT Smart City finalists, cataloging their existing data and mobility modeling capacity and ongoing initiatives, identifying common themes (as briefly noted above), and identifying common gaps in data, analysis, and capability. The results, detailed in a laboratory report,[47] were instrumental in informing follow-on efforts within the US Pillar, most notably TNC impact studies and the Mobility Energy Productivity metric development.

2.1.1.1 *Smart City Data Initiative Findings*

Each Smart City finalist prioritized a robust and continuously upgraded data infrastructure to monitor and inform decisions and to provide performance-based measures to assess progress toward its goals:

- A robust data sharing and exchange platform was prioritized by all seven Smart City finalists as critical to their larger Smart City initiative. Most cities were pursuing this through organic, collaborative efforts in partnership with local stakeholders (universities, MPOs, nonprofits). The implementation the Smart Columbus Operating System, funded as part of the grant award, is purpose-built, not an extension of an existing system, and is a core enabler of its portfolio of projects in Smart Columbus.

- Most data infrastructure efforts are based on data warehouse and/or legacy geographical information system architectures. Such approaches offer the capacity to store data sets but are less adept at data sharing and transaction interfaces such as application programming interfaces. Legacy approaches are also challenged by complex user access rights needed to protect personal privacy as well as navigate licensing of commercial data sets. Newer approaches, encompassed in open source and agile development techniques, are more adept at enabling robust data architectures, but cities struggle to adapt such frameworks.

- Most urban data initiatives incorporate existing mobility data from sensors or data from existing services such as public transit or parking revenues. New technology-driven, commercial, crowd-sourced, and/or internet-of-things-based methods have the potential to scale quickly. Such new data sources minimize cost and provide timely or even real-time data availability, but they require big-data expertise and computing resources typically beyond that of most municipalities.

2.1.1.2 *Smart City Mobility Modeling and Analysis Capacity*

The transportation demand modeling capacities and capabilities within the Smart City finalists range from the most modern methodologies such an agent-based, behavioral-science-founded activity models coupled with a dynamic traffic assignment network model to more traditional approaches (four-step with static traffic assignment):

- The pace at which an urban area adopts the newer transportation demand modeling methodologies varies based on needs, resources, and the nature of model development, which tends to be on an 8- to 10-year cycle. Activity based models (ABMs) with a dynamic traffic assignment network framework is the most modern and (at the time of the Smart City interviews) was anticipated to be sufficient to model ACES mobility technology. However, at the time of the interviews, the ABM + dynamic traffic assignment architecture lacked the research data to adequately reflect behavioral response (mode choice) of emerging modes. The ability to use the ABM + dynamic traffic assignment architecture to reflect impacts of ACES has since been demonstrated in the SMART Workflow modeling process, as well as in other research and academic initiatives. As research initiatives like these lay the groundwork, deployed travel-demand models within urban areas will begin to adopt and gain confidence in ACES modeling methodologies and results.

- Travel-demand modeling capacity is typically housed within the corresponding MPOs, with some exceptions, particularly when there are multiple principal cities within the MPO's region, such as in San

Francisco. Cities see the travel-demand model primarily as a rearward-facing tool, informing traditional mobility (vehicle and roadway use) to project roadway needs (and justify subsequent roadway capital investments). Transportation-demand models are not viewed as dynamic models to inform on quickly emerging mobility technologies such as deployment of automated shuttles, or on management of TNCs or micromobility. Current travel-demand model practice is resource intensive, requires large amounts of data, and requires a multiyear effort to construct and calibrate. Nimble and agile tool suites addressing the rapidly evolving urban mobility landscape would be a welcome advancement.

- The standard outputs from transportation-demand models related to energy are aligned with the Environmental Protection Agency's MOtor Vehicle Emission Simulator (MOVES)[48] software, which provides emissions estimates based on the operating speed and volume of roadway segments. MOVES can be adapted for viable energy estimates, though they are not as accurate as DOE-based tools. More sophisticated energy tools that integrate with transportation-demand models are needed to tailor energy estimates based on consumer fleet composition as revealed by vehicle registration data, amount of shared ridership, and projections of future vehicle mix and ridesharing, aligning transportation-demand models with priorities of energy-efficient mobility systems.

- Any urban area is a complex mixture of multiple authorities and actors that include the primary city, adjoining incorporated areas, townships, adjoining cities, the transit authority, the MPO, and business and economic growth organizations. The needs of the primary city (typically with a dense central area) within an MPO region with respect to emerging mobility compete with those of less populous, less dense jurisdictions. Traditional transportation-demand models, although having some capacity to address varying density with differently sized traffic analysis zones, do not accommodate the need for "micro-resolution" within dense urban development where new mobility modes are blossoming, and parking availability and curb space congestion may govern mode choice. "Multi-resolution" approaches, adapting higher resolution in the mobility network where and when they are needed, are requisite to reflect the impacts of emerging mobility technology as population and activity densities dictate.

2.1.1.3 *Overall Smart City Gaps and Opportunities at the Junction of Mobility and Energy*

Aspiring Smart Cities seek to harness new data, communication, and mobility technologies for the benefit of its citizens. Mobility is unique in that it is not perceived as an end goal or objective in itself, but as a means to an end for improved economic productivity, equitable access to health care and employment, and as an overall enabler of a higher quality of life. The common themes and gaps from the interviews with all the Smart City finalists include:

- The impacts of TNCs such as Uber and Lyft were within the spectrum of awareness for most cities with respect to concerns over the long-term benefits and sustainability. TNC data availability emerged as a critical data gap, and perhaps the most urgent to begin to analyze, understand, and model mobility-as-a-service within our urban spaces.

- The airport has emerged as the "front door" to medium and large cities, being the primary transportation hub welcoming visitors or connecting its citizens to both national and international destinations. As the rate of air-travel growth is about twice that of VMT (2.2% air travel growth per year between 2019 and 2039[49] as compared to projected 1.1% VMT)[50], the airport is emerging as a primary indicator of mobility behavior shifts, a sort of "canary in the coal mine." Collection and monitoring of airport access data provide critical insights into the rate of alternative mobility technology adoption, of which other parts of the metropolitan area may follow.

- Lastly, and of greatest importance, appropriate metrics for mobility analysis and effectiveness are lacking. Mobility itself is typically not a Smart City goal, but rather an enabler of improved quality of life. Metrics that quantify the ability of a city's various transportation networks to connect citizens with the goods, services, and employment to increase the city's productivity and improve citizens' lives are needed.

While new technologies are enabling new data collection, modeling, and planning considerations, the research and science that can inform the future of cities need to keep pace. Data and model integration, visualizations, and analytics will continue to emerge, and a goal of this initiative was to further enable data-driven decision making for urban areas. The curation initiative identified gaps in knowledge and practices, which in turn exposed opportunities for the DOE EEMS initiative to contribute to Smart City objectives while gaining insight and valuable data from Smart City programs. These identified gaps directly fueled research into the impact of TNCs (as reported next), and to the effort to develop the Mobility Energy Productivity (MEP) metric, as reported in the next section. These identified gaps and knowledge gained from the curation stakeholder engagement initiative also significantly influenced other SMART research, including curb topology and employer-provided mobility.

2.1.2 Transportation Network Company Impacts on Mobility Choices at Airports

New mobility options, prominently led by TNCs, have emerged within the last decade, creating a new norm for smartphone app-based mobility. However, the extent of use of TNCs and their impacts on urban mobility (both positive and negative) are challenging to assess as data from these companies are not widely shared. Even though some TNC data sets are beginning to emerge (most notably from Chicago[51] and New York[52]), systematic monitoring of the extent of TNC use in urban areas remains problematic to assess. Airports provide a unique opportunity to quantify the impact and modal disruption, noting that fifteen percent of Uber's booking came from trips to and from the airport in 2018.[53] Airports, generally a sub-jurisdiction to the city and a primary mobility hub, typically charge access fees to any commercial transportation service operating at the airport. Such fees generate significant revenue for the airport and provide a data trail to quantify the growth of TNCs and their impact on other modes. Data obtained from open records requests at several airports revealed revenue patterns that reflected rapid shifts away from other forms of transportation and toward TNC use. Such data inform about impacts at the airport—the major transportation hub of any medium to large city—informing future airport access and revenue generation. With respect to overall share of mileage associated with airport access, at least 2% of VMT for regional travel is for trips to and from the airport.[54,55] Although results from airports are not directly transferable to other parts of the city due to the unique nature of airport trips, the data still inform of the trajectory of the impacts with respect to parking and transit. Examining the number of ground transportation transactions and revenue shifts at airports, along with passenger loads (enplaned and deplaned passengers), provides one of the few consistent benchmarking opportunities for adoption and impact of ride-hailing services.

Methodology: Data requests to airports and transit agencies serving major metropolitan areas that reflected shifts in revenue over the last several years as TNCs have entered markets

Data: Transactions, revenue, and passenger data reflecting ground access to the airport. This includes number of enplaned and deplaned passengers, parking, rental car, transit, and commercial vehicle (taxis and TNC) access charge revenue.

Analytical Methods: Analysis of patterns within each airport and across airports that reflect consistent national trends, testing of the "independence of irrelevant alternatives" property to estimate and forecast mode shifts

The US Pillar assessed TNC impacts at major airports through analysis of airport revenues (e.g., parking fees, rental car surcharges, TNC and taxi surcharges), revealing the significant impact on parking (see Figure 13) and rental car business.[56] This analysis revealed consistent trends across many airports. One to two years after TNCs begin to provide service to an airport, parking revenue peaks and then begins to decline on a per-air-passenger basis. Overall parking revenue remained steady or even slightly increased as air-passenger growth overcame the decrease in parking utilization. However, anticipated revenues based on passenger load failed to meet projections. The same pattern is seen in rental car revenue as well. The ramification for airports is that in the near term, the reduction of ground access revenue as a result of TNCs is resulting in airports failing to meet revenue projections from ground access (such as parking and rental car surcharges). Gaps in revenue are only partially offset from fees charged for TNC access. However, in the long term, airports nearing capacity with respect to parking can continue to grow without substantial capital investment in additional parking. Not only did this research and analysis spark a discussion among airports on the impacts of TNCs, it also pointed toward the potential for similar impacts (perhaps at different scale) within other parts of the city that are not directly measurable.

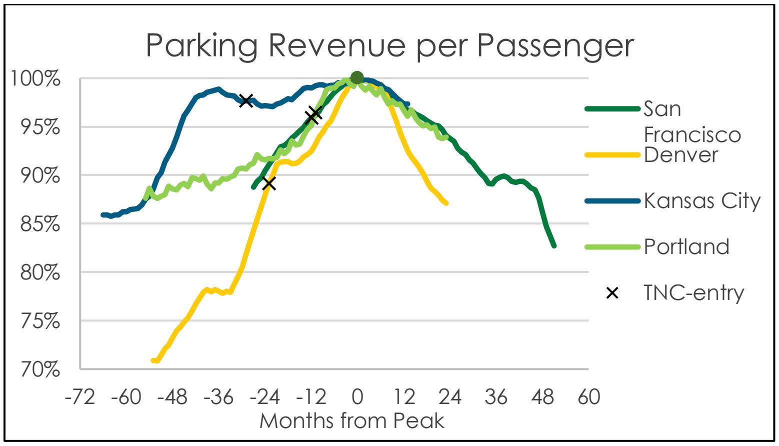


Figure 13. Trends of parking revenue per passenger at airports with respect to TNC market entry

Data collected from the Denver and Seattle airports included a full spectrum of airport access modes, including TNCs, taxis, car rental, parking, and transit, in order to infer modal impacts as a function of TNC adoption.[57] Figure 14 is a visualization of such data for the Denver International Airport (DEN) from 2014 to 2018, tracking the transactions per air passenger for five modes (transit, parking, car rental, taxis and TNCs). For example, in 2014 there were 20 transit transactions for every 100 air passengers.

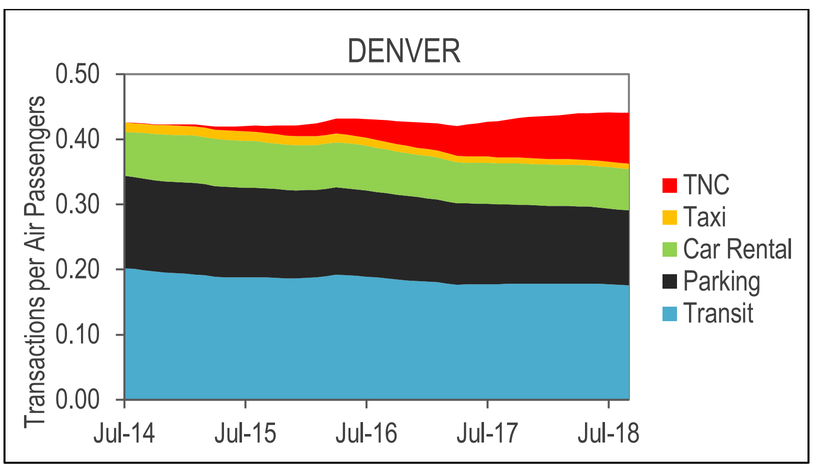


Figure 14. Revenue transactions per air passenger at Denver International Airport

Analysis of mode replacement (Figure 15) indicates that during the period from 2014 to 2018, for every 100 new TNC transactions for ground transportation to and from the Denver airport, 35% replaced transit, 39% replaced parking (someone driving their personal vehicle to the airport), 16% replaced car rental, and 10% replaced taxis. For example, for every three ride-hailing trips, roughly one parking space may no longer be needed at airports. Furthermore, analysis of the independence of irrelevant alternatives property—the assumption that the ratio of probabilities of choice between alternatives remains unchanged following the addition of TNCs—shows that only car rental passes the independence of irrelevant alternatives test. Transit, parking, and taxi modes are differentially impacted in a statistically significant manner. The differential results suggest that alternative-specific modeling methods such as multinomial probit models or nested logit models may be appropriate to reflect observed passenger mode-choice behavior.

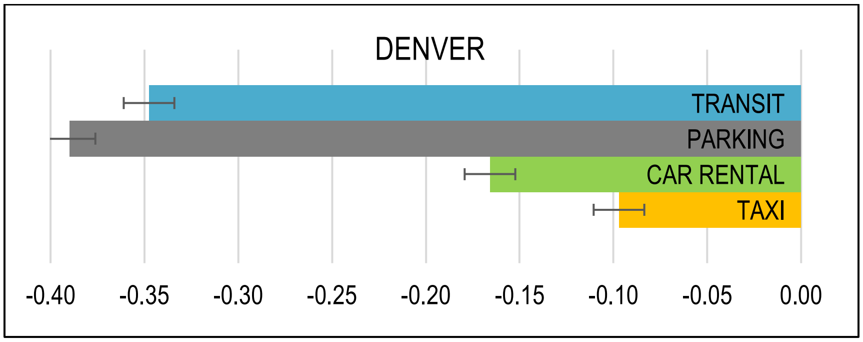


Figure 15. Decreases in other modes due to TNCs at Denver International Airport

Airports are anticipated to continue leading in their management of and responses to new mobility changes, as they are critical mobility hubs in cities. Continued monitoring to ascertain adoption rates, peaking or saturation of TNCs, and adoption of other mode choices as they emerge will help to inform similar dynamics of mobility throughout the city.

2.1.3 Urban Typology

Mobility patterns, technology adoption, and associated energy outcomes vary across settlement types, as acknowledged by the DOE in that "the ways connected, automated and shared vehicles are integrated in rural areas may differ substantially with how they are integrated into urban areas."[58] The range of projects conducted within the SMART Mobility initiative is broad, while the in-depth application of the Modeling Workflow process is, at present, limited to two metropolitan areas: Chicago and San Francisco. A key goal of the urban typology research was to determine how findings from one location may be translated for implementation or insight to another location. This increases the value of the SMART Consortium research and modeling and enables research outcomes to become more meaningful to informing mobility strategies in other urban locations. However, identifying how implementing or modeling of emerging mobility technologies in one city may play out in another is not simple; the context with respect to multiple variables that define the settlement type is important.

Methodology: The typology approach is to cluster locations by key social, economic, techno-infrastructural, and other mobility-relevant attributes

Data: Census block group-level data for about 15 indicators across independent and outcome variables

Analytical Methods: Scaling techniques to normalize the data, factor analysis to reduce dimensionality, hierarchical clustering to group similar block groups, and build distinct multidimensional socio-spatial typologies

Goal: The urban typology effort undertaken by the US Pillar seeks to examine how various geographic factors that span social, economic, techno-infrastructural, and environmental contexts impact variations in adoption, use, and associated outcomes of new mobility technologies.

The urban typology methods were initially demonstrated in the State of New York.[59,60] The methodology initially applied produced four distinct typologies (see Figure 16). The four typologies were interpreted (and labeled) as core urban (11% of total population), urban (37%), suburban (37%), and rural (15%). It is important to note that these four identified settlement typologies are the result of the clustering of key social, economic, techno-infrastructural, and other mobility-relevant attributes, and not any particular independent variable or preexisting spatial classification such as from the census, as the cluster labels may suggest. Upstate

New York is dominated geographically by the rural typology, while suburban and "working class" urban typologies are found in or near every major city, as well as in many smaller cities. There are small pockets of core urban typologies in cities, including Buffalo, Rochester, and Albany, while the majority is concentrated in New York City itself, though New York City has elements of all four typologies.

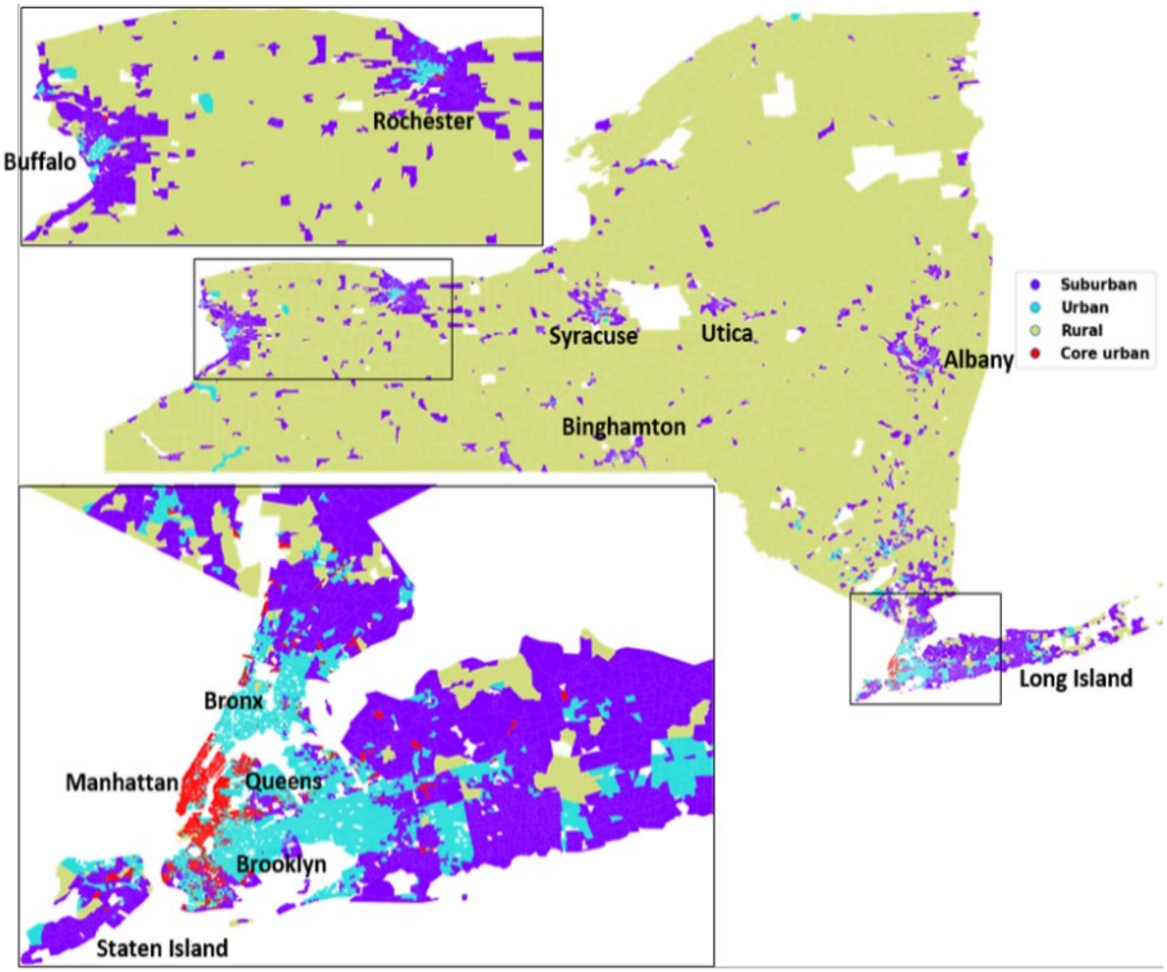


Figure 16. Map of clustering results from New York State

The spider plots in Figure 17 highlight the different indicators across which each of the typologies varies. Urban (working class) and core urban typologies unsurprisingly rank high on measures of density and job access. They also see higher air pollution (concentrations of atmospheric particulate matter that have a diameter of less than 2.5 micrometers (PM2.5)), cancer, and air toxics than suburban and rural areas. Homeowners comprise the vast majority of the population in suburban and rural typologies but are largely absent in urban and core urban areas. Household income disparities among the typologies highlight the socioeconomic segregation of the state, with affluent urban cores and suburbs standing in stark contrast to working-class inner cities and rural areas. However, the H+T affordability index[61] offers some nuance. Rural and suburban populations spend 59% and 56% of their income, respectively, on housing and transportation combined. In contrast, working class urban and core urban dwellers, the poorest and wealthiest income classes, spend 39% and 44%, respectively.

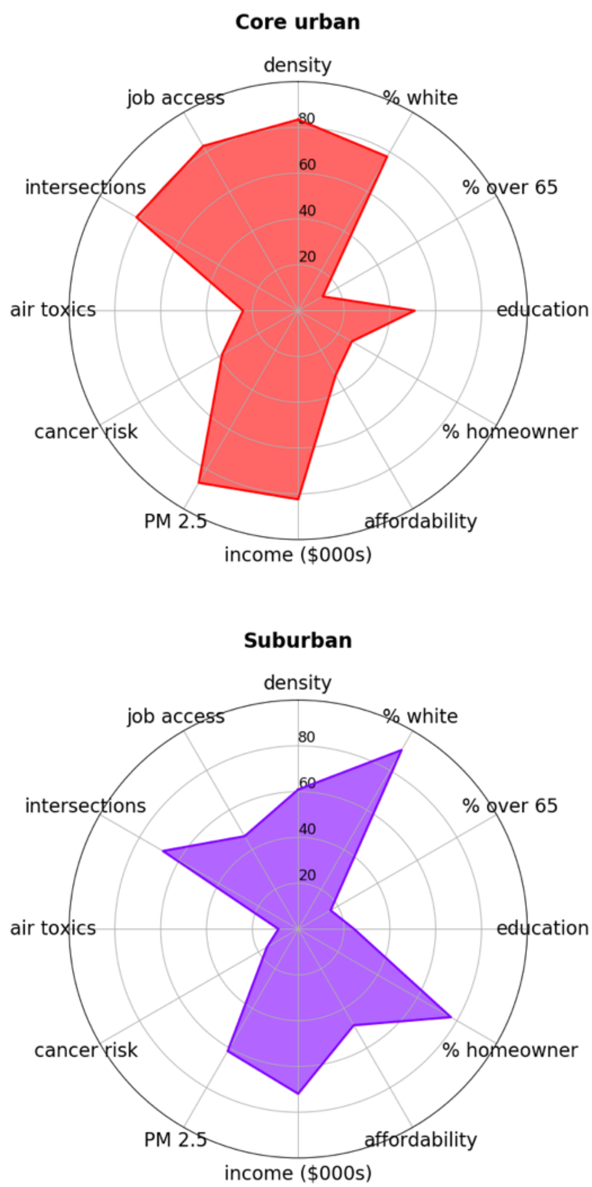


Figure 17. Spider plots showing indicators of independent variables, in scaled relation to each other, for each of the four cluster settlement types

The typology categories were tested against dependent variables such as EV adoption rates, vehicles per household, average fuel economy, and alternative commuting modes (anything other than single-occupancy vehicle travel), with the results illustrated in Figure 18. This typology demonstrated insight into various mobility behaviors. For example, for EV adoption, the core urban population—which are wealthy and highly educated in contrast to other typologies—adopts EVs at three times the rate per capita than the working class urban typology. A preponderance of alternative commuting modes was found to be closely linked with population and employment density, with more than 90% of core urbanites and 70% of the urban typology using transit or other alternative modes, compared with only 22% of suburbanites and 17% of rural residents. Household vehicle ownership also varies, with the number of vehicles per household in rural areas the highest, followed by suburban, urban, and core urban.

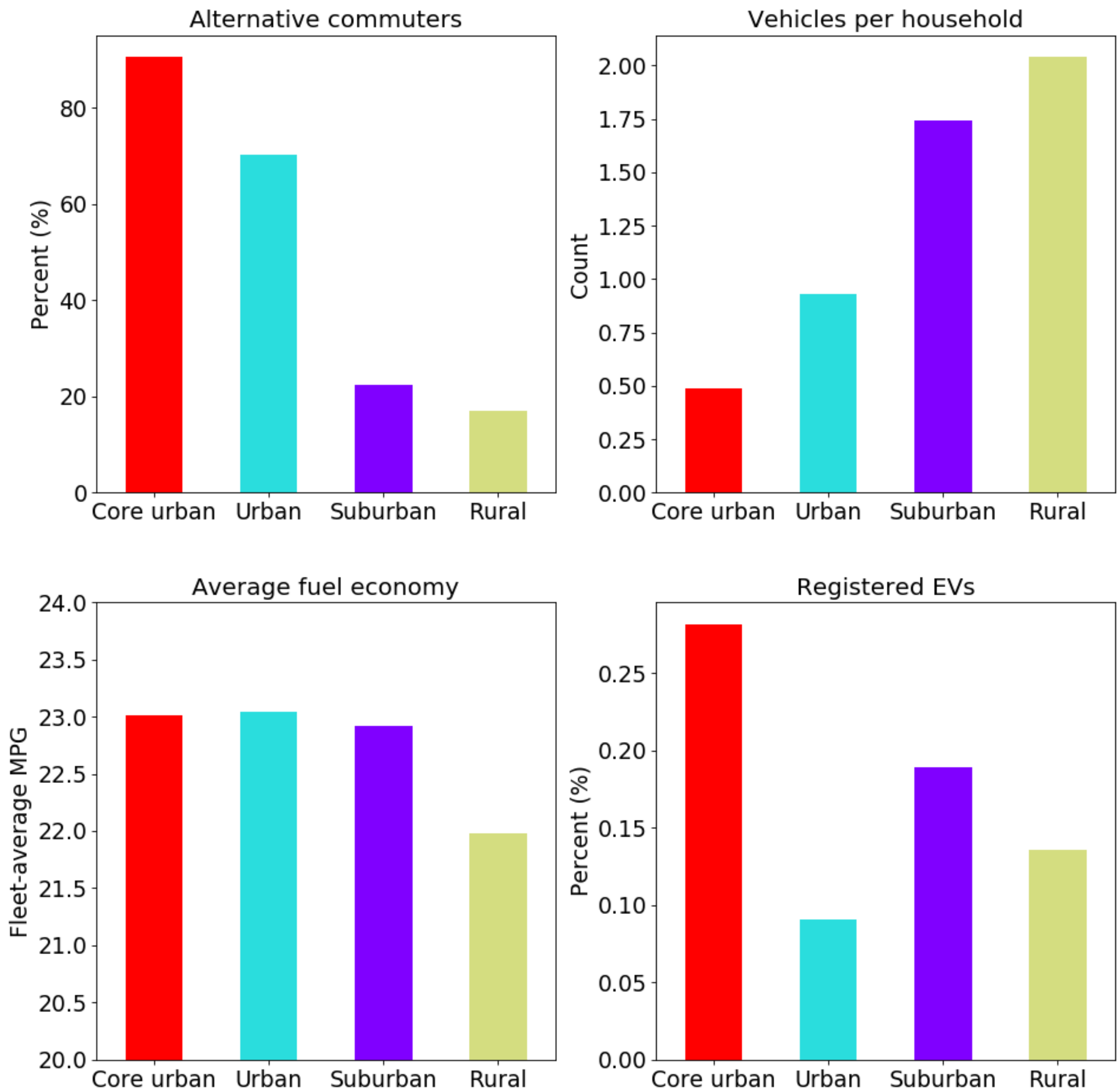


Figure 18. Mobility and energy outcomes by typology

Building on current typology work, future analyses are expanding to a 10-state test bed, with the eventual goal of a nationwide typology aimed at identifying and characterizing mobility typologies that are consistent across the United States to gain insight into similarities of adoption patterns of new mobility technology, and thus anticipated benefits and energy consumption consequences. ***This in turn can be used to extend the results of current SMART Consortium research (in Chicago and San Francisco) to other cities in the United States through use of the geospatial typology breakdown and transferability.***

2.1.4 Employer-Provided Mobility Benefits

Another emerging evolution to mobility systems is appearing in the context of employment. Factors of demography, economics, and infrastructure costs are intersecting to shape the emergence of employer-provided mobility (EPM) benefits. EPM may be described as any employment-based benefit designed to enhance mobility for employees, and it is a subset of broader transportation-demand management efforts. However, both the tools available to employers and the motivation factors have greatly expanded in the last few years. Modern EPM benefits are provided in a manner similar to employer-provided health or retirement benefits, through centrally managed software integrated with other human resources pay and benefits where costs are supported by the employer, sometimes with employee contribution. EPM benefits range in options and may include transit pass subsidies, micromobility memberships, guaranteed rides home, coordinated shared commuting services, and advanced door-to-door shuttle or chauffeured service.

Methodology: Apply results from available EPM case studies conservatively to a broader region to estimation potential impacts

Data: Longitudinal Employer-Household Dynamics data from the U.S. Census Bureau

Analytical Methods: Construct estimated energy outcomes based on likely uptake rates among commuters at various scales: individual employer, city, metro region, and national

EPM provides options for commuters other than single-occupancy driving. Its adoption, or rise in interest in the last few years, is fueled by the need for employers to attract a labor pool that may see vehicle ownership more as a burden than as a symbol of freedom, and to avoid the expense of providing either surface or structured parking. Many potential employees of younger generations may be less inclined to want to own or drive a car,[62] and a benefit to support an employee's commute to work may be a strong reason to choose one employer over another. The desire to reclaim productivity (either personal or business) lost to driving and congestion may also play a motivating factor.

EPM benefits were estimated for U.S. urban areas with a population over 500,000, which the American Community Survey estimates to contain a total of 77.7 million jobs.[63] Assumed EPM uptakes at a national scale within urban area among employees encompassed an increase of 2% from transit passes, 2% from carpool efforts, 6% from employer-provided shuttles, and 6% from micromobility options, as observed in a recent pilot program in Durham, North Carolina [64] (note that shuttles and micromobility impacts are only within a five-mile radius of the employer). Applying these assumptions at a national scale to urban areas yields annual energy savings of 352 million gallons of gasoline. This is approximately equivalent to the gasoline consumption in the United States for one day.

For the previously mentioned EPM uptake, Figure 19 considers the potential savings broken out by EPM mode. The largest potential for energy and emissions savings in terms of EPM mode comes from transit passes and carpooling.

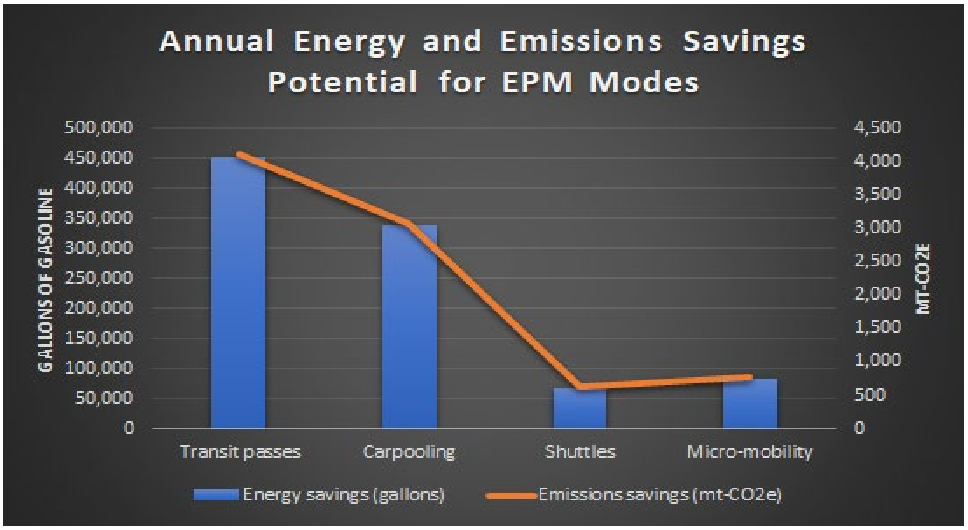


Figure 19. Estimated employer-provided mobility impacts at national scale

To date, the most prominent implementations of EPM have emerged in high-tech areas of dense employment on the West Coast, but notably are beginning to appear in much less dense cities such as Buffalo, New York; Columbus, Ohio; and Denver, Colorado.[65, 66, 67, 68] Some municipalities are increasingly looking to employers to help mitigate the impact of large numbers of commuters on roads at peak times of congestion, the reduction of which could result in further energy savings.

2.2 Development of the Mobility Energy Productivity Metric

The Smart City data and model curation activity exposed a gap with respect to having holistic metrics in the urban mobility space to measure progress towards a maximum-mobility, minimum-energy future. The US team created a new paradigm for evaluating mobility options within an urban area. This metric, termed the Mobility Energy Productivity (MEP) metric, is at its heart a location-based accessibility metric appropriately weighted with respect to travel time, affordability, and energy[69]. Mobility is assessed with respect to the ability of a transportation system to connect citizens to a wide variety of goods, services, and employment that define a high quality of life. The metric is assessed for any mode, encompasses a spectrum of trip purposes informed by established literature, and creates a quantitative measure of the potential mobility of an area with which to monitor fundamental advances in the urban mobility system with respect to efficiently connecting people to opportunities which encompass employment, health care, groceries, retail, entertainment, education, and recreation. Subsequently, the MEP metric was adopted as the central lens to assess the DOE EEMS program, with results from the SMART Workflow Modeling initiative represented by MEP analysis.

The MEP metric is versatile in that it can be computed from readily available data sources or derived from outputs of regional travel-demand models. The MEP shares many attributes of popular mode-specific consumer indices such as *walk score*, *bike score,*[70] and *transit score,*[71] but is open source, standardized, and can be applied to any mode (vehicle, transit, bike, walk), modal technology improvement (automated, connected, electrified, or shared), mobility infrastructure investments (highway capital improvements or mass transit), land-use planning (transit-oriented development, for example), or transportation operations or policy decisions (bike lanes, high-occupancy vehicle lanes, tolling, etc.). The MEP metric is a lens or metric through which a mobility research portfolio can be assessed, and future goals could be established with respect to the impact of investments in research or infrastructure. A toolkit has been developed to efficiently implement the MEP metric at the city level. The toolkit has been applied to baseline MEP calculations for more than 60 U.S. cities.[72] The MEP metric, integrated into the SMART Modeling Workflow process, has served as the top-level assessment of changes in mobility of scenarios, allowing for visuals of future scenarios and quickly comparing before and after for future adoption scenarios of ACES vehicles, as well as their policy, land use, and infrastructure ramifications, all within the lens of the effectiveness of connecting citizens to a spectrum of opportunities to enhance quality of life.

The MEP metric is a holistic metric that quantifies the effectiveness of a transportation system to connect citizens to a variety of goods, services, and employment that define a high quality of life. The ability to measure the effectiveness of transportation systems allows Smart Cities and SMART Consortium researchers to answer questions associated with the impact of emerging technologies and evolving demographics on the mobility, energy, and productivity of a region. A location with high-quality mobility offers multiple effective transportation options to a diverse number of opportunities while minimizing time, cost, and energy consumption.

The MEP metric expands upon familiar and popular metrics such as walk, bike, and transit scores,[73,74] which are propriatary and mode specific. The generalized MEP formulation weights accessibility (such as those proposed by others[75,76,77,78]) with respect to travel time, affordability, and energy. For example, it can indicate how many employment opportunities, healthcare facilities, grocery stores, restaurants, parks, and entertainment destinations exist within 20 minutes of a location using different modes. The resulting numeric MEP score provides a robust assessment of the mobility potential of a given location, assuming that an average traveler has access to all modes of transportation available at that location (such as personal vehicle, bus, train, TNC (e.g., Uber, Lyft), bike, or walk). The MEP metric measures how well each mode—as well as a combination of modes—connects the traveler to a variety of opportunities. Furthermore, by limiting the modes, or weighting modes based on availability or personal preference, the MEP metric can be customized to a sociodemographic, such as those with disabilities that limit their mobility choices, or even individual characteristics, providing a customizable lens to reflect equity and accessibility concerns. A conceptual formulation of the MEP metric is shown in Figure 20, which depicts the various data layers and spatial analysis needed to derive a MEP score.

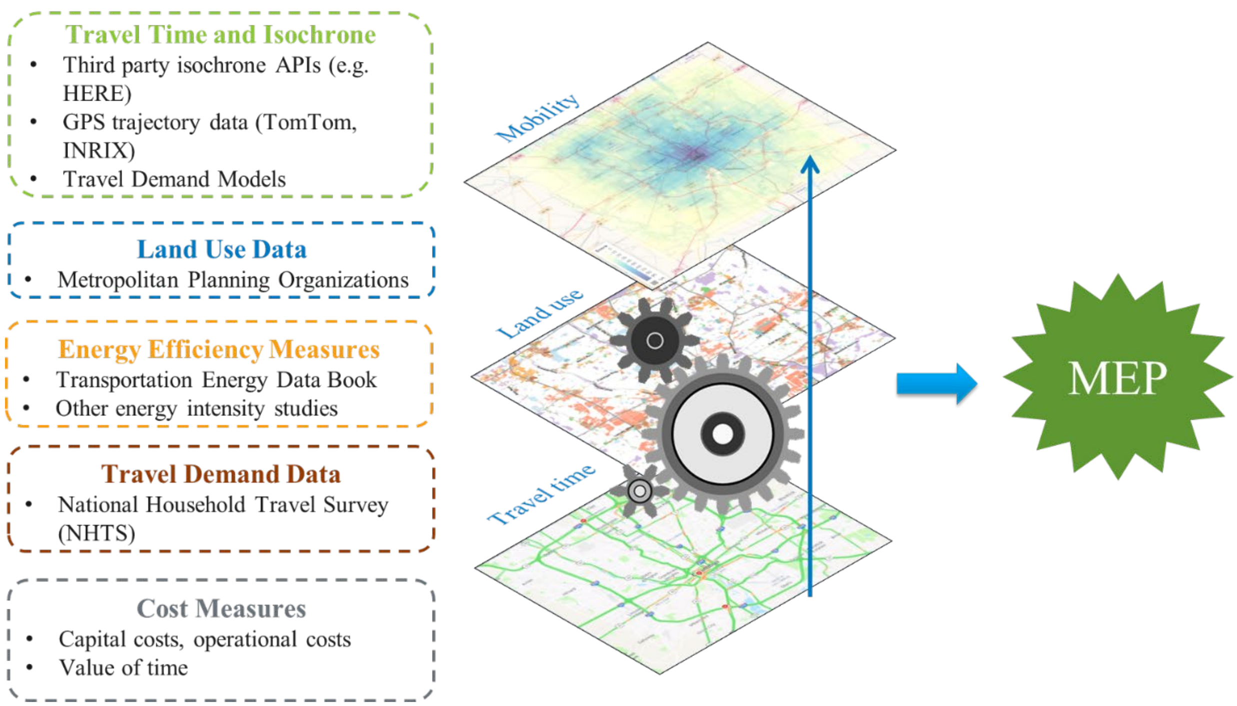


Figure 20. Computation framework and data input for the MEP metric

At the heart of the MEP metric are accessibility measures that build on existing accessibility theory and methodologies, assessing the number of jobs, goods, and service opportunities available within prescribed travel times from a location. This approach is fundamentally a geospatial analysis, providing both a visual map for comparative analysis and a numeric score to baseline performance metrics. Data to support travel-time calculations and land use (i.e., available goods, services, and employment opportunities) are readily available using third-party travel data or outputs from regional travel-demand models along with land-use data from cities, MPOs, or commercial entities. Isochrones—that is, lines on a map of a region showing what can be accessed within a given timeframe using a selected mode of travel—are constructed for each mode. Figure 21 is an example of a 30-minute isochrone showing reachable opportunities (color coded by land use) by bicycle from a location in Columbus, Ohio (roughly corresponding to the campus of Ohio State University).

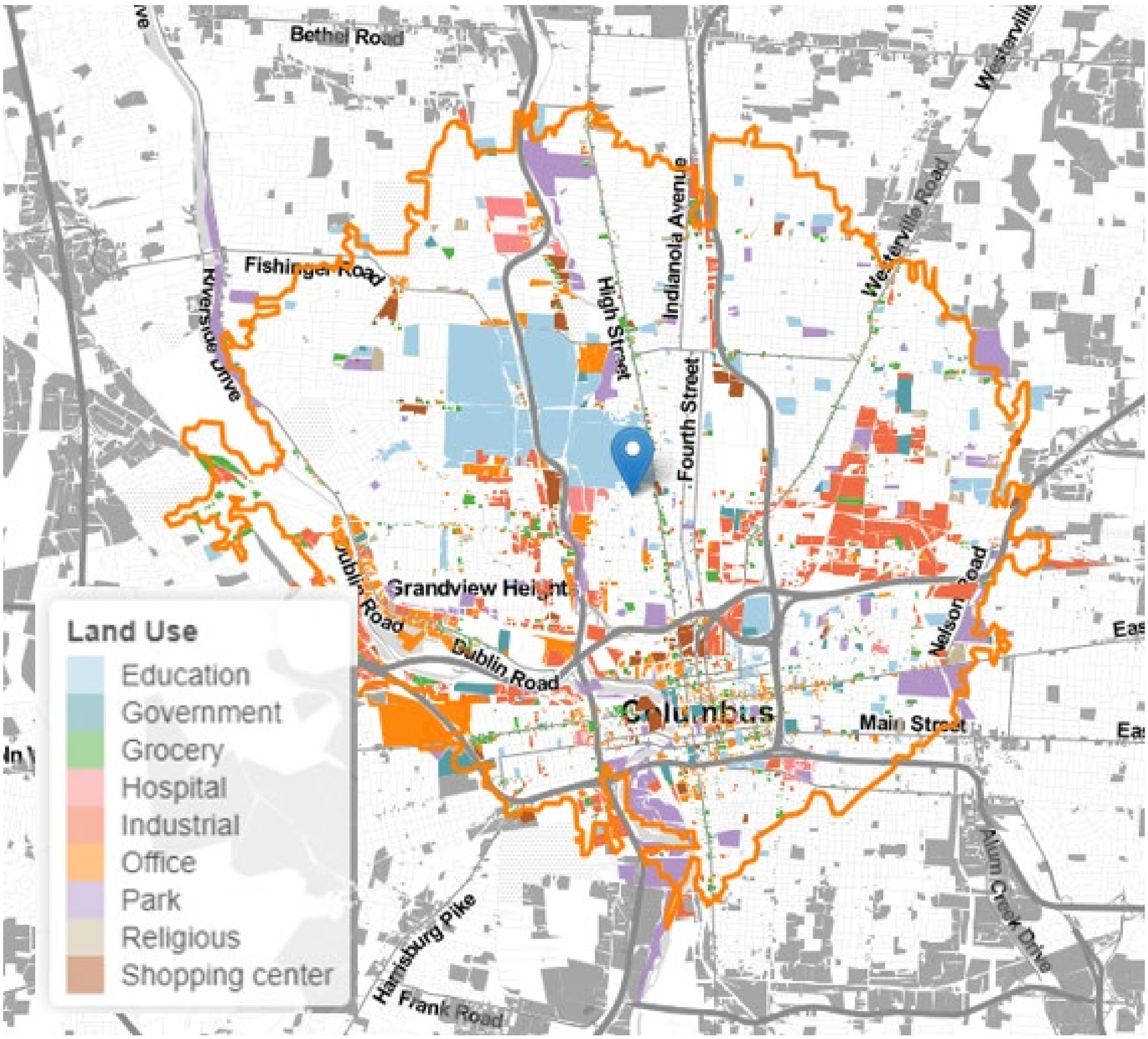


Figure 21. Thirty-minute isochrone for biking

The MEP formulation from a visual-graphical sense is to create isochrones for each location (grid cell) and each mode to reflect how far an individual can travel within 10, 20, 30, and 40 minutes from a location by walking, biking, driving, or using public transit. The job opportunities, grocery stores, restaurants, recreation facilities, medical service providers, and other destinations located within an isochrone are counted. These opportunity counts are appropriately weighted based on travel time, affordability, and energy use of each mode. Each opportunity count (job, grocery stores, medical services, etc.) is also appropriately weighted based on the frequency with which people make those sorts of trips, as revealed by travel surveys. Land use is indexed to purpose (e.g., education, shopping-retail, health) as well as to job-opportunity potential (number of employees or jobs).

From a mathematical perspective, this process is enumerated as given in the following summary equations. The forms of the equations are similar to other accessibility or generalized-utility equations used in activity-based travel models.

The quantity of opportunities for each type of activity is standardized by activity normalization constants and activity engagement frequencies and weighted by time, cost, and energy coefficients. The normalization constant helps convert scales of different types of opportunities into a unified opportunity measure. This constant is derived based on data from multiple cities and simply equates the relationship between number of opportunities of one type with the number of opportunities of a different type (explained with an example below). The activity engagement frequencies reflect known trip frequencies associated with various activity types. The MEP equation is:

$$\mathrm{MEP}_i = \sum_k \sum_t \left(o_{ikt} - o_{ik(t-10)}\right) \cdot e^{M_{ikt}}$$

where o_{ikt} is the opportunity space measure, which represents the number of opportunities that can be reached by mode k in time t from location i; and M_{ikt} is further defined as:

$$M_{ikt} = \alpha e_k + \beta t + \sigma c_k$$

where:

M_{ikt} is the modal weighting factor for opportunities accessed by mode k with travel time t from location i

e_k is the energy intensity (kWh per passenger-mile) of mode k

t is travel time

c_k is the cost (dollar per passenger-mile) of using transportation mode k

α, β, and σ are weighing factors.

Modal weighting factors account for travel time (which reflects the speed), affordability, and energy of each mode. The MEP metric considers the frequency of different trip types as well as the relative spatial equivalency of different types of opportunities. To account for the frequency of trip type and relative spatial equivalency, opportunities are standardized using a benchmarking measure as shown in the equation below:

$$o_{ikt} = \sum_j o_{ijkt} \cdot \frac{N^*}{N_j} \cdot \frac{f_j}{\sum_j f_j}$$

where:

o_{ijkt} is the number of opportunities for activity j that can be accessed by mode k within the travel time threshold t from the i^{th} pixel

N^* is the total number of benchmark opportunities across multiple cities (e.g., number of meal opportunities across multiple cities)

N_j is the total number of opportunities for activity j (e.g., number of shopping opportunities)

f_j is the frequency that people access opportunities of activity j.

The $\frac{N^*}{N_j}$ measure is a normalization constant based on data from a number of cities in the United States. This proportioning factor is derived based on data from multiple cities. For example, if across multiple cities there are 34,000 meal/restaurant opportunities and 200,000 shopping opportunities, taking meal as the reference category, the $\frac{N^*}{N_j}$ factor for shopping would be 0.17 (in other words, one meal opportunity is mapped to be equivalent to approximately six shopping opportunities). This factor remains constant for application of the MEP metric in any city, whereas the raw opportunities measure o_{ijkt} will vary from city to city.

The analysis framework culminates into a MEP score for a grid cell, which can be aggregated to any desired geographical resolution (e.g., neighborhood, city) by weighting with appropriate population-density measures. The example shown below in Figure 22 evaluates MEP at the resolution of a square kilometer of land, referred to as pixels. The one-square-kilometer pixels were chosen to balance the granularity needed for analysis against the data complexity and computational burden, as well as the underlying homogeneity and variation of mobility from place to place. The resolution of the MEP calculation can be at a greater aggregation (which may be appropriate for rural-based MEP calculations) or more granular (which may be appropriate for highly dense central urban cores). Figure 22 (panels A–C) shows the MEP metric (for all opportunities) in the Denver metropolitan region for different modal combinations. Note not only the visual contrast, but also the difference in scale between the modes in panels B and C, reflecting that the spectrum of opportunity accessible to a person is severely compromised if relying only on transit, walking, and biking as compared to vehicle access.

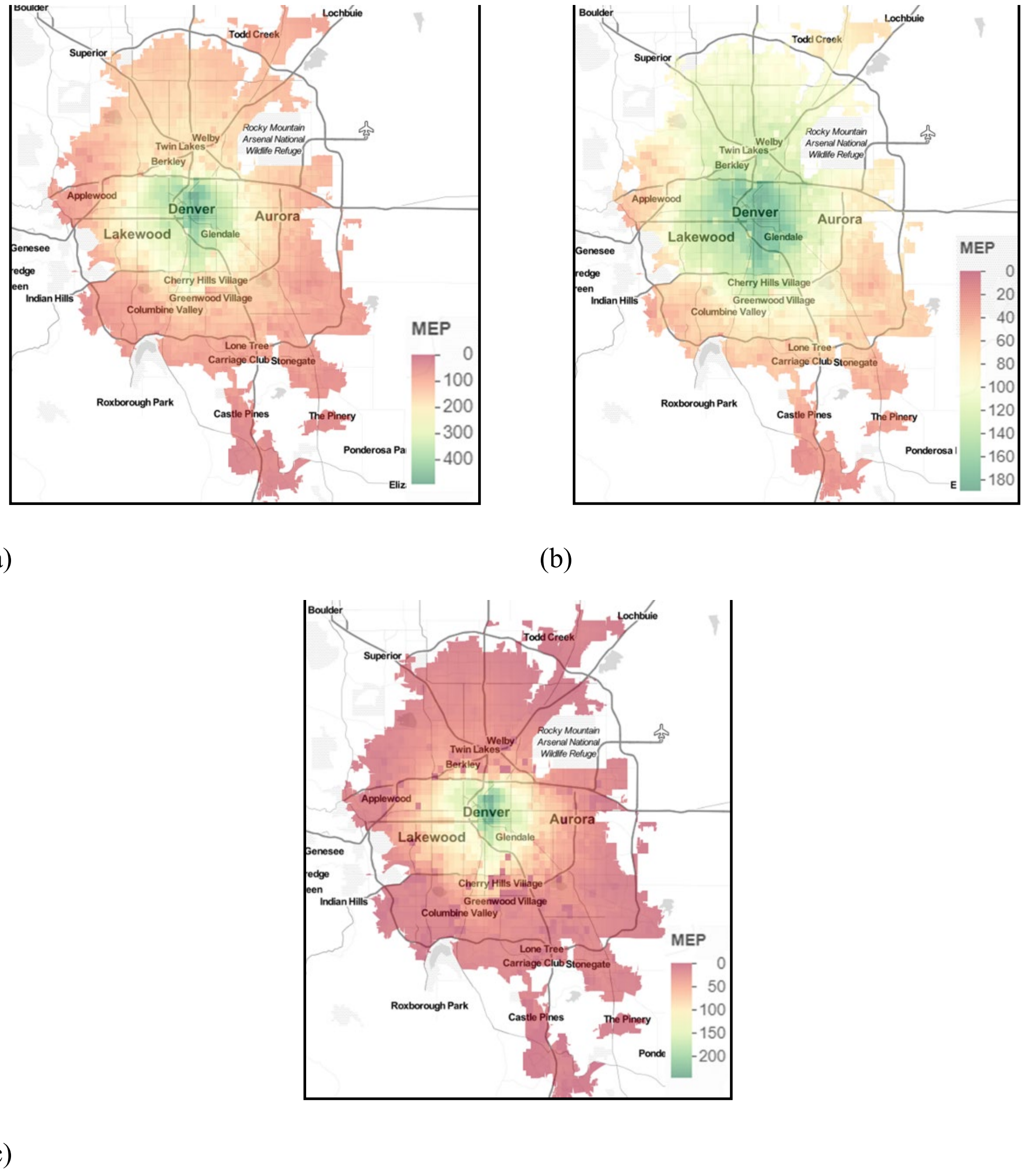
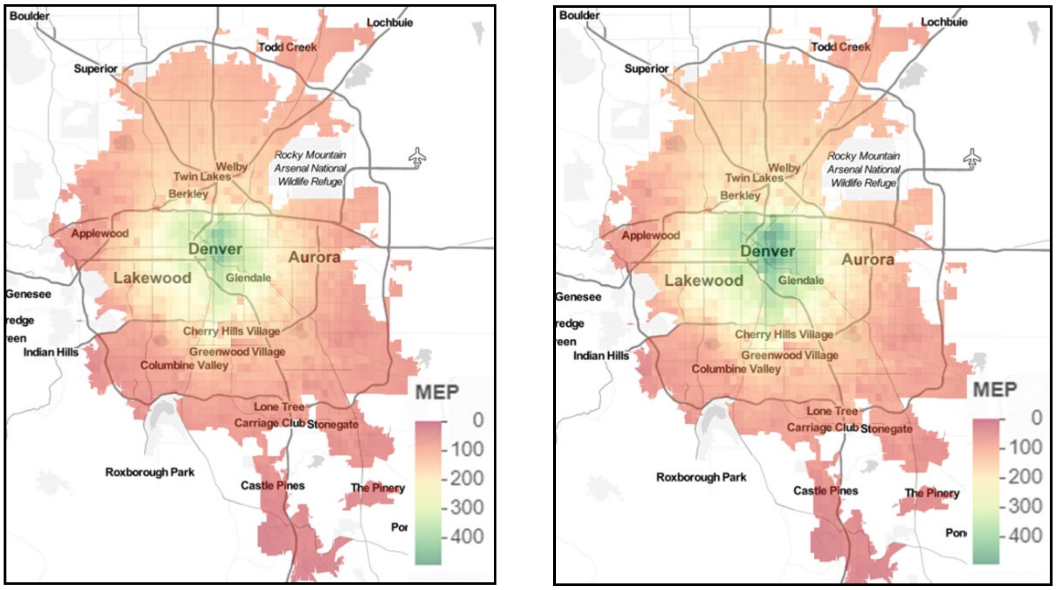


Figure 22. MEP maps by mode for Denver: A) all modes, B) car, and C) transit, walk, and bike combined

TNCs (such as Uber, Lyft, and Via) are shown to increase mobility in many urban areas, providing convenient transportation accessed through a smartphone. A first-order approximation of TNC-specific MEP was calculated in a fashion similar to driving. Travel times were adjusted to account for the delay in waiting for a TNC pickup, costs were adjusted upward as typical of TNC use, and energy was adjusted to account for deadheading (vehicles circulating with no passenger). This initial approximation does not account for any induced congestion as a result of the introduction of this new mode. Figure 23 shows the MEP maps for Denver before and after inclusion of TNCs as an additional mode. Observing the scores at the level of each pixel, it was found that ***MEP scores for TNCs are at best equal to and almost always less than that of car mode, owing to higher (wait) time, cost, and energy intensity factors compared to car mode***.



a) Before TNC

b) After including TNC mode

Figure 23. MEP maps for Denver before and after TNC mode

The city-level aggregated MEP scores before and after adding TNCs came out to 150 and 176, respectively. Therefore, given the assumptions made for wait time, cost, and energy intensity, the ***Mobility Energy Productivity score for Denver increased by ~17% with the introduction of TNCs.*** Note that in all of the results presented above, assumptions were made to show first-order effects. Coupling the MEP calculations with agent-based travel microsimulation models can fully capture all effects, not just primary impacts such as energy intensity, but also impacts of adoption rates, induced (or reduced) congestion, and other secondary and tertiary impacts that can arise from these scenarios.

Acknowledging the importance of capturing secondary impacts of emerging transportation technologies in capturing transportation system efficiencies, SMART researchers have linked the MEP calculation procedure to sophisticated ABMs (i.e., Polaris and BEAM) as part of the SMART Modeling Workflow process, so that the results of any scenario analysis can be used to generate MEP metrics. Details of the integration between MEP and ABMs are discussed in "Workflow Capstone Report" in Section 4.5 (for Chicago), and Section 5 (for San Francisco).

New mobility choices will have critical impacts on the functioning of metropolitan areas and decision making for transportation, energy use, and infrastructure. Communities of the future will need to measure the quality of a multitude of modal options, infrastructure investments, and policy adoptions available to enhance mobility of their citizens and do this in light of sustainability concerns. A methodology for the comprehensive MEP metric quantifies the effectiveness of a city's transportation system to connect citizens with a variety of goods, services, and employment weighted by time, energy, and affordability. The MEP metric allows communities to disaggregate the score to isolate the impacts of certain mobility options at specific locations and track progress over time, as well as aggregate upward to reflect an overall dashboard of fundamental impacts citywide. Recognizing the potential for the MEP metric, ASCE is partnering with US researchers to create standardized formulation of the MEP metric for use in cities.[79] Although several refinements and extensions of the MEP metric continue, the basic framework and theory of operation—that of assessing the overall effectiveness of a transportation system to connect citizens with goods, services, and employment relative to travel time, affordability, and energy—fill a fundamental gap identified through Smart City stakeholder interaction and provide a central lens for mobility work.

2.3 Urban Infrastructure & Built Environment Synergy with Mobility

Our transportation systems connect us with the physical destinations that house goods, services, and employment. As transportation systems evolve, so also do the physical structures that accommodate the mobility system (such as roads and curbside), as well as the end structures themselves. The famous movie quote from the film *Field of Dreams* stating "If you built it, they will come" is often cited within transportation planning circles with respect to transportation improvements such as new freeways or major transit facilities, and how such improvements spark housing, retail, and commercial development. In a parallel fashion, emerging mobility modes such as TNCs and bike and scooter shares are causing a rapid evolution of the curbside space once dominated by vehicle parking, as well as overall decrease in parking demand (as discussed in Section 2.1.2). The US Pillar examined the interaction of physical space with the impacts of ACES in three research initiatives whose results are discussed below.

2.3.1 Extending Urban Land-Use Models with Dynamic Mobility Models

Identifying how cities and systems within cities respond to the rapidly changing mobility environment is crucial to understand which of the emerging technologies and practices are most viable as transportation professionals attempt to plan for and meet near future mobility needs. The US Pillar extended the open-source UrbanSim[80] model to include a lightweight dynamic traffic assignment feedback loop so that the impact of SMART technologies on future land-use scenarios can be assessed. The model extension had three phases:

- Phase I: Extend UrbanSim with lightweight traffic models required to facilitate the generation of activity plans
- Phase II: Develop operational software infrastructure to automate the integration of UrbanSim with agent-based travel models such as those used in the SMART Modeling Workflow process
- Phase III: Run fully integrated scenarios using travel demand ABMs (such as BEAM and Polaris) to perform 30-year forecasts with intra-simulation feedback loops as part of the Workflow process.

The first phase was accomplished and reported on in this US Capstone document. Phases II and III were integration efforts into the SMART Modeling Workflow process; see the *Modeling Workflow Capstone Report* for details and results.

The first phase of the project was achieved through development of the open-source ActivitySynth[81] software, which is software that generates daily activity plans for a specified population. Development and integration of this suite of microsimulation models enabled quick generation of basic activity plans for a synthetic population based on the land-use characteristics as simulated by the UrbanSim land-use simulator.

The second phase developed an operational workflow for using UrbanSim and ActivitySynth to perform integrated land use and transportation modeling. This kind of closed-loop integration has long been the gold standard for regional forecasting (travel demand, traffic, or land use) but has rarely been implemented at scale. To achieve this integration, the UrbanSim codebase was refactored to be travel model agnostic by relying solely on the use of generalized cost- and travel-time-based "skims" for computing the accessibility-based parameters upon which land-use forecasting models rely. In addition, software was developed to automate the high-level tasks of executing UrbanSim and ActivitySynth and facilitating the transfer of data between the land-use platform (UrbanSim with integrated ActivitySynth) and travel-modeling platforms (such as Polaris and BEAM used in the SMART Workflow Modeling).

The third phase of the UrbanSim extension involved actually using the software developed in Phases I and II to execute 30-year forecasts per the SMART Modeling Workflow Common Scenarios. The primary objective was to facilitate the incorporation of more realistic land-use data inputs into the mesoscopic travel-demand models used by the SMART Workflow Modeling initiative, the results of which are reported in the *Workflow Modeling Capstone Report*.

Initial results from the tight integration of land-use models with BEAM show that scenarios associated with higher urban traffic congestion (regardless of whether it was from traditional vehicles or AVs), and therefore longer travel times, are associated with land-use outcomes such as people choosing residential locations closer to their jobs. Experimental results like these that match intuition suggest that the feedback loops are having the intended effect. More detailed results arising from integration of the enhanced UrbanSim model with model runs with BEAM for San Francisco are conveyed in the *Workflow Modeling Capstone Report*.

2.3.2 Automated Mobility District Toolkit

Major disruptive technologies are set to redefine the way in which people view travel, particularly in dense urban areas. Already, cities are experimenting with low-speed automated shuttles in various pilots and demonstration projects from vehicle and system manufacturers such as EasyMile,[82] Navya,[83] Local Motors,[84] MayMobility,[85] and RoboticResearch.[86] Along these lines, a concept called the "automated mobility district," or AMD, has emerged that describes a campus-sized implementation and deployment of automated, connected vehicle technology to realize the full benefits of an AV shared-mobility service within a confined geographic region or district. In an AMD, a fleet of shared, automated vehicles (SAVs) serve the majority of public mobility needs, dissuading (or perhaps prohibiting) the use of personal vehicles, and providing both last-mile and intra-campus circulator service. The concept of an AMD is depicted in Figure 24.

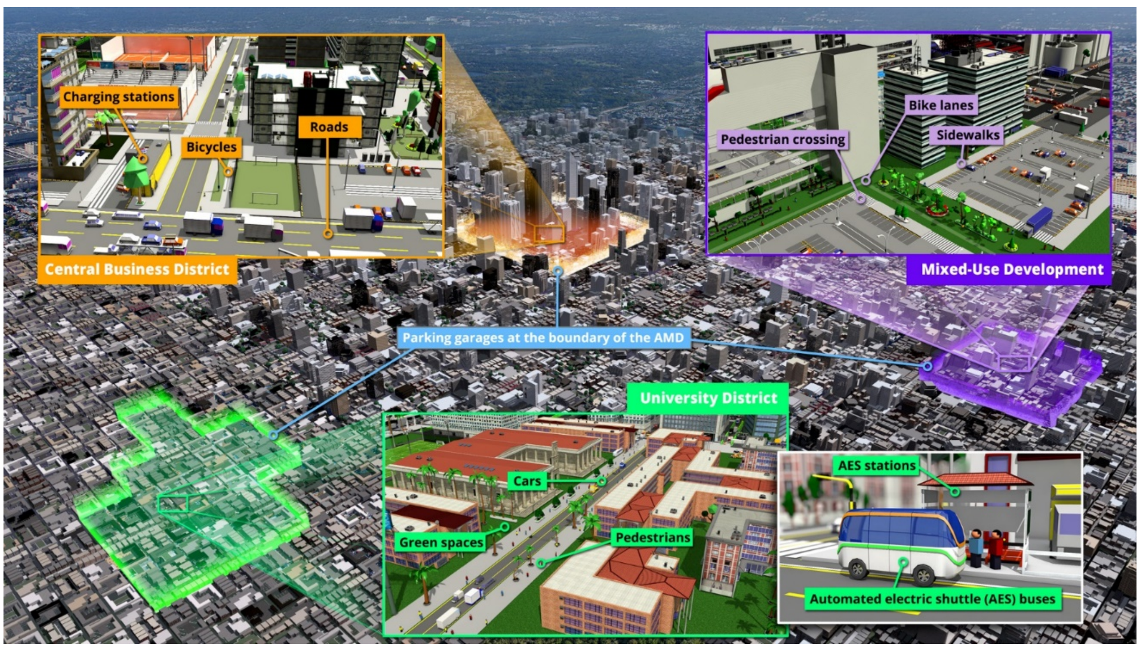


Figure 24. Graphical depiction of Automated Mobility Districts

AMDs are envisioned to be applicable for dense, high-demand areas such as central business districts, business parks, and university campuses; all these are akin to areas termed as special generators in existing four-step travel-demand models or more sophisticated agent-based travel models.

2.3.2.1 AMD Operational Analysis

AMDs as defined above are now certainly within the near- to medium-term planning horizon for dense urban settings, as evidenced by the continued growth of pilots and demonstrations of SAVs. Such demonstrations are progressing from the simple desmontration of capablity such as those on the Columbus Scioto-Mile[87] or Arlington, Texas,[88] to more mobility purpose-driven demonstrations such as those currently in deployment at Texas Christian Univeristy[89] and Columbus Linden neighborhood.[90] However, the availability of practical and efficient planning tools appropriate for analyzing the complexities of AV fleet operations within AMDs is a significant issue. The breadth of options for operational planning of AMDs ranges from aggregate calculations to advanced ABMs and microsimulations of people and vehicles. While aggregate "back-of-the-envelope" calculations are an inexpensive solution in terms of both time and cost, the estimates produced by such calculations are too coarse for optimal deployment and operations of fleets of automated electric shuttles. On the other hand, ABMs combined with traffic microsimulation can produce precise results that can help plan the best possible deployment.

Addressing this gap, the AMD modeling and simulation toolkit is intended to augment existing transportation demand models and provide a way to model travel patterns (at the microscopic level) in geofenced regions with high travel demand. Figure 25 depicts the modeling framework of the AMD toolkit.

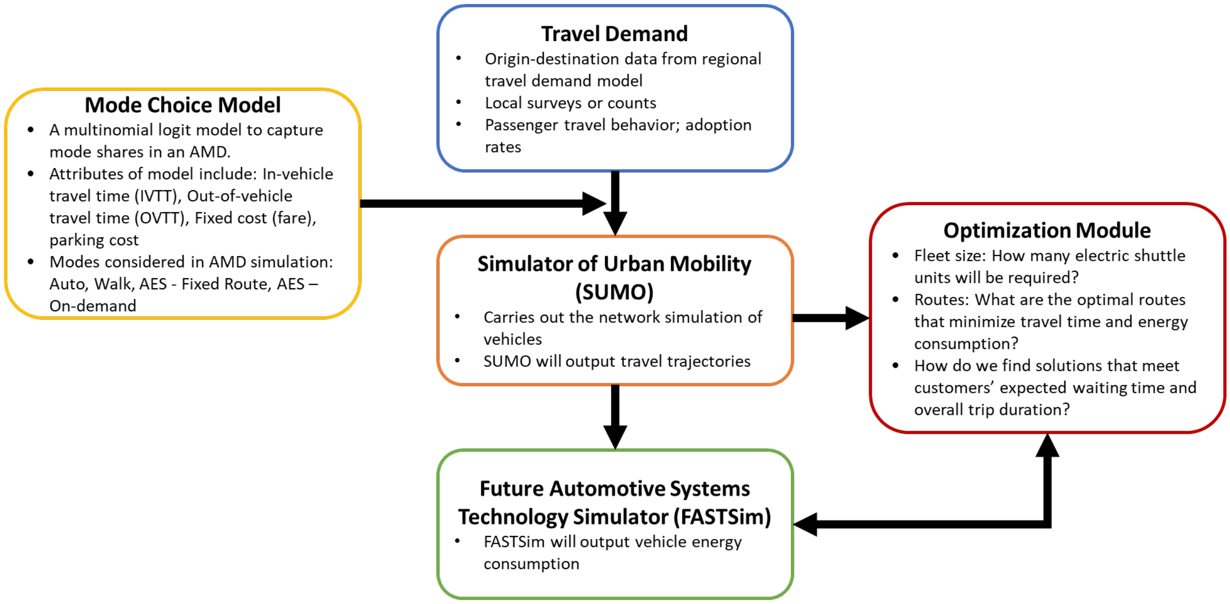


Figure 25. Workflow of the AMD Modeling and Simulation Toolkit

A detailed explanation of the Simulation of Urban MObility (SUMO) and FASTSim models can be found elsewhere.[91,92] The SUMO and FASTSim modules at the base of the AMD toolkit were first exercised on hypothetical networks[93] and previous automated people-mover studies on a university campus,[94] the details of which are available in the reference publications. The foundation for a multipurpose AMD modeling and simulation toolkit provided by SUMO microsimulation and FASTSim energy modeling were then augmented with mode-choice modeling and fleet-optimization modules to provide a full-breadth tool to assist in planning and deployment of AMDs. The following sections present additional detail on the optimization and mode-choice modules developed by the US Pillar.

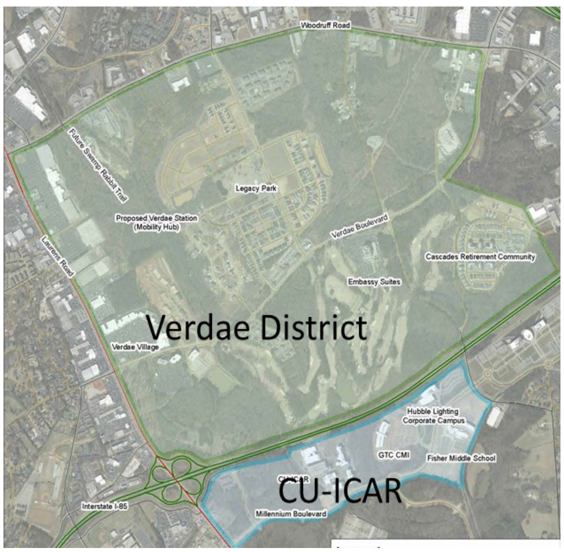
2.3.2.2 Optimization Module

The optimization module within the AMD toolkit aims to assist in decision support related to:

- Routes for a given configuration of the automated shuttle (e.g., passenger capacity, distance range) and demand profile (number of on-demand requests, pick-up and delivery window, and waiting time threshold)
- Sensitivity of optimal fleet size and routes to range constraints for electric shuttles, customer waiting time, and passenger travel demand level
- Feasibility check regarding the fleet size.

The optimization model is first formulated (Step 1) to determine the number of shuttles needed (a fixed-integer approach with respect to optimizations algorithms) to satisfy demand within the constraints provided (vehicle capacity and EV battery size, for example). Using the minimum number of vehicles derived in Step 1, the optimization problem is formulated to identify the routes that these shuttles should take in order to minimize system-wide travel time (which is the generalized "travel cost" in the optimization jargon). Computational resources scale as the size of the problem (the network and the number of on-demand requests) increases. To address the challenge, a Tabu-search is adopted that accounts for the on-demand requests and also provides a reasonably better solution compared with the base case (i.e., no route optimization with minimum fleet size determined in Step 1). The proposed solution method uses a two-phase heuristic where the first phase constructs the initial routes and the second phase refines the initial routes towards acceptable improvement.

To demonstrate the applicability of the optimization model and developed solution technique, AMD deployment scenarios for the Greenville, South Carolina, network were analyzed. The Greenville A-Taxi (or AMD) deployment, as described in the FHWA grant proposal,[95] consists of two phases as depicted in Figure 26. Greenville County provided the detailed road network and traffic-demand data for the region.



(a)

(b)

Figure 26. Taxi Test Field Phase 0 (CU-ICAR) and Phase 1 (Verdae District) at Greenville (a) satellite image, (b) AMD simulation network and fixed-route configuration

The solutions from the Tabu search, explained above, are compared with the solution from a strategy commonly used in practice by the TNCs and a few automated fleet management entities around the world. This strategy, called "real-time solution with rolling horizon" routing, uses limited information about future requests from the customers in solving the optimization problem for minimizing travel cost over the entire network—a method not unlike what a human would do if dispatching vehicles in response to real-time demand, vectoring vehicles to pick up customers based on a request submitted 5, 10 , or 15 minutes in advance. The technique can adopt a flexible rolling horizon depending upon the data availability and prediction model in effect.

Figure 27 shows the system-wide travel cost metrics as obtained from the Tabu-search-based optimization at different demand levels and charging ranges. Travel cost in this context is a cumulative travel time (total system travel time) for all vehicles deployed to serve the travel demand in the AMD. Travel cost for a scenario is calculated by summing up all the link level travel times for all SAVs serving passengers. Additional parameters (such as turn penalties and wait times) can be added to the travel cost function in a straightforward manner. The capacity of the shuttle and maximum passenger wait time are assumed as eight passengers and 120 seconds, respectively.

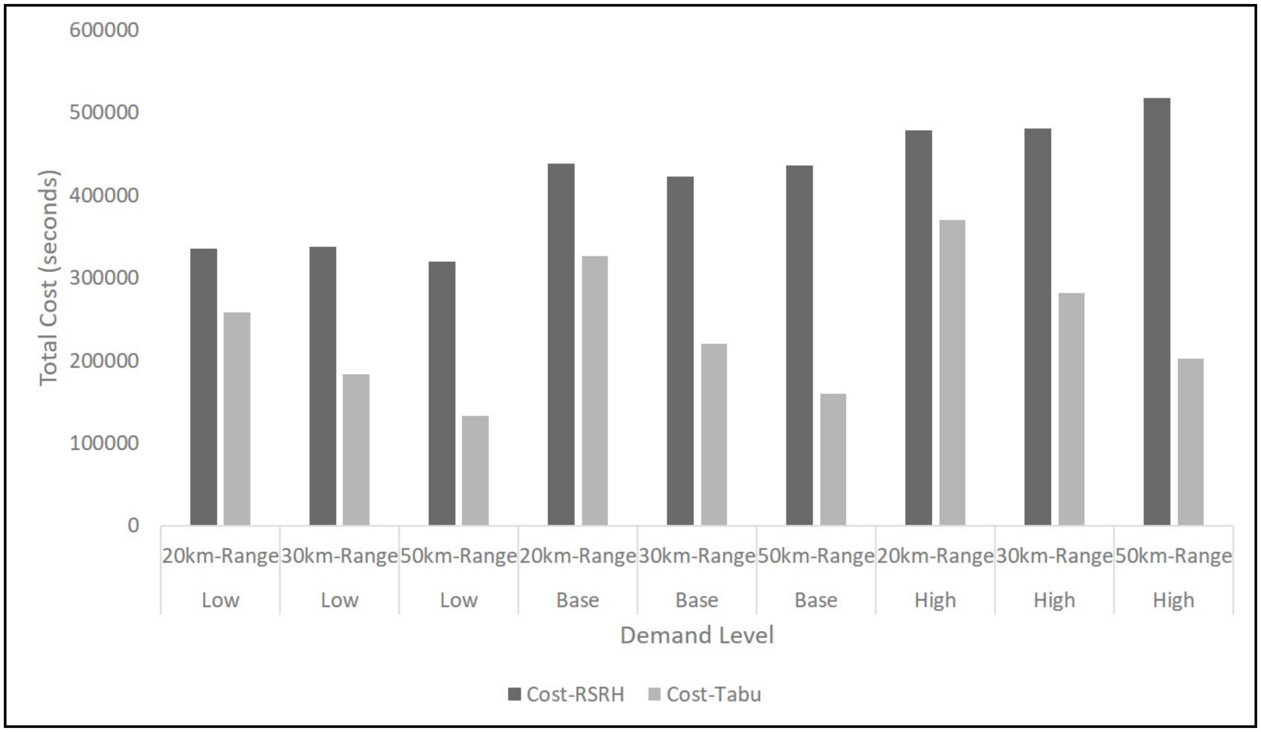


Figure 27. Travel costs with Tabu-search-based optimization and real-time solution with rolling horizon

Two trends are worth noting in Figure 27. First, observing any given range (for example, 20 km) across low, base, and high demand, the system-wide travel cost (total system travel time) increases with increasing demand, which is to be expected. Second, ***for any given demand, the travel cost decreases with increasing battery range for the shuttles***. The optimization within the AMD toolkit estimates how much travel cost (or travel time) savings is possible with increasing shuttle range, informing benefit-to-cost ratio tradeoffs in vehicle purchase decisions. It should be noted here that charging constraints for electric SAVs are not accommodated in the current simulation. Future research efforts will incorporate additional constraints such as en-route vehicle charging and stochastic demand generation.

Figure 28 illustrates the total system energy consumption in kilowatt-hours using EVs with different charging ranges under three demand levels. At an initial glance, this figure might seem counterintuitive as it shows higher energy consumption with increasing battery range. This is because in case of higher battery capacity, the line search algorithm determines that fewer electric SAVs are required to meet the anticipated passenger demand. Further, ***an investigation of the route-level metrics revealed that the total distance traveled in the 50-km range scenario is much higher compared with the other two battery ranges. This could be due to sparsity of the demand observed in the Greenville simulation and a higher number of start/stops of the vehicles with higher battery ranges*** (as they can remain in service longer).

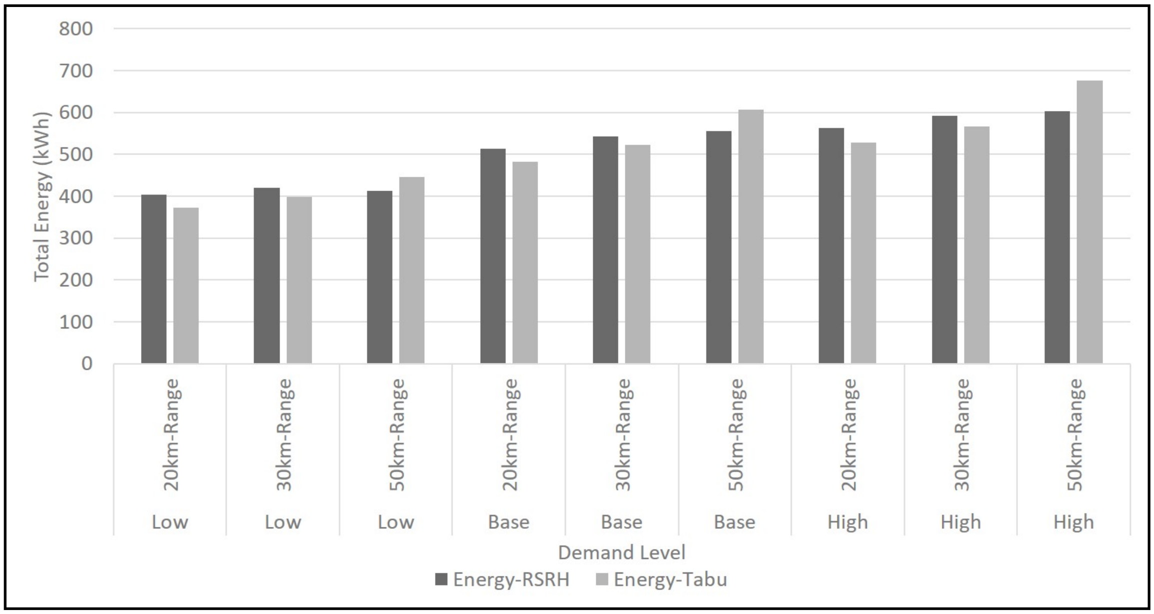


Figure 28. Energy costs with Tabu-search-based optimization and real-time solution with rolling horizon routing

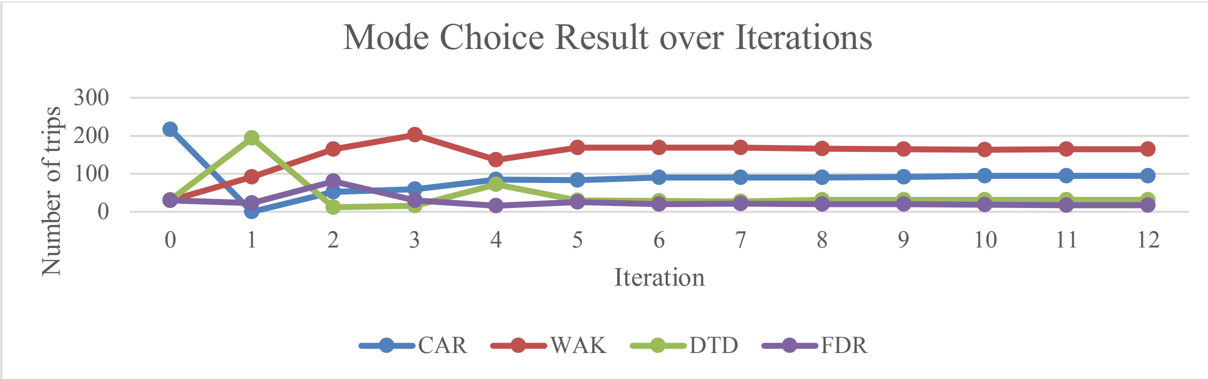
2.1.1.4 *Mode-Choice Model*

It is safe to say that data for modeling individual preferences for SAV modes are practically nonexistent, as the world has yet to experience such modes in reality. Some studies have shed light on the application of the empirical unit cost of travel time and distance information to model preferences for SAV mode. The AMD toolkit adopted a multinomial logit mode-choice model using a mode-choice model considering SAV modes together with car and walk modes.[96]

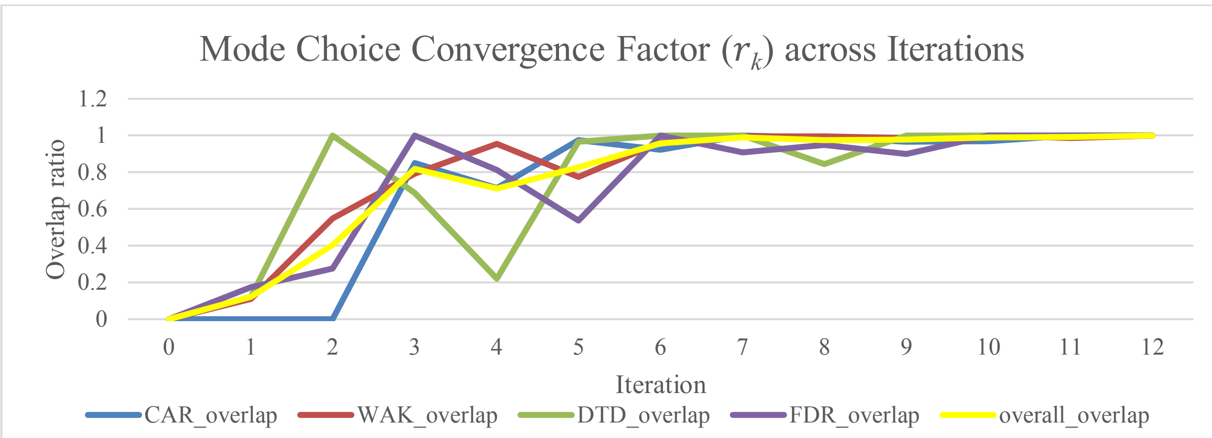
The mode-choice simulation results for the proposed Greenville system for consecutive iterations are presented in Figure 29. The mode-choice simulations considered four modes:

- CAR – Privately owned automobile
- WAK – Walk
- DTD – On-demand door-to-door SAV ridesharing
- FXR – On-demand fixed-route SAV ridesharing.

The DTD and FXR modes are the two shared mobility services, both of which are served by SAVs. DTD mode is able to conduct pick-ups and drop-offs anywhere in the network, while FXR mode SAV runs on designated routes with fixed SAV stops. It can be observed from Figure 29 that mode shares fluctuate drastically in the first few iterations before they start converging around iteration 10, finally resulting in mode shares of 94, 165, 31, and 18 trips for CAR, WAK, DTD, and FXR modes, respectively.



(a)



(b)

Figure 29. Mode choice results over iterations (a) trip numbers, (b) overlapping rates

From Figure 29 it can be observed that the proposed iterative framework was able to provide an equilibrium mode-choice solution within a reasonable number of iterations. The network outputs from the SUMO simulation module include (1) service performance metrics and (2) network traffic condition. The network traffic condition is depicted by link-level statistics consisting of average speed (mph), and travel time (s) in a specific time interval. The service performance metrics are computed based on SUMO simulation results, such as vehicle trajectory, vehicle stop, passenger loading, and service operation plans. The service performance metrics for the two ridesharing modes and car mode consist of:

- Vehicle miles traveled (VMT) in miles for DTD, FXR, and CAR modes
- Vehicle travel time (VTT) in seconds for DTD, FXR, and CAR modes
- Vehicle deadheading distance (VDH) in miles for DTD and FXR modes
- Vehicle loading rate (VLR) for DTD and FXR modes. VLR defines number of passengers onboard weighted by the vehicle distance traveled for all SAVs. VLR is an indicator of a vehicle's efficiency in transporting more people per mile of travel.

- Vehicle detour factor (VDF) for DTD and FXR modes. VDF is calculated as trip distance of ridesharing modes divided by trip distance of regular car mode of time-dependent shortest path. An efficient rideshare mode is expected to have a lower VDF.
- Passenger waiting time (PWT) in seconds for DTD and FXR modes
- Passenger walking time (WKT) in seconds for FXR mode.

Table 2 presents the simulation performance metrics of CAR, DTD, and FXR modes. Walk mode is excluded from this table as it has no direct impact on traffic in the simulation experiment. It should be noted that although FXR mode has a total of six SAVs available, only four SAVs (the ones in Phase 1) were used in the simulation depending on the trip requests because the number of trip requests in Phase 0 was very low.

Table 2. Performance Metrics of Mode Choice Results

Metrics	DTD	FXR	CAR
Overall Mobility Performance			
# of vehicles	4	4	94
Total VMT (mi)	110	87	223
Total VDH (mi)	60	43	-
VDH/ VMT	0.55	0.49	-
Total VTT (s)	20022	15297	30013
Avg. VLR	0.49	0.72	1.00
Trip Average Performance			
# of trips	31	18	94
Avg. VMT (mi)	3.55	4.83	2.37
Avg. VTT (s)	646	850	319
Avg. VDF	1.21	1.55	1.00
Avg. PWT (s)	324	294	0
Avg. WKT (s)	0	990	0

Comparing the SAV modes, DTD has a higher VDH/VMT ratio. This is consistent with expectations, because DTD mode can pick up and drop off passengers anywhere in the network, leading to detours with empty vehicles. In fact, ***this factor comes out to be very close to the studies of VDH/VMT ratio for TNC vehicles such as Uber and Lyft.***[97] FXR mode, on the other hand, travels on a fixed route and is not allowed any detours. The average vehicle passenger loading (avg. VLR) is higher for FXR mode because travelers may need to cluster at SAV stops, which could increase vehicle occupancy.

At the trip level, DTD mode has lower average VMT, VTT, and VDF than the FXR mode, which may be attributed to the routing flexibility of DTD mode. CAR mode beats both shared modes in average VMT, VTT, and VDF, as private cars do not need to detour for sharing. From the results, it can be deduced that some mobility benefits accrue from SAV modes. ***A total of 49 trips are served by eight SAVs, meaning each SAV is displacing travel from six regular cars over the course of the simulation***. This benefit, however, comes with a cost in that passengers have to wait longer (as evidenced by PWT and WKT factors), and vehicles have to travel longer (as evidenced by VDF factor) in the network, meaning a higher amount of energy consumed per vehicle. Note that no time penalties for accessing the vehicle (walking to where vehicle is parked), searching for parking, or walking from the parked location to the final destination are included in this initial mode choice, a critical factor for dense development areas, though not critical for this lower-density area in Greenville.

To understand the sensitivity of mode choice to SAV waiting times, a set of waiting time thresholds (from 1 min. to 30 min.) was tested with all other simulation settings remaining the same. As expected, ***mode shares for DTD and FXR increased gradually with the increase in waiting time thresholds***. An interesting observation here is that mode-share increments in SAV modes come from corresponding decrements in CAR mode, with walk-mode shares remaining almost constant.

2.3.2.3 Fleet Size and Seating Capacity Analysis

The functionality of the overall AMD toolkit, combining its base capabilities with that of the optimization and mode choice modules, was exercised in analyzing the impact of fleet size and capacity in the Greenville scenario. For this exercise, given the low travel demand for FXR mode in Phase 0 of the Greenville AMD, the analysis concentrated on varying size and capacity of DTD SAVs, and analyzing the impact on mode share. In this relatively low-demand scenario, fleet sizes of one, two, three, and four vehicles and vehicle capacities of one, two, three, and four seats were tested with all other configurations remaining the same. ***It was observed that a decrease in fleet size had a sudden and abrupt impact resulting in SAV mode share reduction, as opposed to reduction in seat capacity, which had a more gradual impact on SAV mode share reduction. Tradeoffs between fleet size and seat capacity of SAVs will help rightsize the fleet for a given deployment context***.

2.3.2.4 AMD Toolkit Summary

To conclude, the creation of the AMD modeling and simulation toolkit entailed the following tasks. First, a travel microsimulation module (SUMO) was integrated with an energy estimation module (FASTSim) in order to model the operations and energy consumption of low-speed automated shuttles in geofenced deployments. Using this toolkit, an AMD initiative with a functional operations plan to deploy shuttles can be simulated to quantify the travel, mobility, and energy impacts of SAVs deployed in geofenced regions. Through the process of developing and applying the toolkit and presenting it in various venues, a couple of vital functionalities were recognized and added.

The first of these additions was an SAV optimization module. Building on the AMD toolkit's capability of simulating travel movements and quantifying energy impacts for a given configuration, the optimization module added functionality to optimize for level of service with respect to the size and capacity of the AV fleet, as well as its routing, accounting for distribution of customer demand, and expectations on level of service such as passenger waiting time. The optimization module takes input from a baseline scenario run in the SUMO microsimulation model, and then builds on top of the baseline scenario to optimize for operational planning under various scenarios.

The second addition to the AMD toolkit was that of a mode-choice module to understand and predict the interactions between performance of shared mobility services and user adoption of SAVs in light of competing modes. This module facilitates testing of different fare and wait time threshold structures for deploying SAVs. While the optimization module informs planning and deployment of automated shuttles in an AMD, the mode-choice module predicts utilization and the factors that influence mode choice.

2.3.3 Curbside Topology

Competition for curb space has intensified as a result of TNCs, e-commerce, and micromobility. Curbside area, once nearly wholly reserved for vehicle parking, is being reallocated to allow for safe and efficient pick-up and drop-off (PUDO) of passengers and freight. Micromobility services such as e-scooters and bike shares require storage when not in use. These storages areas, referred to as "corrals," also require space either from the curb or the sidewalk. The Curbside Topology research initiative documented the issues and responses from cities and industry in response to this evolving pressure on curbside use and introduced a curbside value model to appropriately allocate space for various competing purposes. Just as TNC impacts and mode replacement are amplified at airports, so also are these curbside topology impacts most pronounced in areas of high activity demand such as central business districts (as illustrated Figure 30). In such areas, the density of employment, services, and people combined is such that the curbside is a dynamic mobility space for both people and goods.

The US Pillar refers to this competition for space at curbsides near concentrated activity as "topology," defined as exploration of interactions and demands for street, curb, and other public right-of-way space. Vehicles and activities that demand use of these public spaces have expanded beyond traditional on-street car parking, public transit stops, pedestrian and bicycle activities, and traditional freight delivery to include on-demand mobility activities (ride-hailing, car share, bike share, e-scooter, and other dockless micromobility), and increased "microfreight" arising from the rapid expansion of e-commerce (parcel deliveries and food deliveries).

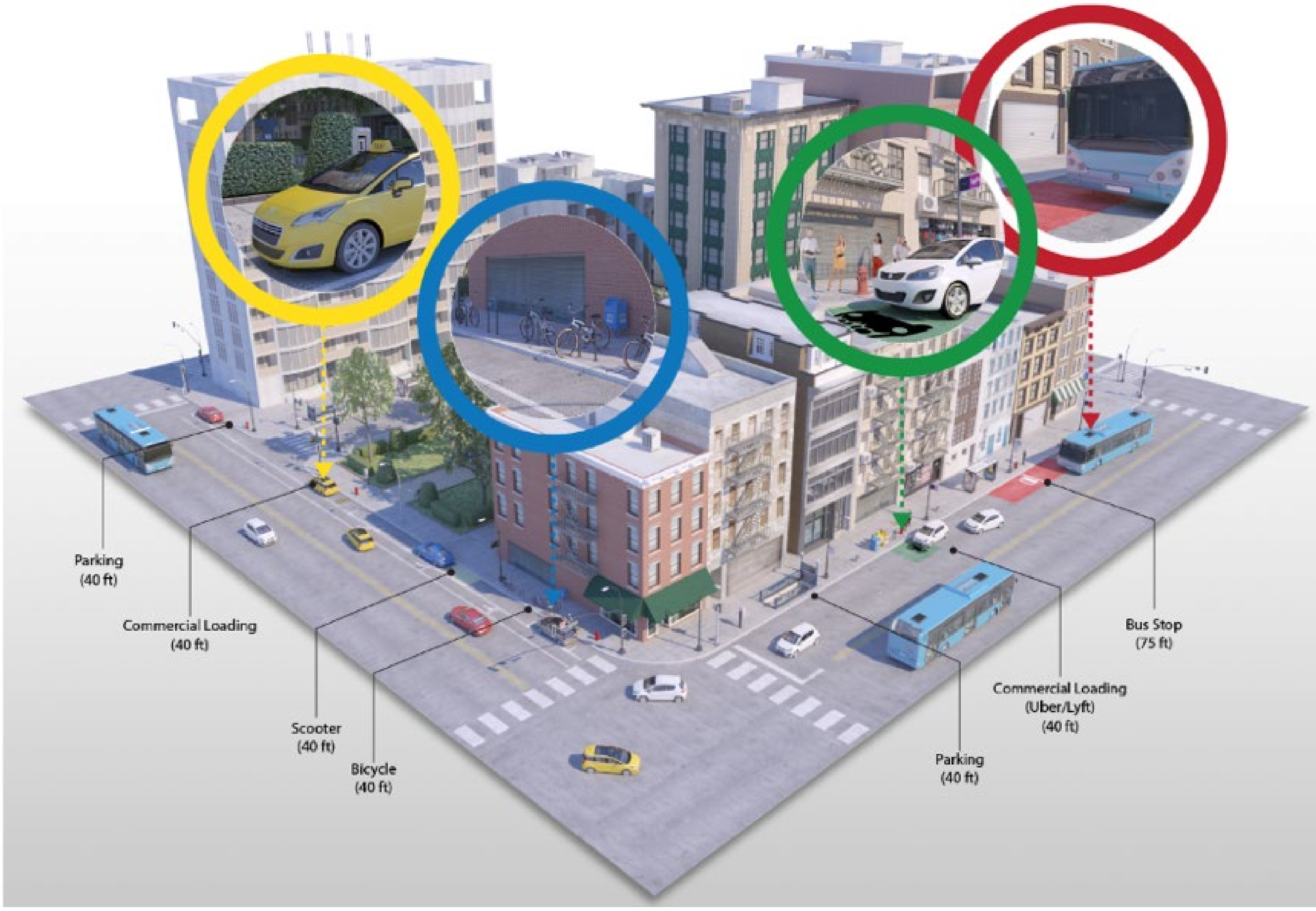


Figure 30. Curbside topology diagram showing competing uses for curb space

The objectives of the Curbside Topology research initiative were as follows:

1. Establish how urban areas are currently handling the changing pressures on their curbside space through direct interviews of cities, MPOs, and airports. This series of interviews revealed how jurisdictions are responding, both organizationally and operationally, and exposed common concerns, gaps, and practices.

2. Develop a rational curbside allocation model. Existing practices that allocate the vast majority of curbside space for car activity (e.g., metered parking, residential permit parking, etc.) in dense urban areas are becoming increasingly unviable; thus, the capability to rationally and optimally make decisions to reallocate curbside is required. The generic methodological approach developed can be employed by transportation network managers to support rational reallocation of curbside space, capable of optimizing

competing outcomes (vehicle throughput, vehicle parking and micromobility corrals, and passenger and goods exchange from transit and TNC activity) in order to maximize the overall productivity of the curb space.

2.3.3.1 Identification of Current Practices and Municipal Needs

The first task of the Curbside Topology research was a semi-structured interview approach to learn how municipalities are adapting to these new pressures on their curbside and to identify the specific research needs as perceived by municipalities. Interviews were conducted with senior staff responsible for the curbside policy of ten large U.S. municipalities with populations ranging from ~250,000 to ~5,000,000, the majority of which are the central city of their respective metropolitan region. Interviews were also conducted with two airport operators and two MPOs.

The interviews identified several new findings about how curbside management is changing, which are summarized in Table 3. Note that the 10 municipalities remain anonymous and are identified as simply A through J. First, an organizational shift has occurred in most (eight of ten) of the municipalities with respect to restructuring and increasing staff to respond to these curbside pressures. Second, flows of data between ride-hailing operators and municipalities were found to be highly diverse, with some cities receiving data on PUDO activity that other cities reported not being provided. Third, cities reported that operational failures at the curbside spill over into travel lanes of their arterial network, with impacts on public safety that are particularly acute in situations such as at closing times of bars in nightlife districts. Allocating curbside space was seen as a complex tradeoff of municipal revenue, serving land uses efficiently, congestion management, and safety of the public. Finally, cities reported seeking more real-time data on curb activity in the future, as well as the ability to manage the curbside dynamically.

Table 3. Summary of selected findings, organized by city ID

	A	B	C	D	E	F	G	H	I	J
Theme #1: Organization Structure										
Increased staffing during past five years	X	X	X	X	X	X	-	X	-	X
Municipality has staff team that regulates TNCs	-	-	X	-	-	O	-	-	-	-
Theme #2: Current Curbside Activity										
Rapid growth in TNC usage	X	X	X	X	X	X	X	X	X	X
TNCs are regulated on the state level (i.e., pre-emption of municipal regulation)	X	X	O	O	-	X	X	X	X	X
Theme #3: Curb Management Pilot Projects										
Curb management pilot project	X	-	X	X	X	X	X	X	X	-
Freight curb management pilot project	-	-	X	X	X	-	-	O	-	-
Micromobility curb management pilot project	X	-	X	O	O	-	-	O	-	O
Monetary charges for using curb space	-	-	-	-	-	-	-	-	-	-
Theme #4: Research Needs and Envisioned Future of the Curb										

	A	B	C	D	E	F	G	H	I	J
Additional curb-related data are sought	X	X	X	X	X	X	X	X	X	X
Additional data aggregation and visualization tools are sought	X	X	-	-	X	-	X	-	-	-
Digital curb inventory is sought	X	-	X	-	X	X	X	X	-	X
Capability to manage the curb dynamically is sought	X	X	X	X	-	X	X	X	-	X
Asset-free curb and flexible payment technology expected in future	-	X	X	-	-	X	-	X	-	X
Autonomous vehicles expected to have future impacts	-	-	-	X	X	X	-	-	X	X

X = Yes; "-" = No; O = Unknown

2.3.3.2 Optimization Framework

The second task of the Topology research was to develop a new framework to support road network operators to make optimal curbside management decisions. This is a novel research question, as transportation modeling has typically focused on road segments and intersections, neglecting curbside activity, and hence providing no decision support to guide policy actions targeted at the curbside.

The optimization framework developed simulates various types of activities competing for curbside space, with each linear portion of curbside space being allocated to the use that is optimal for it. The framework builds on the foundation of the bid-rent theory of urban land use,[98] with extensions to account for the unique curbside context.

Using a small-scale simulation (Figure 31), the proposed framework was implemented to model how a network manager would optimally reallocate curbside space from on-street parking to a ride-hailing PUDO zone. The optimization process is flexible, so it can incorporate outcomes such as economic welfare (as in this example), energy efficiency, or travel time minimization. Within the case study model depicted in Figure 31, central business district zones are lettered (A through D) and outlying zones are numbered (1 through 4). Green arrows conceptually show one set of travel demands between outlying zones and the central business district, and orange arrows show similar demands between two outlying zones that pass through the central business district. In the numerical case study, the decision is how to allocate the curbside discretely into 25-foot parcels for parking and through access, and 50-foot parcels for PUDO zones.

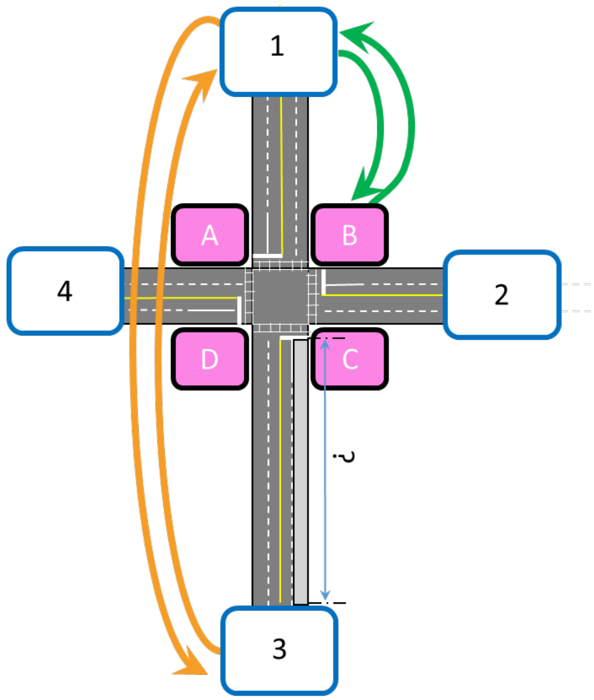


Figure 31. Schematic spatial layout of Curbside Topology reallocation model

In this initial case study, the tradeoffs between on-street parking, PUDO zones, and adjacent roadway throughput were evaluated based on the tenets of bid-rent theory. Note that roadway throughput is affected through reserving curb space near the intersection for either turning movements or additional through lanes. Table 4 shows results from a range of sensitivity analyses using the optimization framework developed, demonstrating intuitive and reasonable sensitivity to a range of stimuli. For instance, decreasing the demand for PUDO activities leads to the optimal solution being to allocate less space to this activity, and more to parking for private automobiles (see Scenario #2).

Table 4. Results from case study sensitivity analyses

Scenario #	Description	Optimal number of 25-foot increments allocated (starting at stopbar) to curbside lane for through travel	Optimal number of 50-foot increments allocated to PUDO zone	Optimal number of 25-foot increments allocated to on-street parking
Baseline	--	6	4	26
2	Decreased PUDO demand	6	3	28
3	Increased PUDO service rate (i.e., decreased the time taken for each PUDO maneuver)	6	3	28
4	Increased value of time (measured in dollars per hour)	6	4	26

Scenario #	Description	Optimal number of 25-foot increments allocated (starting at stopbar) to curbside lane for through travel	Optimal number of 50-foot increments allocated to PUDO zone	Optimal number of 25-foot increments allocated to on-street parking
5	Increased on-street parking demand	5	3	29
6	Decreased through-travel demand	3	4	29
7	Increased on-street parking dwell time (i.e., number of hours each car is parked)	5	3	29

The primary takeaways of the topology work include:

- Municipalities have been making ad hoc rule-of-thumb curb-management decisions for many decades. With the rise of on-demand mobility and e-commerce and new uses of the curb space seeking access to the same physical space that has historically been allocated mainly to parking, ad hoc decision making is becoming untenable.
- Early in the Curbside Topology initiative, outreach to municipalities at the forefront of the rise of on-demand mobility identified a wide variety of current practices, but a similar set of research and data needs.[99]
- Topology proposed a new framework[100] to allow municipalities to optimize curb space allocation decisions, built on longstanding theory of urban real estate markets. The next steps will enrich the framework's applicability to larger-scale real-world sites.

2.4 The Signal Control Network as the Urban Mobility Nerve Center

Whereas metropolitan inter-regional transportation is governed by the quality of freeway traffic flow, the quality of transportation within urban districts is governed by the performance of the signal control algorithms at intersections where traffic lights are employed to safely deconflict traffic movements and promote efficient progression. Signal control originated with pretimed sequences implemented with electromechanical controllers, a few of which are still in operation today. However, most control has been turned over to software within modern signal cabinets, many times operating with simple pretimed sequences (similar to electromechanical controllers) but for particular times of the day and days of the week. A few operate in demand-response mode, altering timing in real-time in response to feedback from infrastructure sensors, primarily inductive loops (and technologies developed to directly replace inductive loops while emulating their signals). Even modern adaptive control systems are fundamentally limited by the information provided to them from inductive loop sensors or one of its many technologies that have been adapted to emulate inductive loop signals such as sonar, radar, video, acoustic, and other technologies. Some corridors use actuated control for side streets, leaving the majority of the green time to the dominant through-street movement. Sometimes sensors are placed on the dominant through-street movement approximately 400 feet in advance of the signal, extending green times when more vehicles are sensed, or shortening green times when sensors detect the queue has been dissipated. In any of these scenarios, the control algorithm is limited by the information that sensors (inductive loops and their equivalent technologies) provide to the controller. Information from sensors placed in the roadway provides, at best, only a partial picture of the traffic state, not comprehensive knowledge of the location and velocity of all vehicles. This is beginning to change with connected and automated vehicles and more sophisticated infrastructure-based sensing which provide the location and speed of all vehicles (and possibly pedestrians, cyclists, and other moving objects) in order to optimally control intersection movement.

Under this research theme, the US Pillar investigated the potential reduction in delay and energy and increase in safety that can result from the heightened observability that is possible with CVs and with enhanced infrastructure sensing. CVs provide a full description of the vehicle and its path along a corridor through a communications link to the signal controller, such as dedicated short-range communication or possibly 5G. The controller can effectively see all CVs as they approach the intersection. If the percentage of vehicles equipped with CV technology is sufficient, the controller can infer detailed traffic characteristics with which to further optimize signal timing. Enhanced infrastructure sensing refers to spatial sensors such as LiDAR, radar, and modern video image processing that provide full trajectory estimates of the vehicles as they approach an intersection. Infrastructure sensing (either LiDAR, radar, or video image processing) differs from traditional intersection sensing in that it provides full trajectory information for each vehicle, and not just an indication of the presence of a vehicle or a queue. The limits of infrastructure spatial sensing (ISS) are primarily its zone or range (that is, how far away from the intersection a vehicle can be detected and tracked) and its reliability of detection.

The research and insights in this section cover five primary research initiatives. In the first area of research, signal optimization routines are developed using modern reinforcement learning (RL) techniques to examine the tradeoff between optimizing signal control to minimize delay versus minimize energy. These results, first tabulated assuming 100% CV penetration, are then explored to understand the relationship with the CV penetration rate and assess the critical penetration threshold needed to begin to gain optimization benefits.

In the second area of research, modern stochastic control theory is applied to a street grid with signal controllers at the grid intersections (as opposed to a signalized corridor) to examine the envelope of benefits of stochastic control under the assumption of full observability, as provided by connected vehicles. The algorithm attempts to balance traffic queues across the grid and thus minimize delay across the network of controllers that determines north–south and east–west flow quality. Lastly, this effort examined robust methods to detect and compensate for CV faults, that is, errors in the data communicated across the CV system.

As AV technology continues to advance, the fundamental sensing technology that detects, classifies, and tracks objects in space (referred to as spatial sensing) also continues to advance rapidly. A handful of companies have begun to apply this sensing technology on the roadside, particularly at intersections, to detect and track all objects in the field of view. These companies are providing either demonstrations or initial commercial systems that detect, identify, and track objects in the field of view based on either LiDAR, radar, or video imaging processing of some sort. The third area of research characterizes the traffic control benefits of spatial sensing that perceives, classifies and tracks object in this manner. The benefits in efficiency (either delay or energy) resulting from applying richer information to the controller are characterized as a function of the sensor range necessary to provide the equivalent benefit of a 100% CV penetration scenario.

The fourth area of research addresses safety implications and its relationship to energy. All intersection control is first and chiefly governed by safety, allowing for safe progression of conflicting traffic movements by sequencing through and servicing all legs of the intersection. Approximately 50% of all crashes occur at intersections. Quality signal timing has been shown not only to decrease delay, but also to increase safety through the reduction of crashes.[101,102,103] Whereas energy benefits resulting from more efficient vehicle flow and avoidance of stops have been demonstrated through improved signal timing (as in the first research initiative), this effort takes a holistic analysis of the energy consequences of improved safety. This includes energy consequences from avoiding fatal, injury, and property-damage-only incidents. Such benefits result not only from avoidance of traffic congestion, but also more prominently from avoidance of loss of human capital and its associated economic productivity from either fatal or debilitating injuries. The results of this research suggest that energy consequences from enhanced signal control may be significantly understated when only energy from enhanced vehicle flow or avoidance of stops is considered.

In the fifth area of research, in support of the Smart Columbus initiative, industry trip trajectory data sets were demonstrated as a scalable method to assess traffic signal performance and identify where pretimed signal control requires maintenance. Industry trip trajectory is becoming increasingly available, providing georeferenced vehicle data in terms of latitude and longitude at varying time intervals from second-by-second data up to one minute or more for a small portion of the traffic stream. This research initiative leveraged this probe vehicle trajectory data to demonstrate scalable signal performance assessment without major investments in sensor and controller upgrades. This is critical as the large majority of signal control throughout the United States remains pretimed with limited or no sensor data. Furthermore, the performance measures derived from this research were analyzed with respect to crash history, revealing the relationship between crash risk (safety) and well-timed signals.

2.4.1 Energy and Delay Minimization with Reinforcement Learning and Connected Vehicles

In the research, reinforcement learning (RL) techniques combined with CV technologies are leveraged to efficiently control the signalized intersection in an urban environment. The CV environment provides traffic-state observability in real time through Basic Safety Messages communicated by vehicles to the traffic controller, allowing for the development of data-driven traffic flow control schemes. A data-rich CV environment with data from Basic Safety Messages combined with signal phase and timing (SPAT) data from the signal controllers provide an avenue for leveraging machine-learning-based traffic control such as RL, which is well suited for dynamic environments like the road traffic network.

In this research, the U.S. DOT-provided real-world NG-SIM data,[104] which contain detailed vehicle trajectory data collected on U.S. Highway 101 and Lankershim Boulevard in Los Angeles, California, were utilized to build and calibrate a signalized arterial model using the Vissim microsimulation tool.[105] The RL algorithm was implemented under the assumption of 100% CV penetration with three different strategies or goals: (1) minimize only delay, (2) minimize only energy/fuel, and (3) minimize energy/fuel simultaneously with a penalty for the number of stops at the signalized intersections.[106] Under Scenario 1, delay could be minimized, reducing queue delay by 16.7%, but at the expense of a 10.5% increase in energy. With Scenario 2, it was possible to reduce energy consumption by 47% compared with the base case, which was the existing signal setting in the Lankershim Blvd. corridor of Los Angeles over which the NG-SIM data set was collected. However, the average travel time increased by 256% when only energy was minimized. To address the tradeoff, Scenario 3 was implemented, which considered energy optimization but also introduced penalty values for stopping vehicles. ***Scenario 3 was iterated over varying penalties for a stopped vehicle; the results show it is possible to have an 8.48% reduction in average travel time and an 8.49% reduction in energy consumption compared with the base case (see the purple rectangle in Figure 32).*** The performance metrics in the table are mean values obtained from a set of experiments with different random initial conditions for each simulation. The improvements are reported at a 95% confidence level.

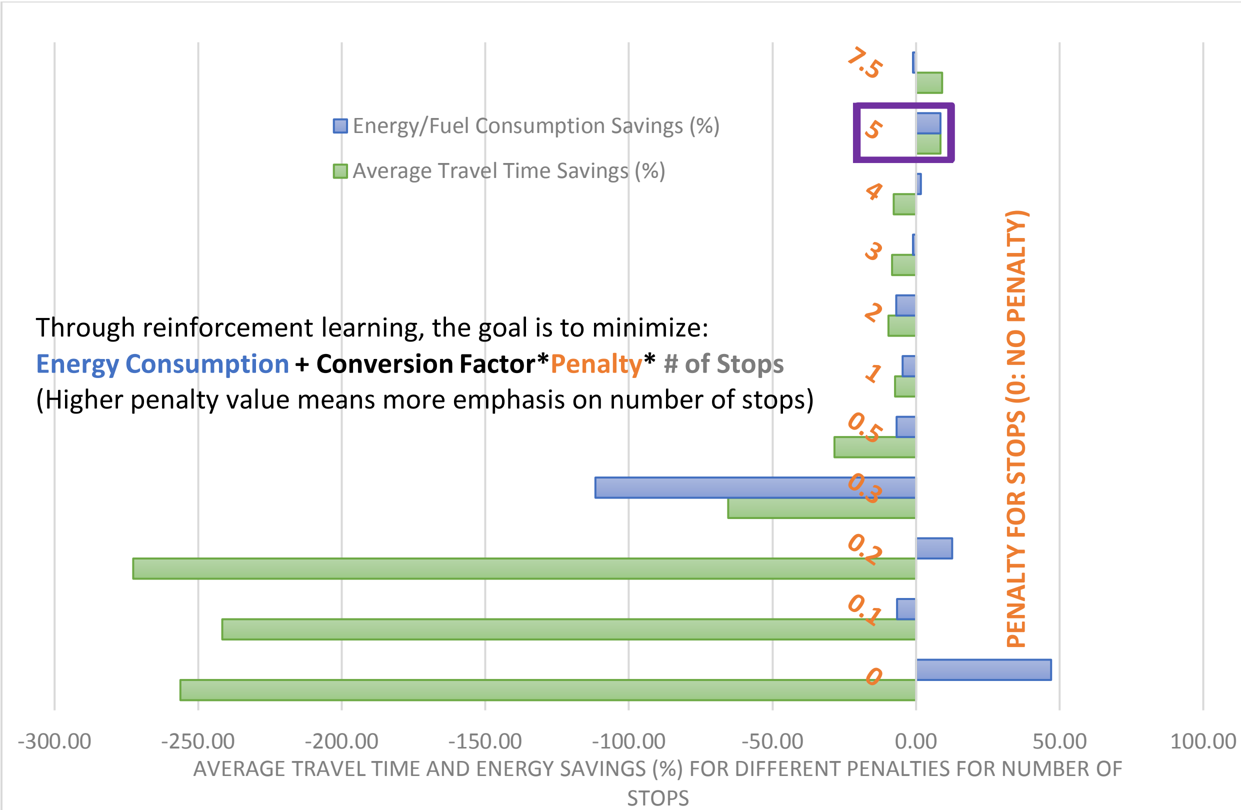


Figure 32. RL-based optimization results minimizing energy with a penalty for stops

Further research explored the performance of RL-based signal control algorithms in a mixed environment with less than 100% market share of CVs keeping the same initial framework, that of optimizing for energy with a penalty for stops.[107] In a simulation environment, the impact of partial connectivity on the performance of the signal control algorithm was explored for two test networks, including a four-intersection arterial in Lankershim Boulevard in Los Angeles (same as above) and a portion of downtown Springfield, Illinois, with 20 intersections, as shown in Figure 33.

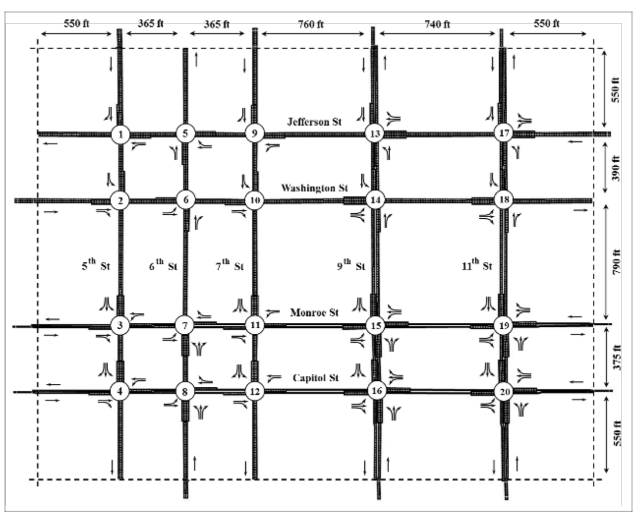


Figure 33. Case study in downtown Springfield, IL

On the four-intersection arterial, the simulation provided insights regarding the impact of CV technologies on the practical implementation of traffic signal control algorithms that leverage the data-sharing capability of a connected environment. Simulation results for scenarios with 40% or more market share of CAVs showed improvement in the performance metrics, which consisted of travel time, queue time, and energy consumption. If the CAV penetration rate fell below 40%, benefits from RL-based optimization were no longer observed.

Figure 34 shows the mobility and energy performances of signal control based on optimizing for energy with penalties for stops for various CV market penetration rates for the 20-intersection network shown in Figure 33. An increasing trend in both mobility and energy performance with increasing CV penetration rates was observed. At 100% CV penetration rate, as the traffic volume increases (from 50% of saturated demand to 100% of saturated demand), the number of completed trips increases. A vehicle completes a trip if it enters and exits the network during the simulation period. A noncompleted trip indicates that the vehicle was in a queue and was unable to complete a full traverse of the network (end-to-end) during the simulation period. Other network performance measures (total travel time, queue time, fuel and energy consumption) also improve with 100% CV penetration. However, these trends are not consistent at CV penetration rates less than 100%. For example, at 90% CV market share, 50% saturated traffic demand completed more trips than conditions with higher traffic demand. This implies that as traffic volume near saturation, even 10% non-CVs lead the system to be unstable to the point of seriously impacting the performance of the signal control. Consistent with expectations, saturated demand reaches a gridlock condition faster than other demand patterns when CV penetration is less than 100%, as indicated by fewer completed trips.

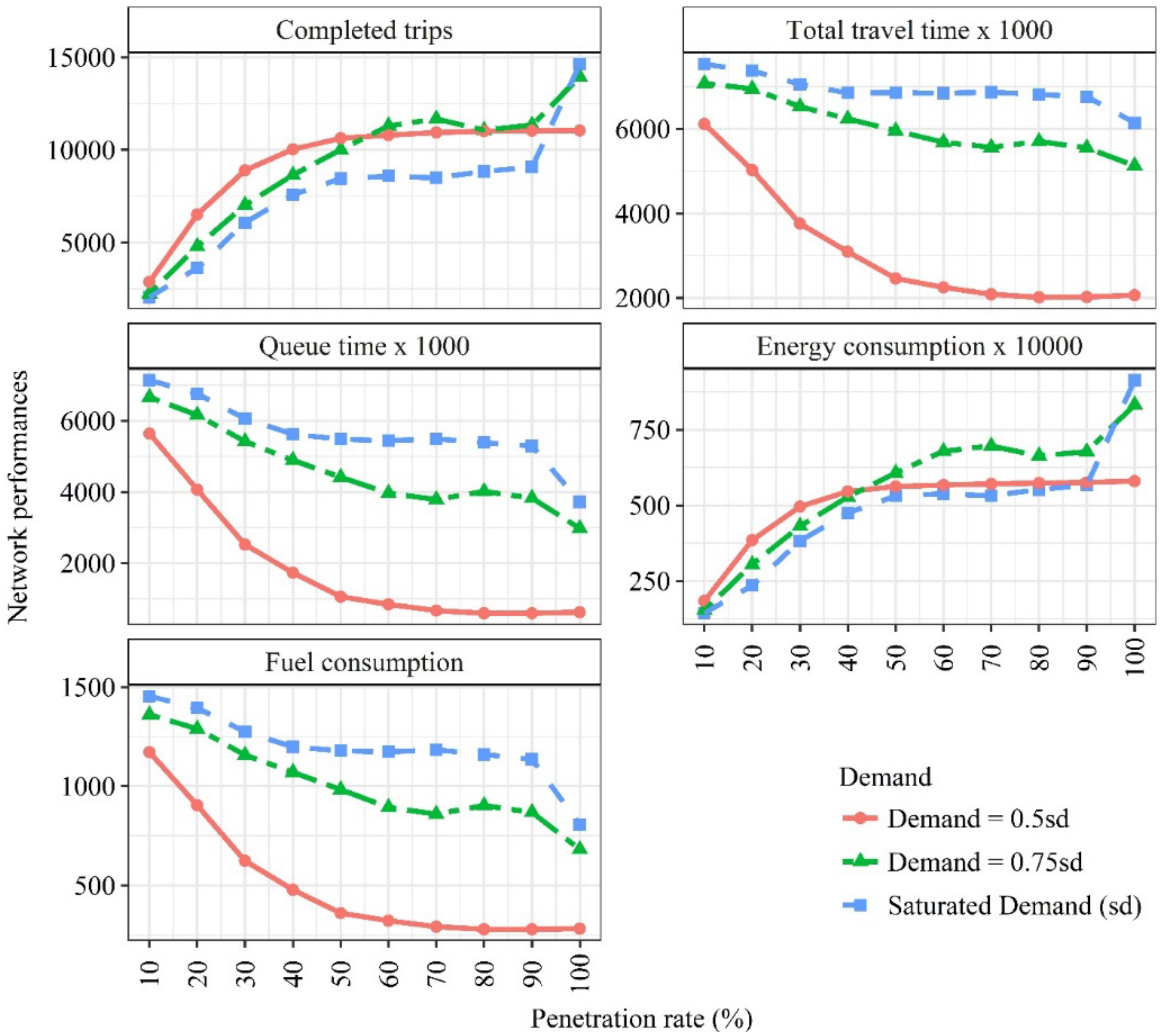


Figure 34. Performance comparison under various CAV penetration rates and demand levels (20 intersections)

These two investigations into CV penetration rates suggest that the minimum CV penetration rate required for signal control benefit is not constant but varies based on demand and context (corridor versus grid.)

2.4.2 Stochastic and Distributed Signal Control with Connected and Automated Vehicles

This research initiative applied stochastic control principles to a signal-controlled grid network with 100% CAV penetration. Assuming a randomized arrival pattern of vehicles approaching an intersection, the vehicle queue length—which determines delay—at intersections is also a random variable. In an optimized approach to signal timing, the vehicle queue length (and thus associated travel delays) is minimized, leading to smooth traffic flow (with implied minimized energy consumption.) Such an approach belongs to stochastic control theory where the objective for real-time, closed-loop control is to shape the queue length at each approach (and thus travel delays) in terms of their mean and variance, ultimately controlling the shape of the associated probability density functions that fully determine the queue. In this research, stochastic distribution control theory[108] was applied to a network of traffic signals to minimize traffic delays under the assumption of full observability, as would be provided by 100% CAV penetration. CAVs increase the observability of the traffic flow conditions, yet they do not change the random nature of traffic flow dynamics (i.e., the number and pattern of vehicles approaching an intersection during any time interval remain random.)

The fundamental objective was to use stochastic distribution control theory[109] to develop signal timing control so that the queue length distribution over the grid network was as uniform as possible, smoothing traffic flow over the area, which in turn minimizes energy consumption.[110] For each intersection, the input is the signal timing settings (percent green time given to each approach and movement) and the state of the vehicles (position and speed), and the output is measurable traffic flow state reflecting travel delays and the probability density function of the approaching vehicle queue length. The optimized control algorithm uses the travel flow states, such as the output queue length probability density function, as a feedback signal and compares it with the desired probability density function (a narrowly distributed Gaussian with minimum mean value) so as to generate signal timing for the intersection. This analysis considered 100% CAV penetration in the initial work, and assumed that its data, or information, is 100% correct without faults in the initial analysis. In further research this assumption was relaxed, and fault diagnosis and fault-tolerant controls were developed.[111,112] Combined with 100% CAV penetration, fault-tolerant control allows for the equivalent of signal controls at non-signalized intersections.

This research consisted of the following three aspects:

- Modeling for networked intersections in terms of signal timing and traffic state (such as the queue length of approaching vehicles and travel delays, etc.)
- Development of implementable real-time feedback signal control strategies to achieve smooth traffic flow at intersections
- Fault-tolerant intersectional control for 100% CAV penetration.

A first-order dynamic model was built for a typical single intersection, which shows the basic relationship between traffic state (travel delays or approaching queue length) and signal timing. This model provided stochastic distribution control for the concerned networked intersections. Using these novel modeling tools together with step response testing, a multi-input and multi-output (MIMO) model was established that reflects the dynamics of networked intersections for the city of Bellevue, Washington, as shown in Figure 35. This model was also subjected to random vehicle demand, i.e., the number of vehicles approaching the area.

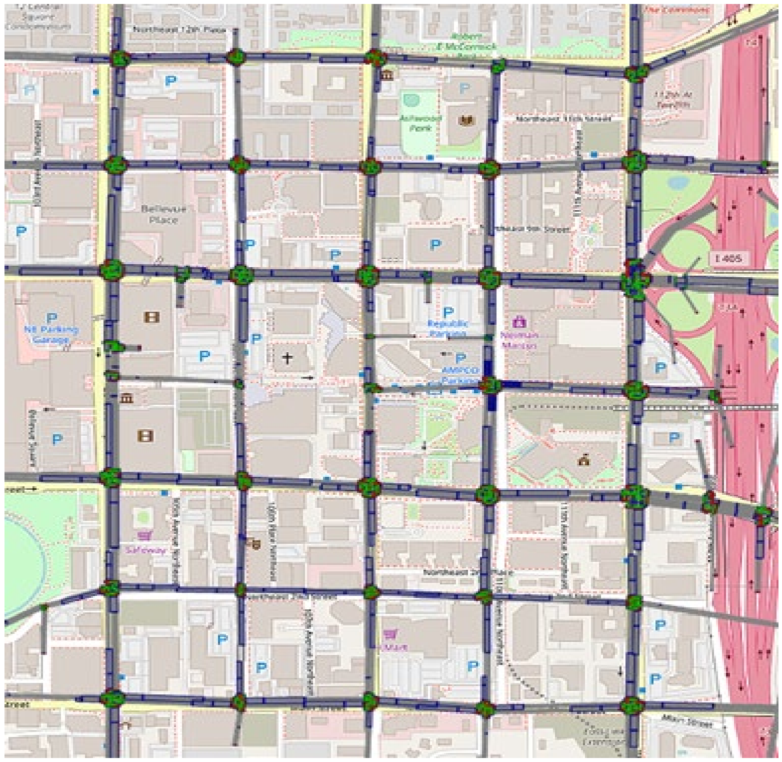


Figure 35. Vissim simulation model for the studied comparisons traffic network

Using a multi-input and multi-output model, a simple feedback H-matrix control and stochastic linear optimal control strategy[113] was designed capable of achieving global control over the roadway grid network shown in Figure 35, with individual signal control at each intersection. The purpose is to control the signal timing of these 35 intersections so that the travel delays at each intersection are minimized. The simulation results using Vissim are shown in Figure 36 and Figure 37. Figure 36 plots average vehicle delay through the simulation. The linear optimal control method (solid line) had better performance than that of the pretimed and simple linear controls. Figure 37 presents the distribution of approach delays over the simulation period using a normalized histogram. The linear optimal control had fewer large delays than pretimed and linear control. The obtained collaborative real-time feedback controls for signal timing of networked intersections in this example were shown to reduce the average travel delays by up to 40% compared to the existing pretimed controls.

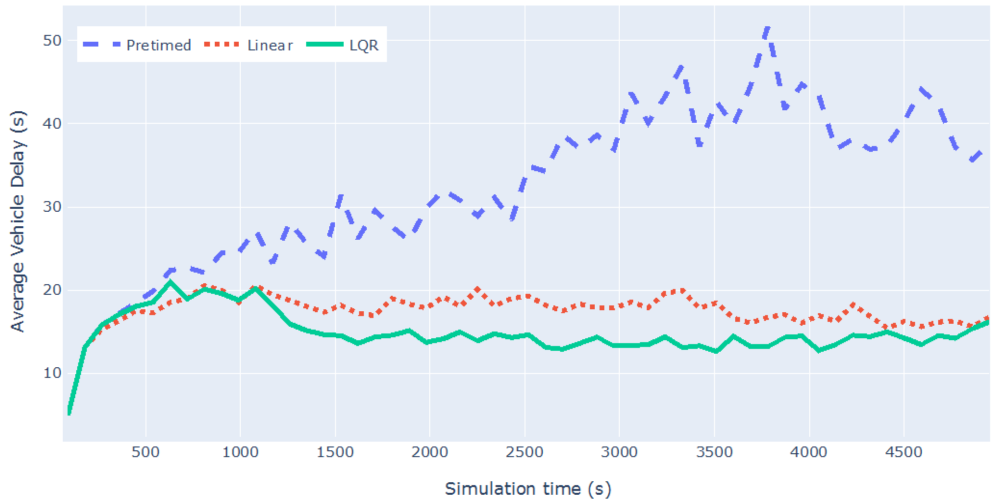


Figure 36. Average vehicle delay during the simulation test period for three types of control: pretimed, linear control, and linear optimal control (LQR)

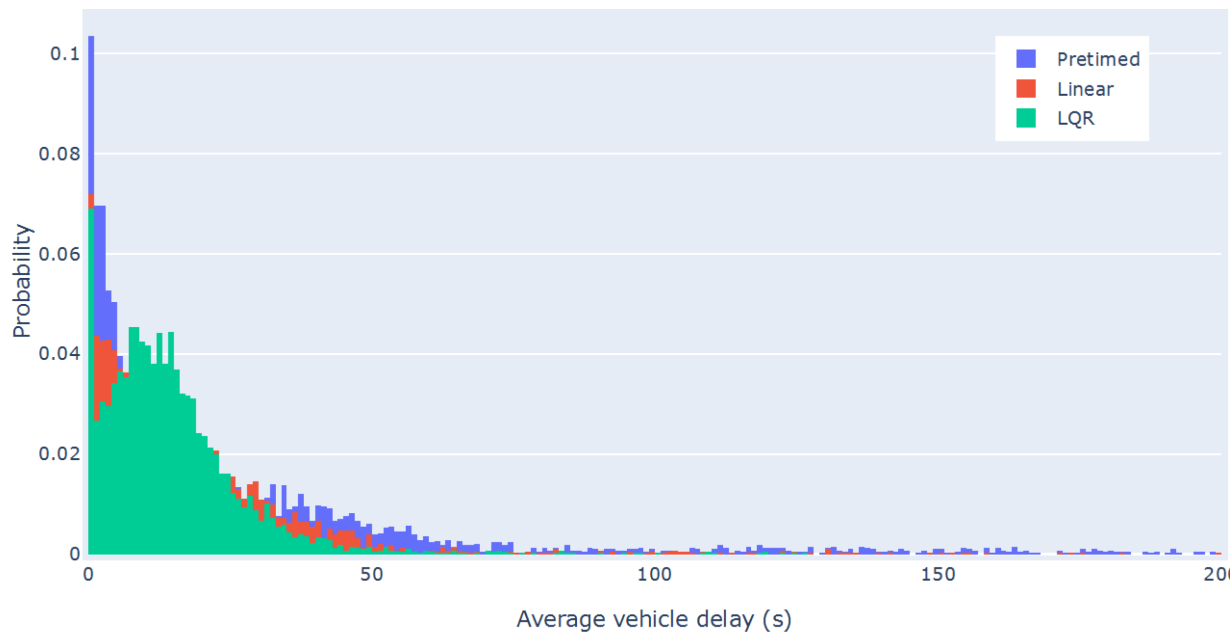


Figure 37. Distribution of the delays over the simulation test period for pretimed (base case), linear control, and linear optimal control (LQR)

In a 100% CAV penetration scenario, intersection controls can, in theory, be realized by CAVs through vehicle-to-vehicle communications, allowing fully autonomous control of the vehicle's movement at an intersection without the need for physical signals (red, yellow, and green lights). This leads to consideration of operation at non-signalized intersections where the vehicle passing safely and smoothly through the intersection can be directly achieved using coordinated multivariable controls among all the vehicles at the intersection. The research challenge is how these CAVs can pass through the intersections safely and smoothly even if a CAV network has developed a fault, that is, if one of the CAVs vehicles erroneously reports its position or speed, or both.

To address this situation, a multiagent CAV movement model that reflects the interactions among CAVs was developed that reflects the coupling effects between CAVs via their vehicle-to-vehicle communications capability. The state-space model form incorporates an additive fault vector to represent such inaccuracies. If there is no fault within the systems of CAVs, then this fault vector is zero. The additive fault vector can generally represent any vehicle fault, such as missing basic safety messages, sensor faults, powertrain faults, etc. This novel model has led to a novel fast fault-diagnosis algorithm for CAV interaction and control. Using the fault diagnosis results, a collaborative fault-tolerant control algorithm was developed for 100% CAV intersection control.[114,115] Preliminary simulation results using this result reflect how CAVs can pass through a network of intersections safely and smoothly, even if there is a fault occurring in one of the vehicles.[116]

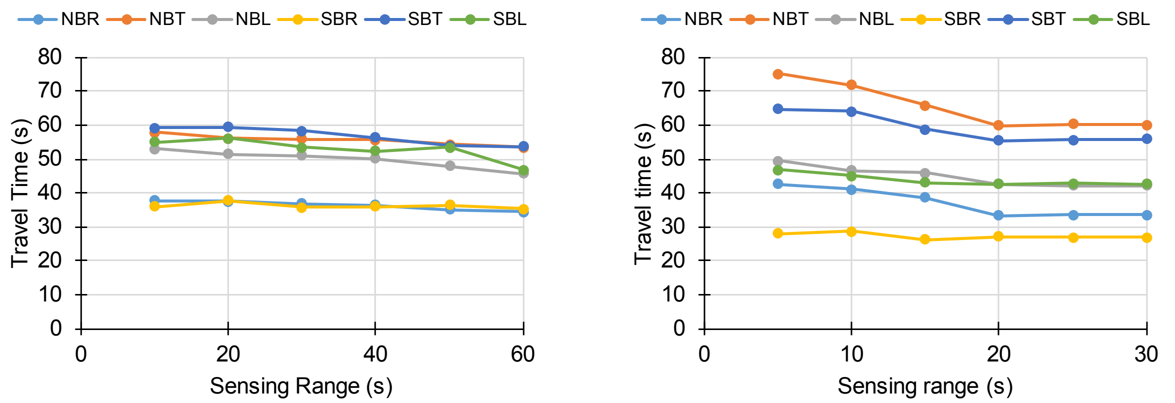
2.4.3 Infrastructure Spatial Sensing at Intersections

This research characterized the benefits of infrastructure spatial sensing in comparison to CV-based signal control. Technologies such as LiDAR, radar, and artificial-intelligence-enhanced video analysis are starting to make it practically feasible to obtain positions and speeds of all roadway users, including vehicles, cyclists, and pedestrians, within the range of view of the sensor. This should theoretically make it possible to achieve the benefits anticipated by CV-based traffic signal control, but by using a sensor-based approach. Whereas the optimization benefits of CVs require a large portion of CV penetration—perhaps 40% or more as assessed in the RL-based study, and which might not include cyclists and pedestrians—using an ISS approach could theoretically capture 100% of the roadway users (including vehicles, pedestrian, and any other micromobility modes), but only in the vicinity of the intersection. The geographic sensing area obtained is limited by the range and capability of the sensors.

The US Pillar identified the potential performance benefit of signal control enhanced with infrastructure-based sensing through simulation and analysis. Algorithms for advanced signal control based on CV data were selected as the basis for research implementation. The assumption is made that 100% of traffic can be detected by the sensor, but only within a defined sensing range. Once within this range, the position and speed of any vehicle, pedestrian, or other moving object are available for signal optimization. The goal of the research is to identify the impact of this sensing range on the control performance.

Work began with a literature review to identify potential algorithms for testing, revealing that numerous algorithms to optimize signals based on CV data have been published. Two of these algorithms were selected for implementation in a simulation environment with ISS, representing two different approaches to signal control. The first of these is a method proposed by a research team at the University of Arizona[117] based on the Real-Time Hierarchical Optimized Distributed Effective System (RHODES) adaptive control system but augmented for CV data. Similar to many adaptive signal control methods, this algorithm identifies a schedule for green times to be provided within a rolling horizon, using an objective of minimizing delay. The second algorithm[118] takes a fundamentally different approach that incorporates vehicle position data into a secondary, or virtual, sensor actuation decision scheme in a more traditional corridor progression signal timing framework. In this scheme, data from vehicles are incorporated into a continuous decision of whether or not to extend the major street green time. For both algorithms, the table of predicted arrivals (based on virtual detection derived from CV data) was replaced with real-time arrivals from infrastructure spatial sensing.

In both approaches, the sensing range from which the traffic information is made available in the algorithms was varied to determine the impact on the performance. Results obtained from a single-intersection test network are presented in Figure 38. Figure 38 (a) shows results for Algorithm 1 (rolling horizon) and Figure 38 (b) shows results for Algorithm 2 (continuous decision). Each chart shows a series of travel times for movements along the major through corridor (not from side streets) for different simulation runs where the sensing range was adjusted. These preliminary charts show a decrease in travel time as the sensing range increased, as anticipated. The impact of sensor range is more pronounced in the case of Algorithm 2. The results from both algorithms converge beyond a sensing range of 20 seconds from the intersection. Algorithm 1 exhibits only a slight difference in performance across the range of values considered. Note that in these initial studies, sensing range was depicted as a time horizon from arrival at the intersection due to expediency of constructing the simulation with time-based data. A corollary of these results is that CV performance can be achieved with infrastructure-based sensing if the sensors can detect vehicles 20 seconds or greater prior to the arrival at the signal (in this case, 20 seconds corresponds to a distance of approximately 250 m).



(a) Algorithm 1 performance (periodic decision based on rolling horizon)

(b) Algorithm 2 performance (continuous decision)

Figure 38. Infrastructure spatial sensing algorithm performance as a function of sensing range (NB = northbound; SB = southbound; T = though; R = right; L = left)

2.4.4 Energy Equivalence of Safety at Intersections

Safety is critical and a prerequisite for adoption of any viable mobility technology. The importance of considering safety is underscored at intersections, where roughly 50% of all crashes occur.[119,120] However, in transportation modeling and analysis with respect to mobility or energy, safety is often taken for granted rather than treated as an independent variable that can influence the performance or sustainability of a system.

The US Pillar extended the concept of exploring the potential mobility and energy benefits of infrastructure spatial sensing at intersections to improve traffic flow to also consider the mobility and energy benefits of reduced crashes. The safety criticality of intersections to deconflict turning movements, safely allowing for vehicles (and pedestrians, bicycles, and scooters) to traverse the intersection, is paramount. The energy equivalence of safety suggests, and underscores, that avoidance of crashes is vital in intersection control. This research showed that increasing safety on roadways can fundamentally conserve energy consumption equivalent to 5.6% of the total U.S. energy consumption, and systems that could reduce the crash frequency could have an order of magnitude (or more) of impact on energy productivity than energy efficiency related to reduced stops or smoother traffic flow.

An initial step in establishing a quantifiable linkage between sustainable mobility, specifically energy efficiency, and safety was to create a first-order approximation of an energy equivalence for each fatal, injury, and property-damage-only (PDO) crash.[121] For each type of crash, the direct and indirect energy impacts were estimated. Direct costs refer to tangible and internal costs directly attributable to crashes, including costs related to property damage, medical rehabilitation, and induced congestion. These costs are relatively straightforward to estimate. Indirect impacts include both human capital costs and what is known as "willingness to pay" in economic terms. Human capital cost is the person-correlated cost associated with loss of long-term future net production (i.e., the difference between future production and future consumption)[122] due to the loss of work capability because of an injury or fatality. Human capital cost measures the value of a person's contribution to society through labor. The loss of human capital includes discounted future earnings and an estimate of the cost related to human suffering. Willingness-to-pay cost is the price that a society (or a person) is willing to pay to avoid the risk and occurrence of fatal and injury crashes. Its value depends on what kind of preventive measures will be applied to the transportation system and the cost of adoption for road users. The intangible willingness-to-pay costs are estimated according to the value of a statistical life[123].

The energy equivalence of various crash types and impacts was structured based on parallel economic impact studies, the most dominant of which was based on 2010 data[124]. The first-order approximation was established with the ratio between gross domestic product (GDP) and total national energy consumption. These first-order approximations of energy equivalence are shown in Table 5. For example, a single fatal accident had a GDP-weighted gasoline gallon equivalent (GGE) of over half a million gallons of gasoline, including direct and, more importantly, indirect impacts. Although just an introductory approach, this research points to the need to consider holistic (human capital, productivity, and willingness to pay) energy aspects related to safety, and not just congestion impacts of crashes. Even if only direct impacts are included, consider that the GDP-weighted energy impact resulting from induced congestion alone for a fatal, injury, and PDO crash (only one aspect of the direct energy impacts) are 358, 153, and 108 GGE, respectively, whereas total direct energy impacts are 10,987, 1,710, and 382, respectively. ***Total GDP-weighted direct energy impacts for PDO crashes (which do not include indirect impacts with respect to lost human productivity or willingness to pay) are over three times larger than the energy impact from induced congestion alone, further underscoring the need for a more holistic approach with respect to energy and safety.***

Table 5. GDP-weighted energy equivalence of fatal, injury, and property-damage-only crashes

All Roads (year 2010)

	Fatal	Injury	Property Damage Only
*Number of crashes on all roads**	30,296	2,969,963	10,565,514
Direct energy cost per crash (GGE)	10,987	1,710	382
Human capital energy cost per crash (GGE)	76,475	694	6
Willingness-to-pay energy cost per crash (GGE)	484,357	6,536	N/A
Total GDP-weighted energy cost/crash (GGE)	**571,819**	**8,939**	**388**
Intersections (year 2010)			
*Number of person–vehicle crashes**	8,682	4,829,008	10,127,014
Number of crash equivalents	7,971	1,686,345	5,780,930
% of crashes at intersections*	**26%**	**57%**	**55%**

**Source: Blincoe, Miller, Zaloshnja, and Lawrence, 2010*

This research effort proposed a framework for estimating the GDP-weighted energy equivalence of safety at intersections based on previous extensive studies of the economic value of crash impacts. Although a first-order estimate, this research suggests that the GDP-weighted energy savings from improved safety in terms of direct impacts as well as human productivity and human capital at a minimum rival those obtained from improved traffic flow and may be an order of magnitude greater.

2.4.5 Harnessing Vehicle Trajectory Data for Performance of Pretimed Signal Optimization

In this research initiative, industry-provided vehicle trip trajectories were demonstrated as a viable data source to assess automated traffic signal performance measures that can be scaled nationally, and thus optimize both delay and enhance safety for any pretimed signal control. Industry-provided vehicle trajectory data are becoming increasingly available, providing a sample of georeferenced vehicle trip data, that is, latitude and longitude coordinates reflecting vehicle position, reported at varying time intervals from second-by-second data up to one minute or more. Such data are typically available in archived data sets, with the first and last few minutes of each trip obfuscated to protect privacy information of the vehicle owner/driver.

This research leveraged a probe vehicle trajectory data set for the state of Ohio to demonstrate pretimed signal performance assessment at a scale that is not available without major investments in traditional roadway sensors and controller upgrades. The dominant majority of signal control throughout the United States remains pretimed. Even most actuated control is contingent on a high-quality fixed timing plan that is adjusted to account for perturbances in expected traffic flow. ***This research demonstrated the use of big data, in the form of trajectory data sets (measured in the hundreds of gigabytes to terabyte scale), combined with machine learning to assess the quality of existing signal control on ten major corridors in Columbus, Ohio, using a method that can scale to a state or even nationally.***

In 2017 the Ohio DOT completed the procurement of cutting-edge transportation planning and analysis data sets from industry sources as part of its support for the Smart Columbus initiative. In terms of size and scope, each year of data approached one terabyte in size and contains data reflecting approximately 2% of all trips made in Ohio. A visualization of one year of such data is shown below to demonstrate its size and extent.

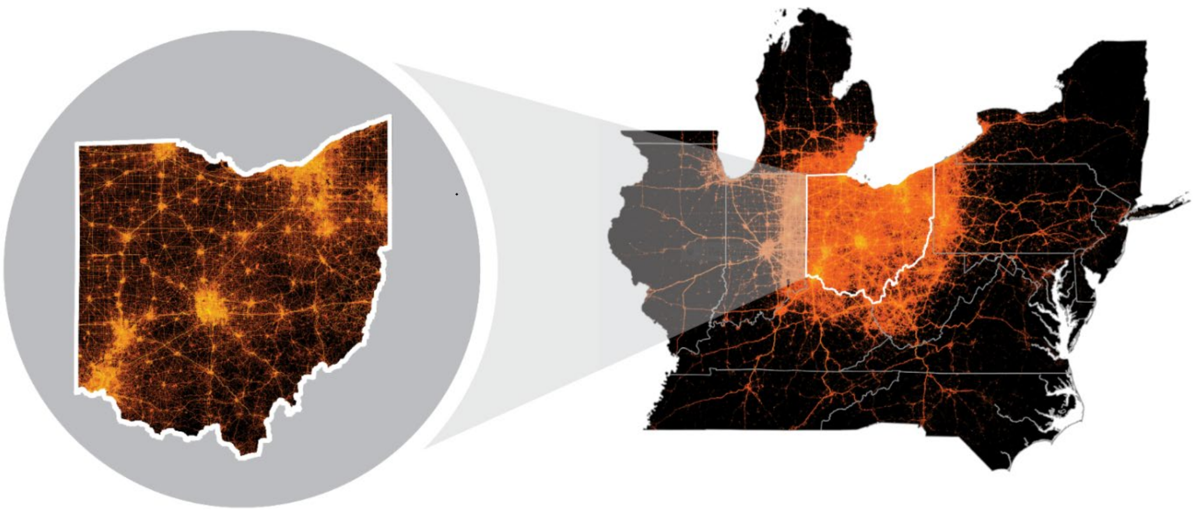


Figure 39. Heat map of trip origins and destinations from Ohio DOT-procured industry trajectory data

Probe vehicle trajectory data from 2018 were used to assess performance and identify opportunities to improve traffic signal timing along ten critical corridors in Columbus, as shown in Figure 40. Building on previous research demonstrated on select intersections in Michigan,[125] this method of utilizing big data sets of sampled vehicle trajectories provides a level of signal performance assessment detail not available otherwise without high-resolution controller data. High-resolution controller data are data reported at one-tenth of a second, reflecting all signal phase and timing as well as all sensor actuations. New performance methods enabled by high-resolution controller data, referred to as automated traffic signal performance measures, provide an in-depth analysis of the traffic signal operations including progression, delay, and queue backup.[126]

Traditional traffic signal assessment (without the use of automated traffic signal performance measures) and retiming are typically performed on three- to five-year timing cycles, and sometimes much longer, prompted only by citizen complaints. The methods used in the research apply industry-leading automated traffic signal performance measures but are applied to scalable data available from industry (not from sensors or controllers), available for any roadway or traffic intersection in the country. A full performance assessment of each of the ten corridors was accomplished in 2019, with sample results of common measures shown in Figure 41. The process was even able to isolate and diagnose abnormal intersection phenomenon, as shown in Figure 42, in which a malfunctioning pedestrian call button was obstructing traffic progression at one specific intersection (and was doing so for the entire year).

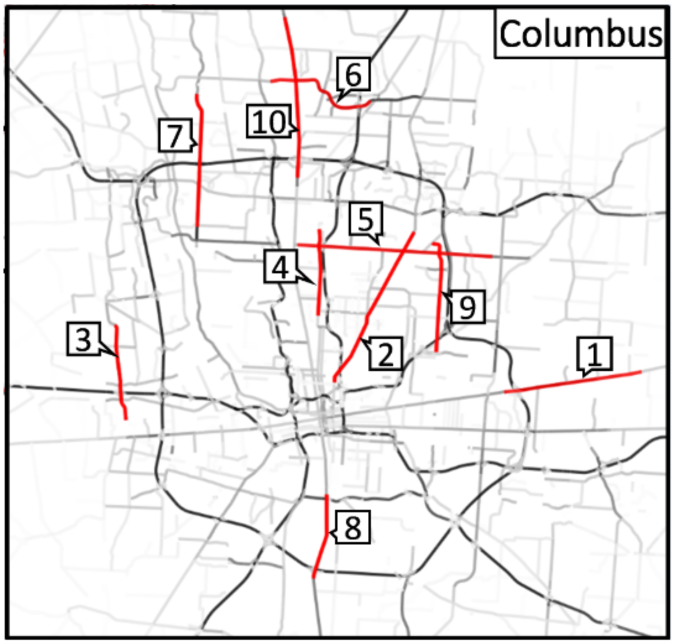


Figure 40. Locations of the 10 critical corridors in Columbus, Ohio

	Delay	Stop	AOG	TTAvg	TT50	TT85	LOTTR	n-value
('SB', 'Morse', 12, 'LOS E')	55.4	0.81	0.19	69.2	65.0	112.0	1.72	307
('SB', 'Innis', 12, 'LOS D')	49.9	0.83	0.17	63.6	62.0	94.9	1.53	338
('SB', 'Morse', 10, 'LOS D')	49.0	0.75	0.25	62.8	57.5	108.0	1.88	224
('SB', 'Innis', 10, 'LOS D')	47.6	0.77	0.23	61.7	61.0	95.0	1.56	349
('SB', 'Morse', 8, 'LOS D')	44.6	0.70	0.30	58.5	56.5	99.0	1.75	348
('SB', 'Cleveland', 8, 'LOS D')	44.5	0.93	0.07	58.2	55.0	79.0	1.44	414
('SB', 'Cleveland', 12, 'LOS D')	43.6	0.97	0.03	58.8	56.0	71.0	1.27	216
('SB', 'Morse', 6, 'LOS D')	42.9	0.77	0.23	56.5	50.0	94.0	1.88	287
('SB', 'Cleveland', 10, 'LOS D')	42.7	0.96	0.04	56.5	56.0	69.0	1.23	228
('SB', 'Innis', 8, 'LOS D')	41.2	0.73	0.27	55.2	53.0	88.0	1.66	589
('SB', 'Innis', 6, 'LOS D')	39.5	0.75	0.25	53.5	52.0	85.0	1.63	534
('SB', 'Cleveland', 6, 'LOS D')	39.2	0.86	0.14	52.9	51.0	74.0	1.45	296
('SB', 'Hudson', 8, 'LOS C')	27.6	0.58	0.42	41.3	35.0	70.0	2.00	1141
('SB', 'Hudson', 12, 'LOS C')	27.1	0.57	0.43	40.9	34.0	70.0	2.06	553
('SB', 'Hudson', 6, 'LOS C')	25.7	0.56	0.44	39.3	32.0	67.0	2.09	651
('SB', 'Ferris', 12, 'LOS C')	23.7	0.59	0.41	38.0	36.0	62.0	1.72	498
('SB', 'Hudson', 10, 'LOS C')	22.1	0.48	0.52	35.7	27.0	62.0	2.30	540
('SB', 'Ferris', 6, 'LOS C')	21.9	0.53	0.47	35.8	31.0	58.5	1.89	351

Figure 41. Sample of corridor signal assessment metrics

AOG = arrival on green; TTAvg = travel time average; TT50 = travel time 50th percentile;
TT85 = travel time 85th percentile; n-value = number of sample vehicle traces

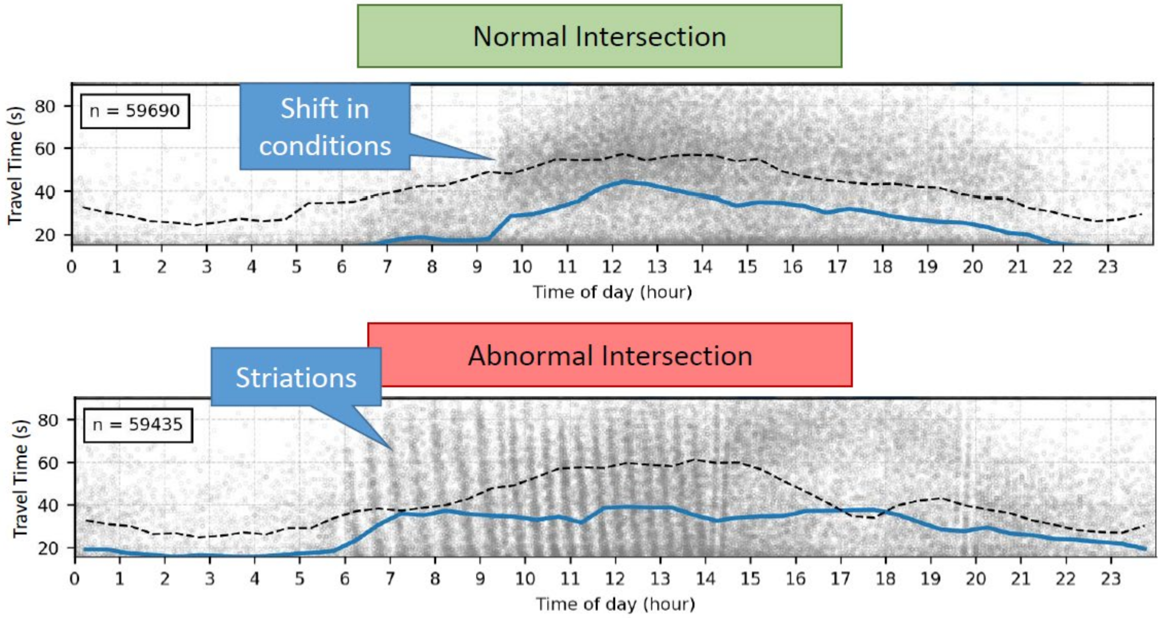


Figure 42. Normal and abnormal (caused by a malfunctioning pedestrian call button) intersections in Columbus, OH

This research holds significant potential for improved mobility, safety, and energy efficiency of traffic movements and improved signal operations with significantly lower financial and personnel resource requirements for any pretimed signal control in the nation. This methodology is now being integrated into the DOE EEMS High Performance Computing for Regional Mobility research initiative, in which a digital twin for the city of Chattanooga, Tennessee, is being created to enhance the energy efficiency of the mobility system in the region.

Recognizing the ties between safety and signal timing quality, researchers assessed the quality of signal timing (measured in percent arrivals on green) with respect to safety (measured in number of accidents). It has long been acknowledged that good signal timing enhances safety at intersections,[127,128,129] but the ability to correlate safety (number of crashes) with the quality of signal timing has been limited to longitudinal studies from a single intersection due primarily due to the inefficiency of assessing signal timing performance with any level of significant detail on a broad scale. In an initial attempt to correlate the two, data from the Columbus analysis were correlated to recorded vehicle crashes at the corresponding intersections during 2018, indexing the number of crashes to the percent arrival on green statistic. An "arrival on green" near 100% indicates a large majority of traffic progresses though the signal without having to stop, an indicator of good signal timing. This initial chart from intersection studies in Columbus is shown in Figure 43. Although this chart has not been normalized and calibrated, the overwhelming evidence as depicted by a negative slope with respect to "percent arrival on green" provides quantitative support of the link between quality signal timing and safety. This, combined with previous work directly linking safety (with respect to number and type of crashes) with energy, begins to bring a holistic analysis research and development framework to the topic of traffic signal control.

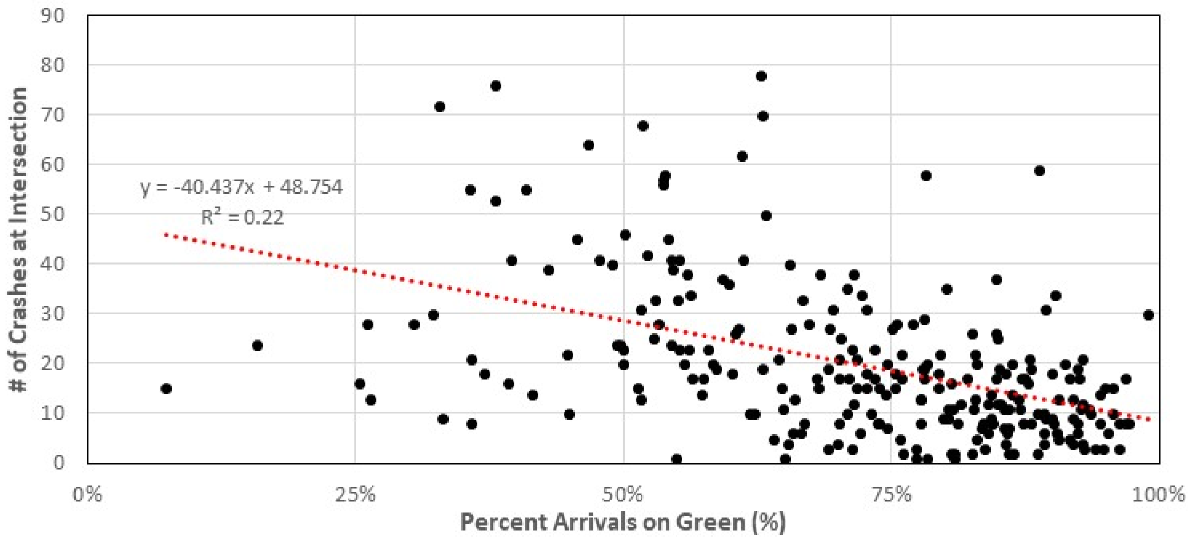


Figure 43. Safety comparison between signal performance and crashes at an intersection

The objectives of this research were to leverage existing commercially available traffic data to provide a deeper understanding of the transportation network, and to demonstrate the ability to scale signal performance assessment without the use of roadway sensors. Using performance measures and optimization techniques, the mobility, safety, and energy use of the national transportation system can be improved with no additional investment related to purchasing, installing, and maintaining permanent physical infrastructure with respect to traditional roadway sensors. Many times, optimization algorithms using new technology are compared against existing signals operations without regard to whether existing signal timing plans are up to date and well maintained, or whether existing equipment (sensors and actuators) are properly functioning. This research demonstrates a scalable method to assess signal timing performance of any fixed-time signal plans anywhere in the United States, providing a path to reduce delay and energy and increase safety at a potentially national scale.

2.4.6 Summary of Signal Control Research

The research initiatives in this theme investigated the potential reductions in delay and energy and increase in safety that can result from the heightened observability that is possible with connected vehicles, enhanced infrastructure sensing, or even industry-sourced vehicle trajectory data. Regardless of the source, knowledge of the location and velocity of vehicles is the basis for improved signal control. Furthermore, considering the relationship of safety (in the form of crash probability and frequency) to signal performance and energy is critical for gaining a holistic understanding of mobility, energy, and safety at intersections, where approximately half of all crashes occur. ***Research results in the US portfolio of signal control point toward the need for a fault-tolerant sensing framework design that utilizes all available data (CV, infrastructure, and trajectory data from fleets) for optimization across delay, energy, and, most critically, safety.***

3 Conclusions

3.1 What does this all mean?

As the preceding research has identified, mobility in urban areas is currently in a state of flux. Although all of the existing modes continue to persist, beneath the surface new capabilities have been integrated into existing modes. The omnipresence of data-enabled communication has allowed new options for travelers who are supplied with more information with which to make alternative choices than ever before. Even as car travel continues to be dominant, the ways in which people drive cars are also changing, with new powertrain choices and dynamic routing information fed to vehicle navigation systems or smartphones. Emerging practices and technologies have dramatically changed the options that people have to travel through urban areas, presenting new modes or new functionality for existing modes seemingly on a daily basis. As travelers adapt their behaviors to changing possibilities, cities and their transportation agencies struggle to adjust infrastructure and funding in support. In this regard, key insights of the work completed in Urban Science centered on the critical need to better understand the changing landscape of mobility and the ways in which people are shifting their travel behaviors, resulting in the development of the MEP metric as a lens through which to quantify mobility, to the benefit of researchers and operators at multiple levels. Additionally, Urban Science researchers identified a need for typology analysis to provide both a way to extend detailed workflow results to other regions and urban areas, as well as to better analyze the transferability of findings between different geographic areas.

Data and information not only enable travelers to make more energy-efficient choices, but also make possible system-scale transportation management in ways not previously attainable. Through networks of vehicle and infrastructure sensors communicating data observations in multiple directions, a nascent system of connected transportation is emerging. This "nervous system" network of sensing devices and communication is a necessary step toward realizing the eventual higher levels of vehicle automation. However, even before AVs become prevalent, other components and practices evolving within transportation systems stand to foster system-wide energy efficiency improvements through better traffic management, reducing congestion and improving traffic flow through dynamic management. A key insight as detailed in this document pertains to how improvements to signal control practices can result in energy savings of more than 8% with current technologies, even in advance of broad implementation of more sophisticated sensing infrastructure. A concomitant benefit is that improvements to signal control can improve safety and resultant GDP-weighted energy impacts of avoiding collisions, equivalent to about 5.6% of total U.S. energy consumption in 2010. More optimized signal control can result in positive shifts for both safety and energy outcomes.

In sum, the ongoing changes in mobility systems are affecting both travelers and the transportation infrastructure through which they move. This spectrum of change is already substantively occurring in the present and will continue to morph and develop into the future, exerting energy implications as well as effects on future transportation planning, operations, and investments. Urban Science research efforts have revealed some of the ways in which cities are adapting and have initialized or built upon nascent approaches to garner data resources toward transportation energy optimization and elevated quality of life.

3.2 What are implications for future work?

As important as innovation through technologies and practices have been on inducing or supporting change in urban travel, there are notable sociocultural shifts that offer the possibility of realizing improvements to transportation energy efficiency at scale. Changes in the perception of mobility, most notably away from the ownership model and toward an on-demand or as-needed relationship with vehicles, have the potential to completely reframe urban travel. Though private vehicle ownership is unlikely to end anytime soon, evidence of a shift is illuminated by the popularity of accessing destinations via mobility-as-a-service modes. Further, younger generations who have more economic constraints as compared to prior generations are planning their lives around reduced car dependence. Employers and municipalities are recognizing these changes, and some are adjusting strategies to accommodate for transforming sociocultural factors, as reflected in updated land-use plans and employee recruitment tactics. What has been made clear during the course of the present Urban Science research work is that people are presented with a wider range of mobility options than have been available at any point during the past several decades. Much of this change has been driven by a combination of technological advances, private capital investment, and transportation operators and governmental entities who constantly attempt to adapt to the latest developments.

Underscoring all of this is the need to continue to track technological advancements while observing how these advancements are being applied in real-world settings. Urban areas have been the focus in much of the work described in this document, though an informed view into factors and concerns emergent in transportation suggests continued evolution of the systems that move people and goods to services and destinations. Central to this is a need to better understand implications of emergent mobility practices across geographic and sociodemographic boundaries, bridging urban, exurban, and rural communities. Moving forward, it is paramount to form a more holistic picture of energy use for transportation and mobility to include all segments of the population and the places in which they live. With further development of the MEP metric, and with approaches designed to observe and receive information across geographic and sociodemographic boundaries, researchers, transportation operators, and others—including planners, developers, realtors, and individuals—can be better informed of the energy implications of the choices they make: how to grow and invest, where to live, where to work, and how to get to the places they need to go.

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